Neural Computing and Applications (2021) 33:4343–4371
https://doi.org/10.1007/s00521-020-05239-1

ORIGINAL ARTICLE

Find optimal capacity and location of distributed generation units in radial distribution networks by using enhanced coyote optimization algorithm

Thai Dinh Pham[1] · Thang Trung Nguyen[2] · Bach Hoang Dinh[2]

Received: 18 November 2019 / Accepted: 24 July 2020 / Published online: 6 August 2020

Abstract

This paper proposes a novel effective optimization algorithm called enhanced coyote optimization algorithm (ECOA). This proposed method is applied to optimally select the position and capacity of distributed generators (DGs) in radial distribution networks. It is a multi-objective optimization problem where properly installing DGs should simultaneously reduce the power loss, operating costs as well as improve voltage stability. Based on the original coyote optimization algorithm (COA), ECOA is developed to be able to expand the search area and retain a good solution group in each generation. It includes two modifications to improve the efficiency of the original COA approach where the first one is replacing the central solution by the best current solution in the first new solution generation technique and the second focuses on reducing the computation burden and process time in the second new solution generation step. In this research, various experiments have been implemented by applying ECOA, COA as well as salp swarm algorithm (SSA), Sunflower optimization (SOA) for three IEEE radial distribution power networks with 33, 69 and 85 buses. Obtained results have been statistically analyzed to investigate the appropriate control parameters and to verify the performance of the proposed ECOA method. In addition, the performance of ECOA is also compared to various similar meta-heuristic methods such as genetic algorithm (GA), particle swarm optimization (PSO), hybrid genetic algorithm and particle swarm optimization (HGA-PSO), simulated annealing, bacterial foraging optimization algorithm, backtracking search optimization algorithm, harmony search algorithm, whale optimization algorithm (WOA) and combined power loss index-whale optimization algorithm (PLI-WOA). Detailed comparisons show that ECOA can determine more effective location and size of DGs with faster speed than other methods. Specifically, the improvement levels of the proposed method over compared to SFO, SSA, and COA can be up to 2.1978%, 0.7858% and 0.2348%. Furthermore, as compared to other existing methods in references, ECOA achieves the significant improvements which are up to 31.7491%, 20.2143% and 22.7213% for the three test systems, respectively. Thus, the proposed method is a favorable method in solving the optimal determination of DGs in radial distribution networks.

Keywords Coyote optimization algorithm · Distributed generation · Real power loss · Operation cost

List of symbols

$AP_{Dg,k}$	Active power of the *k*th DG
AP_{Gr}	Active power which is supplied from grid through substation

✉ Thang Trung Nguyen
nguyentrungthang@tdtu.edu.vn

Thai Dinh Pham
phamdinhthai@duytan.edu.vn

Bach Hoang Dinh
dinhhoangbach@tdtu.edu.vn

[1] Institute of Research and Development, Duy Tan University, Danang 550000, Vietnam

[2] Power System Optimization Research Group, Faculty of Electrical and Electronics Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam

AP_k^{min}, AP_k^{max}	The lower and upper bounds of the capacity of the kth DG
$AP_{Lo,l}$	Active power at the lth load
$AP_{Dg}^{min}, AP_{Dg}^{max}$	The lower and upper bounds of capacity of DG
CV_k^{min}, CV_k^{max}	The lowest and highest values of the kth control variable
$\Delta I_{b,q,p}$	The penalty for current violation of the bth line corresponding to the qth solution in the pth pack
$\Delta V_{j,q,p}$	The penalty for current violation of the jth bus corresponding to the qth solution in the pth pack
$\varepsilon_i, \varepsilon_v$	Penalty factors of current and voltage in fitness function
F_A	Objective function of total power loss
F_B	Objective function of voltage deviation index
F_C	Objective function of total operation cost
$FF_{q,p}, FF_{q,p}^{new}$	Fitness function of the qth old and new solution in the pth pack
F_{OF}	Multi-objective function
F_i	The food source position of the ith dimension corresponding to the salp position
I_b	Current magnitude in the bth branch without DGs
I_b^{max}	Maximum limitation of the current magnitude in the bth branch
$I_{b,q,p}$	The current magnitude in the bth line of the qth solution in the pth pack
$I_{Dg,b}$	Current magnitude in the bth branch with DGs
It	Current iteration
It^{Max}	Maximum iteration
N_{Br}	Number of branches in the distribution network
N_{Bu}	Number of buses in the distribution network
N_c	Number of coyotes in each pack
N_{Dg}	Number of DGs in the integrated distribution network
N_{Lo}	Number of all loads
N_p	Number of packs
N_{ps}	Population size
N_c	Number of coyotes in each pack
O_{cv}	The number of control variables
$OF_{q,p}$	Objective function of the qth solution in the pth pack
$\omega_A, \omega_B, \omega_C$	The coefficients of the multi-objective function
$Pos_{Dg,k}$	The position of the kth DG
Pos_k^{min}, Pos_k^{max}	The lower and upper bounds of the position of the kth DG
P	The number of individuals in the sunflower population
r, r_2, r_3	Random numbers in range from 0 to 1
R_b	Resistance of the bth branch
$S_{best,p}, S_{worst,p}$	The best solution and the worst solution in the pth pack
$S_{best,rd1}, S_{best,rd2}, S_{best,rd3}, S_{best,rd4}$	The best solutions picked up randomly from different packs
$S_{cent,p}$	The center solution in the pth *pack*
S_{g_best}	The best solution in the population
$S_{q,p}, S_{q,p}^{new}$	The current and new solution of the qth coyote in the pth pack
$S_{rd1,p}, S_{rd2,p}, S_{rd3,p}, S_{rd4,p}$	The randomly picked up solutions from the pth pack
S_i^1	The leader salp position corresponding to the ith dimension
S_i^k	The position of the kth salp corresponding to the ith dimension
TAPL	Total active power loss of the network without any DG
$TAPL_{Dg}$	Total active power loss of the network with DGs
ub_i, lb_i	The upper bound and lower bound of the ith dimension in determining the salp position
V_j	Voltage at the jth bus
V_j^{max}, V_j^{min}	Lower and upper limitations of bus voltage magnitude
$V_{j,q,p}$	The voltage magnitude at the jth bus of the qth solution in the pth pack
X_i, X^*	The ith current position and the best position of the current sunflower population

Abbreviations

ABC	Artificial bee colony algorithm
BB-BC	Big bang-big crunch
BFOA	Bacterial foraging optimization algorithm
BSOA	Backtracking search optimization algorithm
COA	Coyote optimization algorithm
DG	Distributed generation unit
DGs	Distributed generation units
GA	Genetic algorithm
GA/PSO	Hybrid genetic algorithm and particle swarm optimization
HAS	Harmony search algorithm
PSO	Particle swarm optimization
PLI-WOA	Combined power loss index-whale optimization algorithm

Pu	Per unit
SA	Simulated annealing
SFO	Sunflower optimization
SSA	Salp swarm algorithm
WOA	Whale optimization algorithm
TAPL	Total active power losses
TOC	Total operation cost
VDI	Voltage deviation index

1 Introduction

In recent years, the penetration of DGs in distribution networks has increased dramatically. A distributed generation unit can be defined as an electrical source which is integrated in electrical distribution networks [1] where their benefits are highly depended on the installation position and sizing of DGs [2–5]. The proper installation of DGs in a distributed system can effectively support the system performance improvement such as the voltage profile, reliability, stability and power quality [6]. However, if placing and sizing of DGs are not determined appropriately, some negative problems could affect on the distribution networks such as voltage flicker, voltage sags as well as raising fault currents, increasing the harmonic distortion and power loss [7, 8]. Therefore, determining the suitable place and size of DGs in the distribution system is an important role in planning and operating the distribution networks [9]. In this research trend, there have been many publications focusing on the objectives of reducing power loss and improving voltage by optimization methods. For example, GA [10] was applied to determine the position and capacity of DGs in distribution networks where the proposed approach has searched the optimal solution for installing a single DG in the 33-bus and 69-bus IEEE distribution networks. The report results have discussed the operation performances of the distribution systems before and after installing a single DG in terms of voltage fluctuation improvement and power loss reduction where the performance of the system with the suitably installed DG has been better than that of the system without any DG. Besides, to investigate in more general cases, in [11] the authors used the same method and objective function as proposed in [10] for a higher number of DGs in the distribution networks. The obtained results show that there are definitely relationships between the number of installed DGs and the improvements in network's operation. According to [11], the benefit of installing two DGs is better than that of installing one DG and three DGs is better than two DGs. However, the proposed GA method cannot guarantee optimum and the quality of optimal solutions also significantly deteriorates by the problem's size. To improve the convergence of DG's optimization problem, a famous method called PSO was also considered in [12, 13] where the proposed approach is applied to find the most suitable position and capacity of DGs for satisfying the bi-objective function of power loss and voltage deviation. In these studies, the installation location of a single DG is investigated throughout various places of the distribution network with a range of power capacities, so that it could achieve as small active power loss and voltage fluctuation as possible. Although PSO is a good method; however, it also has a disadvantage as possibly trapped into a local optimum point. To avoid the disadvantages and take advantages of both GA and PSO, a hybrid method named GA/PSO has also been created in [14]. It includes two implementing stages at each iteration where GA was applied in the first stage for determining the best siting of DGs and the second stage was based on PSO to find the best rated power for DGs and then both the position and the rated power have been evaluated to determine the best solution among the current solution set. Thus, the proposed method is more complicated than GA and PSO as well as takes more processing time. Simulations with three methods: GA/PSO, GA and PSO in two distribution networks have been implemented to evaluate the improvement aspects, such as the voltage profile, voltage stability index and reducing losses when installing three DGs. The compared results show that the hybrid GA/PSO method can find more promising solutions than GA and PSO alone.

Besides the popular methods, such as GA and PSO, another positive method called SA has been created to solve the optimal place and size of DGs [8, 15]. These studies have demonstrated that power loss reduction and voltage profile depend closely on the allocation, sizes and number of DGs in distribution networks. From obtained results, the applied method has stated that SA is one of the best techniques in the field of optimization. Similarly, the authors in [16, 17] applied ABC and the authors in [18] used a method named BB-BC for the main purpose of reducing energy loss and improving voltage profile through finding the optimal DGs in a distribution system. The work in [17] analyzed the related impact indices with different load models such as constant, industrial, residential, commercial and mixed loads. The results showed that the optimal position of DGs was almost unchanged and the power capacity of DGs seems to be not significant differences for various load models. In the other hand, the load schedule in 24 hours has been studied in [18] to find the optimal solution corresponding to three load models: residential, commercial and industrial loads. Results from the proposed method are also compared with other published results. Both ABC and BB-BC are considered strong methods in solving optimal problems. However, there is one drawback that the algorithms need the high number of implementing steps in evaluating the fitness function of solutions. As a result, their processing time is quite slow. In the same research area, another modern optimization technique based on the combination of neural network learning ability and PSO [19] was also proposed to minimize the power loss and improve the voltage profile. The proposed method has overcome the difficulty in training process to determine the potential location of DGs in the distribution network. Similarly, a method called BSOA [20] have been suggested for optimal location and sizing of DGs. The authors have made a positive contribution in conducting research with various DG types, such as pure active power, pure reactive power and active/reactive combined power. The results showed that the optimal solution has depended not only on the location and capacity but also on the type of DGs. Besides, in [21] a new approach used HSA for minimizing power loss and enhancing voltage profile by suitably selecting DGs and system reconfiguration. This study has investigated the optimal selection of DGs corresponding to various load levels such as light load (0.6 pu), normal load (1.0 pu) and heavy load (1.6 pu) where the expected solution is to find one the same optimal location plan for all three load levels but different capacity values of DGs at each load level. That paper has also indicated that the combination of optimal DG installation and system reconstruction could make better benefits for the distribution networks. Moreover, to satisfy many problem aspects BFOA [22] have been proposed for solving the optimization issues that have more than two objective functions. In that study, the multi-objective function includes power loss reduction, voltage stability enhancement and operating cost minimization. This research has shown that determining the suitable position and sizing of DGs could significantly contribute to reduce the operation cost. Thus, the optimal selection of DGs in the distribution networks can entirely obtain both economic and technical benefits.

Generally, most previous researches have exclusively applied methods that were already available to solve the optimization problem and thus, the obtained optimal solutions would be not highly effective. Consequently, new enhancements of existing methods could be a positive trend to improve the performance of original meta-heuristic algorithms. Considering many aspects in operation of distribution networks is also a key task for the problems of optimal location and sizing of DGs. Thus, this paper proposed a new method called enhanced coyote optimization Algorithm (ECOA) to solve a multi-objective problem. In operation distribution systems, energy losses depended on the specific characteristics of the structural network as well as power sources, and thus, energy loss minimization is a challenge and vital issue. Therefore, in this study, energy loss reduction is considered to be a part of the multi-objective function. In the other hand, voltage stability is significantly affected by the position and size of installed DGs [23, 24] and voltage index is an important factor to evaluate the stability of the distribution system [25]. Thus, the voltage stability index can be a useful factor in the multi-objective function of our research. Moreover, in the economical view, the installation plan of DGs in the distribution system should be considered as an affecting factor on the operating cost of DGs [2]. In this research, the operating cost is considered as a part of the multi-objective function and it is divided into two components, the cost of active power supplied by substations (from the power system) and the cost for active power supplied by all DGs. In summary, the purpose of this paper's problem is to determine the optimal location and size of DGs, so that it minimizes the multi-objective function including power loss reduction, voltage deviation index enhancement and operational cost minimization under consideration of all constraints of the distribution networks and DGs.

Enhanced coyote optimization algorithm (ECOA) is a meta-heuristic algorithm which is developed from the original coyote optimization (COA) which is inspired by the natural behaviors of coyotes published in 2018 [26]. The social condition and its quality are the two main factors making up this optimization algorithm. With each coyote, its social condition represents an optimal solution; meanwhile, the quality of its social condition represents the fitness of the solution. The coyote community is divided into N_G small coyote groups (or packs) with N_C coyotes in each group. The working mechanism of COA method is implemented by two techniques for producing new solutions, two techniques for comparing and keeping higher quality solutions, and one technique for exchanging solutions between different groups. In the first technique producing new solutions, each group of coyotes produces N_C solutions, and thus, total ($N_C \times N_G$) new solutions are created in this step. In contrast, the second technique producing new solutions only produces a sole solution for each group and N_G new solutions for the whole community of coyotes. Clearly, the first one stronglier affects on the effectiveness of COA because the quality of solutions at each iteration is mainly influenced by the first one rather than the second. However, the first generation is performed around the central solution, which does not have much potential to create good solutions. Thus, this point would reduce the quality of solutions of the next generation and cause the low performance at the first new solution generation. In addition, the second new solution generation has some disadvantages in proposing a global solution and it could limit the ability to search out better new solutions at different areas. In order to overcome that problem, we propose two modifications to improve the efficiency of

COA approach where the first one is to replace the central solution by the best current solution and the second focuses on enhancing the performance of the second new solution generation. The proposed modifications would increase the opportunity to explore better solutions and improve the quality of solutions at each iteration.

To verify the effectiveness of ECOA, we have applied the proposed approach for the optimal determination of DG's location and size for the radial distribution networks. In this kind of network, branches are radiated from the substation. Hence, power flow in this network is characterized as one direction. This network has simpler topology and lower initial investment cost than other networks such as parallel feeder distribution, ring main distribution and interconnected distribution networks. However, the biggest drawback of this network is the low reliability in the power supply. In other words, if a branch in this network fails, the supply to the concerned customer will be affected due to no alternative sources providing electricity to the distributors. In addition, the power supply for the whole network is from the substation at the upstream, the voltages of the last feeders will have large voltage drop and power losses in the transmission line. Thus, the study to integrate DGs on this network is necessary. This study considered the networks of 33-bus, 69-bus and 85-bus IEEE radial distribution networks and also retried three other heuristic algorithms consisting of COA [26], SSA [27] and SFO [28] for the comparison purpose. In addition, to ensure the general evaluation, the results of the proposed method are also compared with those of similar methods as GA [14], PSO [14], GA/PSO [14], SA [15], BFOA [22], BSOA [20] and HSA [21] with the same target. In general, previous solutions have a common drawback that is easy to fall into the local search areas. Specifically, like GA algorithm, crossover and mutation process in the functions are randomly generated [10]. This has a negative impact on the performance and the convergence speed of that algorithm [14]. Not only GA, but another common algorithm, PSO, also has the same problem. With small search spaces, PSO's solutions easily fall into the local convergence zone [12, 14]. Therefore, PSO is commonly used to optimize problems with a small search area. According to the development of mathematics, in order to improve the efficiency in solving complex optimization problems, many other algorithms have been developed such as SA, SSA, BFOA and BSOA. However, different algorithms have different disadvantages. While SA requires a large amount of computation time [15], BSOA, BFOA and SSA have slow convergence and often stuck in local optimal areas [20, 22, 27]. That has spurred research to develop a comprehensive method for solving all the optimal problems, and COA was born. COA is inspired by coyote behaviors, and it has been shown to outperform compared methods such as GA, PSO, SA, SSA, BSOA and BFOA in terms of computing process as well as performance [26]. However, the performance of COA is not high for all cases of optimal problems. In other words, COA only performs well in certain optimal issues. To overcome this, ECOA has improved the new solution generation process by replacing the central solution with the best current solution at the first phase. This has greatly improved the performance of this algorithm. Besides, because the calculation process to select the central solution has been eliminated, this can reduce computation time for each loop. This shows that the calculation speed of ECOA is better than COA. In addition, at the second phase of generating solution in COA, a random selection in upper and lower limits is not an optimal choice for optimal problems. Therefore, ECOA has used two conditions of comparison for choosing to produce a new solution. This has reduced the number of calculation steps and calculation time due to the random selection step elimination. The result of this improvement has contributed to enhance the performance of the algorithm and avoid being trapped in the local search areas. Not only that, COA is known as a method with few control parameters. Thus, ECOA will inherit that advantage of COA. After performing simulations on some systems with different scales, the obtained results have proved that the ECOA is an effective approach for the optimal determination of DG's location and size for distribution networks. After solving three networks with 33, 69 and 85 buses, ECOA has found the best fitness values of 0.2581, 0.2260 and 0.3398, respectively. These values are lower than those from other compared methods, whose fitness is from 0.2583 to 0.3419 for the network with 33 buses, from 0.2264 to 0.2837 for the network with 69 buses and from 0.3406 to 0.3449 for the network with 85 buses. Accordingly, the level of improvement of the proposed method over these compared ones is from 0.0774 to 31.7491% for the network with 33 buses, from 0.1723 to 20.2143% for the network with 69 buses and from 0.2348 to 1.4787% for the network with 85 buses. This has shown that the performance of ECOA is more outstanding in solving the considered optimization problem. To make an objective comparison, 50 trial runs are performed for the implemented methods in three networks. The results have proved that ECOA had more times finding the best solution as compared to others with the second lowest population number, except BSOA of the 33-bus network. Besides, the number of fitness function evaluations that ECOA and COA have used is 1250, 1500 and 2000, while the highest values of the remain methods were 5000, 5000 and 2400 for 33 buses, 69 buses and 85 buses networks, respectively. This numbers have indicated that memory saving and data storage during the calculation process of both ECOA and COA are better than others due to the lower number of solutions proposed for evaluation.

Although ECOA and COA have had relatively good data processing speed compared to implemented methods, due to the improvement in eliminating the random solution generation phase, ECOA has better data processing speed than COA. Therefore, we can conclude the main contributions of this study as follows:

1. Find high-quality solutions for the considered problem: Approximately all solutions of the proposed method have better quality than those of other compared methods. The best fitness of the proposed method is more effective.
2. Reduce complexity, computation steps and simulation time: The proposed ECOA method can overcome the disadvantages of original COA such as slow convergence to high-quality solutions, using many computation steps, depending on randomization highly and taking high computation time. Moreover, ECOA uses smaller number of fitness evaluations than other compared meta-heuristics methods.
3. Indicate the importance of integrating DGs in the power distribution networks: The obtained results of this study show that properly installing the DGs can mitigate the power losses, improve the voltage stability and minimize the operational cost while satisfying all considered constraints of the network's structure as well as DGs.

The remaining parts of this paper include 5 sections as follows: the objective functions and the constraints are shown in Sect. 2, called the problem formulation. The analysis and improvement of ECOA as well as SSA, SFO and COA are presented in detail in Sect. 3, the implemented algorithms. Application process of the proposed method in solving optimal problems when integrating DG in the system is described in Sect. 4, called enhanced coyote optimization algorithm for DGs. In Sect. 5, three systems with 33 buses, 69 buses and 85 buses are used to evaluate the effectiveness of all implemented methods and the obtained results are analyzed in this section, called simulation results and discussion. Finally, Sect. 6 summarizes and concludes the whole work in the paper, called conclusions.

2 Problem formulation

For the optimization problem of the distribution networks integrated DGs, the economic benefits and technical satisfaction depend on the position and sizing of DGs [29]. In this paper, the considered problem is built as a multi-objective function. Thus, numerical method is proposed for minimizing the value of this function in various tasks. The computation for an equilibrium between economic and technical benefits in an exchange model is reformulated as a minimization problem, and this problem is presented by the objective functions and constraints. The proposed solution with the smallest value of function would be the best solution for achieving this equilibrium. The following items present the multi-objective function as well as the constraints of the distribution system applied for the proposed method to optimize the contribution of DGs.

2.1 Objective function

In this study, the multi-objective function, which needs to be minimized, includes TAPL, VDI and TOC. Each component of the multi-objective function can be shown in detail as follows:

2.1.1 TAPL objective function

Reducing total active power losses is considered as an important objective in operation to improve the reliability, the power quality and the operational cost of distribution systems. This aim is established by solving the numerical formula as follows [30]:

$$\text{Minimize} \quad F_A = \frac{\text{TAPL}_{\text{Dg}}}{\text{TAPL}} = \frac{\sum_{b=1}^{N_{\text{Br}}} I_{\text{Dg},b}^2 R_b}{\sum_{b=1}^{N_{Br}} I_b^2 R_b} \tag{1}$$

Here, $I_{\text{Dg},b}$ and I_b are the current of the bth branch for the case with and without DGs; R_b is the resistance of the bth branch. This formula indicates a comparison between total power losses when connecting DGs to the distribution system and that of the original system (no connecting any DGs). Therefore, the variation of F_A will be less than 1 if the installation of DGs is effective.

2.1.2 VDI objective

One of the factors that evaluates the power quality of the distribution system is the voltage stability. This is represented by VDI and the objective function is presented as the mathematical equation below [31].

$$\text{Minimize} \quad F_B = \max\left[\left(\left|V_{\text{ref}} - V_j\right| / V_{ref}\right); j = 1, \ldots, N_{\text{Bu}}\right] \tag{2}$$

where the V_{ref} value is assigned to 1.0 pu. The smaller the F_B value is, the better the voltage stability of the systems.

2.1.3 TOC objective function

When connecting DGs to a specific distribution network, its operational cost can be divided into two components: the first one is the cost of energy taken from the main grid through the substation, and the second is the energy cost of

DGs. Therefore, to reduce *TOC*, both of such components should be decreased as much as possible. The mathematical equation for total cost of operation is defined as follows [22]:

$$\mathrm{TOC} = (\alpha \times \mathrm{TAPL}_{\mathrm{Dg}}) + \left(\beta \times \sum_{k=1}^{N_{\mathrm{Dg}}} \mathrm{AP}_{\mathrm{Dg},k}\right) \tag{3}$$

where α and β are the cost coefficients of power supplied from substation and DGs (\$/kW), respectively. In this paper, the total operational cost is related to the two main components including the cost of energy from the substation and the energy generated by the single DG. The cost coefficients for two their components in Eq. (3) are respectively α and β that their values are selected as 4.0 \$/kW and 5.0 \$/kW [22].

To minimize the total operating cost, a mathematical equation for this objective function is shown by:

$$\text{Minimize} \quad F_C = \frac{\mathrm{TCO}}{\beta \times \sum_{l=1}^{N_{\mathrm{Lo}}} \mathrm{AP}_{\mathrm{Lo},l}} \tag{4}$$

Finally, the multi-objective function is presented in a mathematical form below:

$$\text{Minimize} \quad F_{OF} = (\omega_A \times F_A) + (\omega_B \times F_B) + (\omega_C \times F_C) \tag{5}$$

where ω_A, ω_B and ω_C are the objective weights satisfying the condition of $\omega_A + \omega_B + \omega_C = 1$ and can be chosen within the range of [0, 1] [32].

2.2 Constraints

2.2.1 Active power balance constraint

Before installing DGs in distribution systems, the demand of all loads is responded by the power supplied at slack bus. However, the power of grid supplying to slack bus becomes smaller after installing DGs. In addition, power losses caused by the resistance of conductors are also supplied by grid or DGs. So, the constraint is the balance between consumption side and supply side. Here, the consumption side is the sum of active power of all loads and active power losses in all branches and the supply side is the sum of active power generated at slack bus and active power of all DGs. The constraint can be shown by [18]:

$$\sum_{l=1}^{N_{\mathrm{Lo}}} \mathrm{AP}_{\mathrm{Lo},l} + \mathrm{TAPL}_{\mathrm{Dg}} - \sum_{k=1}^{N_{\mathrm{Dg}}} \mathrm{AP}_{\mathrm{Dg},k} - \mathrm{AP}_{\mathrm{Gr}} = 0 \tag{6}$$

2.2.2 Bus voltage limits

When DGs are connected to the power distribution system, the voltage value at each bus will be changed dramatically. Thus, all bus voltages are considered at the fundamental frequency and should be kept within the limit as follows [33, 34]:

$$V_j^{\min} \le V_j \le V_j^{\max}, \quad j = 1, \ldots, N_{Bu} \tag{7}$$

For keeping the best voltage stability, the lower bound and the upper bound of bus voltage in low and medium voltage–power distribution networks are selected to be 0.95 pu and 1.05 pu, respectively.

2.2.3 Branch current limits

The penetration of DGs can change the power flow, and thus it could make increasing the current in some branches. Therefore, the branch currents must be limited as the inequality equation below [35]:

$$|I_b| \le I_b^{\max} \tag{8}$$

2.2.4 DG's capacity and placement limits

The penetration level of each DG in the distribution system should be considered within a certain limit. Besides, the total capacity of DGs must not exceed the load demand of the distribution system. The DGs' capacity is described by the inequalities [36]:

$$\mathrm{AP}_{\mathrm{Dg}}^{\min} \le \mathrm{AP}_{\mathrm{Dg},k} \le \mathrm{AP}_{\mathrm{Dg}}^{\max} \tag{9}$$

$$0.1 \times \sum_{l=1}^{N_{\mathrm{Lo}}} \mathrm{AP}_{\mathrm{Lo},l} \le \sum_{k=1}^{N_{\mathrm{Dg}}} \mathrm{AP}_{\mathrm{Dg},k} \le 0.8 \times \sum_{l=1}^{N_{\mathrm{Lo}}} \mathrm{AP}_{\mathrm{Lo},l} \tag{10}$$

In radial distribution network, Bus 1 is always slack bus. Therefore, the location of DGs cannot be Bus 1 and follows the inequality below [35]:

$$2 \le \mathrm{Pos}_{\mathrm{Dg},k} \le N_{\mathrm{Bu}} \tag{11}$$

3 The implemented algorithms

3.1 Salp swarm algorithm

Salp swarm algorithm (SSA) was published in 2017 [27], and it was developed based on navigating and foraging behavior of salp chain in deep oceans. In SSA, the population of salp chain is divided into two groups: leader and followers. The location of salp chain is predefined in the n-dimensional search space where n is the variable number of the problem and initial population of salp chain is randomly generated in the search space of variables. Leader in front of the chain has the task of determining food source that has good quality for followers to follow each other. In other words, each salp is evaluated based on the food source quality as the swarm's target and the best position of the food source is assigned to the position of the leader. The updated equation for the leader position is shown as follows:

$$S_i^1 = \begin{cases} F_i + r_1 \times ((\mathrm{ub}_i - \mathrm{lb}_i) \times r_2 + \mathrm{lb}_i), & r_3 \geq 0 \\ F_i - r_1 \times ((\mathrm{ub}_i - \mathrm{lb}_i) \times r_2 + \mathrm{lb}_i), & r_3 < 0 \end{cases} \quad (12)$$

Here, r_1 is the coefficient providing a balance between exploration and extraction capabilities. Its value equals $2e^{-\left(\frac{4\mathrm{It}}{\mathrm{ItMax}}\right)^2}$.

The position of followers should follow the leader's instructions and updated equation for their positions as follows:

$$S_i^k = \frac{1}{2} \times \left(S_i^k - S_i^{k-1}\right), \quad i \geq 2 \quad (13)$$

In the process of finding the best food source (the best solution), the position of the leader and the followers in salp chain is checked and maintained by using boundary conditions.

3.2 Sunflower optimization algorithm

Sunflower optimization algorithm (SFO) is inspired from the motion of sunflowers toward the sun to catch the radiation. This behavior of sunflowers aims to determine the best location for receiving radiation, and this cycle is repeated every morning. Sunflower near the sun tends to be calmer in this area because of the great heat received from the sun. Conversely, sunflowers that receive less heat due to being far from the sun tend to move to the position closest to the sun [28]. Each sunflower (individual) adjusts position toward the sun (the best location) as follows:

$$\vec{s}_i = \frac{X^* - X_i}{||X^* - X_i||}, \quad i = 1, 2, 3, \ldots, p \quad (14)$$

Realistically, each sunflower ith tends to do pollination with another flower. This creates a new sunflower with an updated position. For the flowers far from the sun, they aspire to take more steps for moving closer to the sun and vice versa. The movement is different for each individual because it depends on the distance from each individual's current position to the sun. This phenomenon creates an improvement in finding the optimal position in the sunflower population.

The movement and the position update for each individual toward the best individual are presented as Eqs. (15) and (16), respectively:

$$d_i = \lambda \times P_i(||X_i + X_{i-1}||) \times ||X_i + X_{i-1}||, \quad (15)$$

$$\vec{X}_{i+1} = \vec{X}_i + d_i \times \vec{s}_i \quad (16)$$

where λ is considered as an inertial displacement of the population and $P_i(||X_i + X_{i-1}||)$ is defined as the pollination probability of the ith individual.

To ensure that all individuals are not out of the search space, the forward steps are checked and imposed on a restriction accordingly.

3.3 Original coyote optimization algorithm

In COA, the number of packs (N_p) and the number of coyotes in each pack (N_c) are two components of the coyote population. The population size of the coyote community is N_p x N_c, and the initial population is carried out by the following mathematical equation:

$$S_{q,p} = S^{\min} + r.(S^{\max} - S^{\min}); \quad q = 1, \ldots, N_c \quad \& \quad p = 1, \ldots, N_p \quad (17)$$

where $S^{\min}$ and $S^{\max}$ are lower bound and upper bound of control variable set and determined by:

$$S^{\min} = [CV_k^{\min}]; k = 1, \ldots, N_{cv} \quad (18)$$

$$S^{\max} = [CV_k^{\max}]; k = 1, \ldots, N_{cv} \quad (19)$$

After initialized by Eq. (17) with the bound of the control variables, the quality of each solution will be evaluated based on the fitness function ($\mathrm{FF}_{q,p}$) and the best solution will be determined by the lowest fitness value.

In COA method, the central solutions ($S_{\mathrm{cent},p}$) are determined for each pack and it is an important part to produce newly generated solutions. The value of the central solution is depended on the number of coyotes. There are two coefficients to determine the specific cases which are set as (N_c + 1)/2 and N_c/2 for the odd and even numbers of coyotes, respectively. After selecting the suitable central solution, the new generated solutions are established by the mathematical equation below:

$$S_{q,p}^{\mathrm{new}} = S_{q,p} + r.(S_{\mathrm{best},p} - S_{rd1,p}) + r \cdot (S_{\mathrm{cent},p} - S_{rd2,p}); \quad q = 1, \ldots, Nc \quad \& \quad p = 1, \ldots, Np \quad (20)$$

Once a new solution is created, the control variables $\mathrm{CV}_{k,q,p}^{\mathrm{new}}$ of that such solution must be checked and modified by its predetermined limitations as follows:

$$\mathrm{CV}_{k,q,p}^{\mathrm{new}}=\begin{cases}\mathrm{CV}_k^{\min} & \text{if } CV_{k,q,p}^{new}<CV_k^{\min}\\ \mathrm{CV}_k^{\max} & \text{if } CV_{k,q,p}^{new}>CV_k^{\max};k=1,\ldots,N_{cv},q=1,\ldots,N_c;\quad p=1,\ldots,N_p\\ \mathrm{CV}_{k,q,p}^{\mathrm{new}} & \text{else}\end{cases} \tag{21}$$

Then, the quality of each new solution is also evaluated according to its objective function. The good-quality solutions will be retained, and the poor ones will be discarded like the principle of all algorithms based on the natural selection. This assessment will be subject to the mathematical rules below:

$$S_{q,p}=\begin{cases}S_{q,p}^{\mathrm{new}} & \text{if } \mathrm{FF}_{q,p}^{\mathrm{new}}<FF_{q,p}\\ S_{q,p} & \text{else}\end{cases} \tag{22}$$

$$\mathrm{FF}_{q,p}=\begin{cases}FF_{q,p}^{\mathrm{new}} & \text{if } \mathrm{FF}_{q,p}^{\mathrm{new}}<FF_{q,p}\\ FF_{q,p} & \text{else}\end{cases} \tag{23}$$

In the second generation, each pack will generate one new solution named S_p^{new} and the new solution is a set of control variables $\mathrm{CV}_{k,p}^{\mathrm{new}}$, which is formed based on the following randomizations:

$$\mathrm{CV}_{k,p}^{\mathrm{new}}=\begin{cases}\mathrm{CV}_{k,r1,p} & \text{if } r<P_1\\ \mathrm{CV}_{k,r2,p} & \text{if } r<P_1+P_2\\ \mathrm{CV}_{k,rd} & \text{otherwise}\end{cases} \tag{24}$$

Here, $\mathrm{CV}_{k,r1,p}$ and $\mathrm{CV}_{k,r2,p}$ are the control variables randomly chosen from the first solution and the second solution in the pth pack; $\mathrm{CV}_{k,rd}$ is the kth control variable which is randomly generated in the range of $\left[\mathrm{CV}_k^{\min},\mathrm{CV}_k^{\max}\right]$; and P_1 and P_2 are the scatter and association probabilities, respectively, and described by:

$$P_1=\frac{1}{N_{\mathrm{cv}}} \tag{25}$$

$$P_2=\frac{1-P_1}{2} \tag{26}$$

Then, the quality of the new solution is compared to that of the worst solution in the current pack. If the quality of the new solution is better, the worst solution will be replaced by that such new one.

Before terminating the current iteration and moving to the next iteration, to escape from the possible local optimum traps, COA allows two randomly selected solutions in two random packs swapped each other if the following condition is satisfied:

$$r<0.005\times N_c^2 \tag{27}$$

This swapping ability highly depends on the number of coyotes in each pack. The greater number of coyotes is, the higher swapping probability obtains.

The implementation process of COA algorithm for a typical optimization problem can be described as Fig. 1.

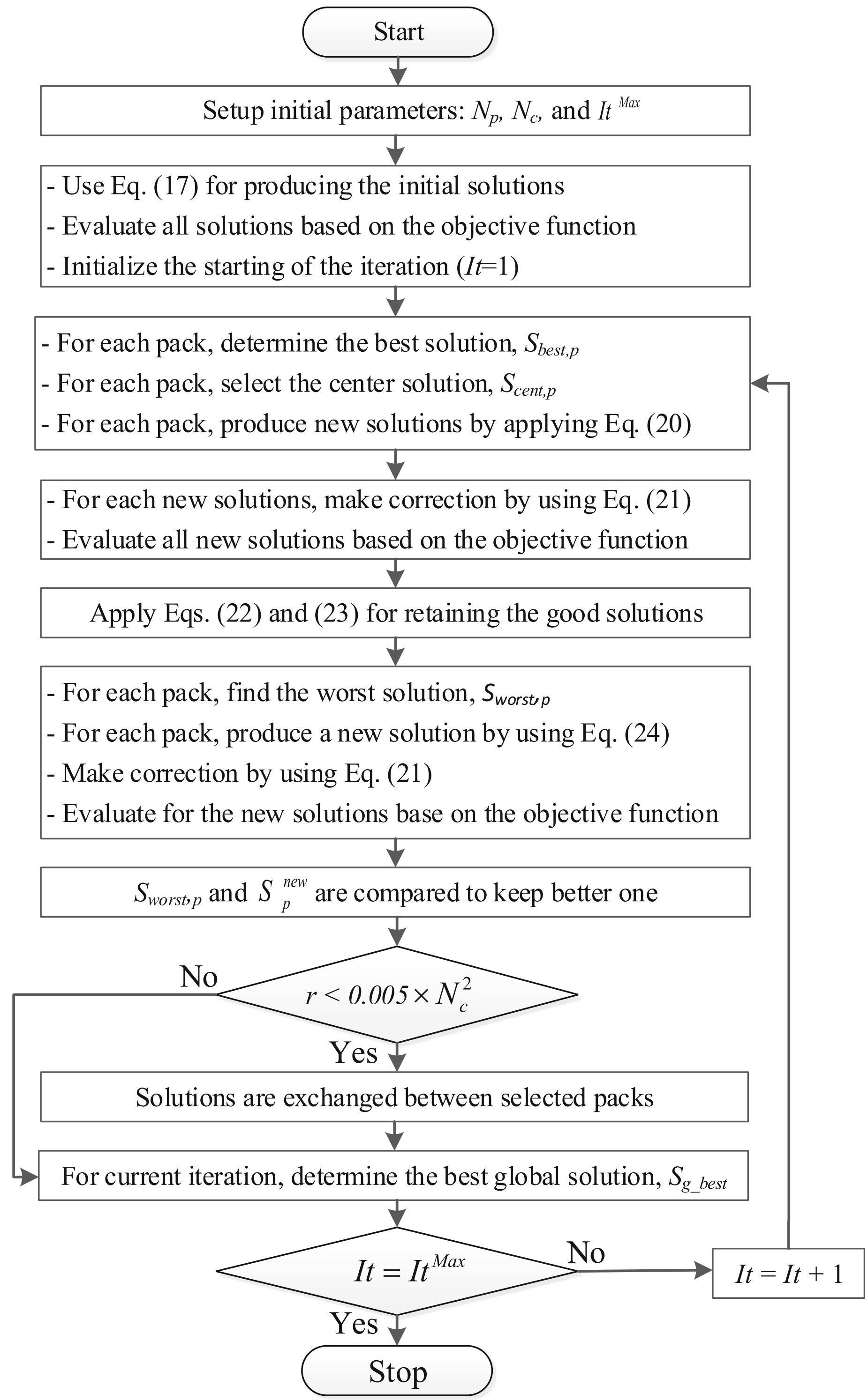
3.4 Enhanced coyote optimization algorithm

As mentioned above, COA creates two new solution generations in each iteration. The first generation implements using Eq. (20) and the second applies Eq. (24) for producing the new solutions. Thus, the quality of the solutions updated through iterations is closely related to the effectiveness of the two formulas (20) and (24). In other words, if the efficiency of the updated equations is not good enough, the quality of the solutions is hardly improved and vice versa. The newly updated solutions can become more effective if the most appropriate step size can be found [37, 38]. Therefore, to improve the performance of the optimization method, we focus on the improvement of determining the updated step size and the quality of new generated solutions. In this paper, we propose some adjustments as explained in the below parts.

3.4.1 The modification in the first phase

Due to natural behavior of coyotes, in the COA algorithm, it selects a central solution for updating the new solutions in each pack. As explaining in [26], a central tendency or a central social condition of all coyotes can lead to creating higher quality new solutions. In the other words, based on this central solution, each coyote could produce a new solution better than the current solution in the searching area. However, in various optimization problems, the central solution seems not to be a positive selection. Similarly, in this study, we found that the use of central variables to produce new solutions in Eq. (20) is really ineffective. In terms of natural and mathematical phenomena, the trend of finding better solutions is not clearly related to the central social condition. In some cases of the Benchmark optimization functions [26], there are central variables of “zero value” making this method effective. However, it should be noted that in the cases, the “zero value” solution (or central solution) is a useful item because it lies between the lower and the upper bound of variables. However, this does not fit to all optimization problems because in general good solutions do not locate around the central solution. Therefore, we propose the idea

Fig. 1 The implementation process of COA for solving a typical optimization problem



of replacing the central solution by the best current solution and Eq. (20) can be modified by the model as:

$$S_{q,p}^{\text{new}} = S_{q,p} + r.(S_{\text{best},p} - S_{rd1,p}) + r.(S_{g\_\text{best}} - S_{rd2,p}) \tag{28}$$

Because the best current solution is the most dominant quality solution of a group, thus creating a new solution using the best current solution obviously is a positive and effective way better than using the central solution. This modification could lead the search approaching the optimal solutions with higher quality, and it is suitable for almost optimization problems compared to the original COA method.

3.4.2 The modification in the second phase

The second proposed modification aims to improve the performance for the second-generation technique as shown in Eq. (24) where the changing taking from a random solution and then also taking from a random in the pack is inefficient according to mathematical logic. Moreover, the two conditional comparisons in Eq. (24), $(r < P_1)$ and $(r < P_1 + P_2)$, will lead to more computational burden and time consuming as well. Besides, Eq. (24) uses random variables that locate within the upper and lower limits. This is not a suitable and reliable choice for optimization problems. Thus, in the second modification, we have proposed a new formula to produce a new solution in each pack as follows:

$$S_p^{\text{new}} = S_{\text{best},rd1} + r \cdot (S_{\text{best},rd2} - S_{\text{best},rd3}) + r \cdot (S_{g\_\text{best}} - S_{\text{best},rd4}) \tag{29}$$

Using this modification, it can reduce the number of computation steps and time thanks to avoiding the randomization-based conditions. Moreover, the quality of the optimal solution of ECOA could be better than that of the original COA method.

The implementation process of the proposed ECOA method is shown in Fig. 2.

3.5 Comparing the general characteristics of the implemented methods

Based on the analysis from the updated equations of generating new solutions and the general characteristics of the implemented methods, the main features of these algorithms are summarized in Table 1.

In the paper, the four methods are implemented for determining position and capacity of DG units for reducing total power loss and total operating cost, and improving voltage profile. In order to replicate the application of the study, readers can follow the main documents below:

1. Forward/backward sweep technique (FBST) [39] is applied to run power flow for getting voltage of nodes and current of lines, and the main code of FBST is taken from [40].
2. The conventional SSA is described in [27], and the main code of SSA can be found from the link https://ch.mathworks.com/matlabcentral/fileexchange/63745-ssa-salp-swarm-algorithm?s_tid=srchtitle.
3. The conventional SFO is presented in [28], and the main code of SFO can be found from the link https://ch.mathworks.com/matlabcentral/fileexchange/69076-sunflower-optimization-sfo-algorithm.
4. The conventional COA is presented in [26], and the main code of COA can be found from the link https://ch.mathworks.com/matlabcentral/fileexchange/68373-coa.

4 Applying ECOA method to solve the optimal location and sizing of DGs

4.1 Population initialization of optimal DG problem

As mentioned, ECOA is developed on the basic of the COA [26]. Therefore, ECOA also includes two main components, N_p and N_c in each package. The production of initial solutions of ECOA will follow the model as follows:

$$S_{q,p} = S^{\min} + r \cdot (S^{\max} - S^{\min}); \quad q = 1, \ldots, N_c \quad \& \quad p = 1, \ldots, N_p \tag{30}$$

In the equation above, $S^{\min}$ and $S^{\max}$ are the lower bound and upper bound of all control variables in each solution and can be described as follows:

$$S^{\min} = [Pos_k^{\min}, AP_k^{\min}]; \quad k = 1, \ldots, N_{Dg} \tag{31}$$

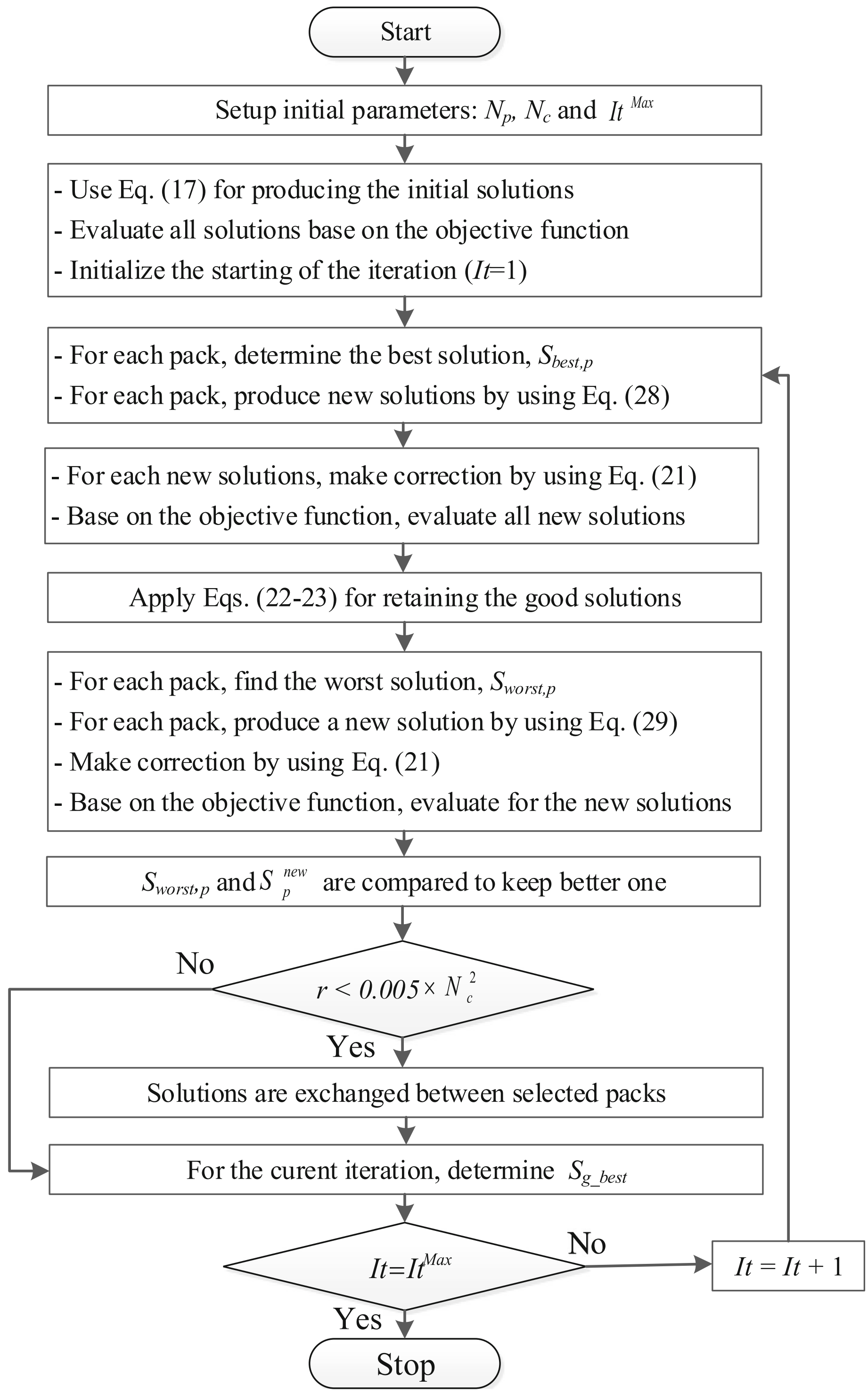
$$S^{\max} = [Pos_k^{\max}, AP_k^{\max}]; \quad k = 1, \ldots, N_{Dg} \tag{32}$$

In this study, the proposed method has been applied on systems with 33 buses, 69 buses and 85 buses where the minimum position of the kth DG is Bus 2; meanwhile, the maximum position of the kth DG is Bus N_{Dg} depending on the considered system. In addition, the limits of capacity for each DG will be predetermined by the designer and $(\text{AP}_k^{\min})$ as well as $(\text{AP}_k^{\max})$ must be within the constraints for the specific system.

After determining control variables for each solution, these variables are assigned to input data of power flow program for running and obtaining other remaining variables such as $I_{b,q,p}$ and $V_{j,q,p}$. In order to satisfy all technical requirements and ensure that the proposed solution is appropriate for distribution system, the evaluation and penalty for each solution are always concerned. Thus, before calculating the fitness function to evaluate the quality of each solution, the penalties for voltage profile and branch current are checked and proceeded by using Eqs. (33) and (34):

$$\Delta V_{j,q,p} = \begin{cases} V_{j,q,p} - V_j^{\max} & \text{if } V_{j,q,p} > V_j^{\max} \\ V_j^{\min} - V_{j,q,p} & \text{if } V_{j,q,p} < V_j^{\min} \\ 0 & \text{else} \end{cases} \tag{33}$$

Fig. 2 The whole search process of ECOA for a typical optimization problem



$$\Delta I_{b,q,p} = \begin{cases} I_{b,q,p} - I_b^{\max} & \text{if } I_{b,q,p} > I_b^{\max} \\ 0 & \text{else} \end{cases} \quad (34)$$

As a result, the fitness function of the qth solution in the pth pack is computed as follows:

$$\mathrm{FF}_{q,p} = F_{\mathrm{OF}q,p} + \varepsilon_i \sum_{b=1}^{N_{\mathrm{br}}} \Delta I_{b,q,p}^2 + \varepsilon_v \sum_{j=1}^{N_{\mathrm{bu}}} \Delta V_{j,q,p}^2 \quad (35)$$

After evaluating the quality of all solutions, the solution with the lowest quality in each pack is the best local

Table 1 Comparing the general characteristics of the methods

Method	Is it much dependent on randomization?	Number of new solution generations per iteration	Global search ability	The rate of being trapped in the local optimization
SSA	Yes	One	Low	High
SFO	Yes	One	Low	High
COA	Yes	Two	Medium	medium
ECOA	No	Two	High	Low

solution ($S_{\text{best},p}$) and the solution with lowest quality in all packs is the best global solution ($S_{\text{g\_best}}$).

In this paper, we solve a multi-objective problem with three single objectives including total active power loss (*TAPL*), voltage deviation index (*VDI*) and total operation cost (TOC). The three single objectives are, respectively, shown in Eqs. (1), (2) and (4). In addition to the objectives, the problem also considers two constraint sets including basic constraints regarding distribution network systems and advanced constraints regarding photovoltaic systems, which are placed in the systems. The basic constraint set is considered to be active power balance shown in Eq. (6), voltage limits shown in Eq. (7) and current limits shown in Eq. (8), whereas the advanced constraint set is comprised of power generation limits of photovoltaic systems shown in formulas (9)–(10) and location limits shown in Eq. (11). An optimal solution of the problem that is stored and reported in numerical results must be checked all constraints after each run based on the fitness function shown in Eq. (35). If the solution can reach $\text{FF}_{q,p} = F_{\text{OF}q,p}$, it is a valid solution and it is stored for reporting the performance. The result of $\text{FF}_{q,p} = F_{\text{OF}q,p}$ means all constraints are exactly satisfied and the run can be called convergence, but the quality of the valid solution cannot be assured to be high. The power balance constraint (6) is always satisfied thanks to the flexibility of power source, which is represented as AP_{Gr}. Power source can generate a high power (i.e., AP_{Gr} can be high) if all DGs produce a low power (i.e., $\sum_{k=1}^{N_{\text{Dg}}} \text{AP}_{\text{Dg},k}$ is low) and vice versa. Bus voltage and branch current are the two factors obtained by running FBST [39]. For all study cases in the paper, the maximum error of the two factors is set to 10^{-4} when running FBST. So, if the two factors can satisfy constraints (7) and (8), the accuracy of solution is always warranted. The two factors are included in fitness function, and they are penalized if violated. As a result, all the basic constraints are controlled and solved accurately. Other advanced constraints in formulas (9)–(11) are solved more easily because active power generation and location of DGs are decision variables. The location and active power generation of each DG are, respectively, verified and fixed. Clearly, constraints regarding DGs are always warranted to be accurate. Consequently, optimal solutions are valid with very high accuracy.

4.2 Processes of newly updated solutions

During this process, ECOA has two stages of generating new solutions. For the first stage, Eq. (28) is applied for generating the new solutions (N_{c}) in each pack (N_{p}). All current solutions are replaced by new solutions. However, it is very different from the second phase where in each pack only one solution is chosen for the update by using Eq. (29). Thus, the new solutions in the first and second phases are $S_{q,p}^{\text{new}}$ and S_{p}^{new}, respectively.

4.3 Correction for the violated new solutions

After each solution is updated, the violation treatment for the new solutions is implemented. If any control variable exceeds its allowable limits, a conversion method is used. This method applies the upper and lower bound as constraints to all control variables as the model below:

$$\text{Pos}_{\text{Dg},k} = \begin{cases} \text{Pos}_{\text{Dg}}^{\max} & \text{if } \text{Pos}_{\text{Dg},k} > \text{Pos}_{\text{Dg}}^{\max} \\ \text{Pos}_{\text{Dg},k} & \text{if } \text{Pos}_{\text{Dg}}^{\min} \le \text{Pos}_{\text{Dg},k} \le \text{Pos}_{\text{Dg}}^{\max} \\ \text{Pos}_{\text{Dg}}^{\min} & \text{if } \text{Pos}_{\text{Dg},k} < \text{Pos}_{\text{Dg}}^{\min} \end{cases} \tag{36}$$

$$\text{AP}_{\text{Dg},k} = \begin{cases} \text{AP}_{\text{Dg}}^{\max} & \text{if } \text{AP}_{\text{Dg},k} > \text{AP}_{\text{Dg}}^{\max} \\ \text{AP}_{\text{Dg},k} & \text{if } \text{AP}_{\text{Dg}}^{\min} \le \text{AP}_{\text{Dg},k} \le \text{AP}_{\text{Dg}}^{\max} \\ \text{AP}_{\text{Dg}}^{\min} & \text{if } \text{AP}_{\text{Dg},k} < \text{AP}_{\text{Dg}}^{\min} \end{cases} \tag{37}$$

4.4 The termination condition of the iterative algorithm

The computing process of determining the position and capacity of DGs will be stopped when the iteration limit condition is met. The maximum number of iteration (It^{Max}) is predetermined, and the searching of optimal solution will finish when its iteration counter (It) equals the maximum number of iterations.

4.5 The whole search process of ECOA for optimizing the installation of DGs

The implementation process of the proposed ECOA method for finding optimal location and sizing of DGs is shown in Fig. 3.

5 Simulation results and discussion

In this study, proposed method (ECOA) together with SSA, SFO and COA has been examined to determine the optimal location and sizing of DGs of three test systems, IEEE 33-bus, IEEE 69-bus and IEEE 85-bus radial distribution networks. At each investigated method, the simulation results have been collected through 50 runs (running times) by using MATLAB on a personal computer with processor-2.0 GHz and RAM- 8.0 GB. In this section, the parameters of the applied methods used in the simulation process can be briefly described as follows:

(1) To implement SSA method, c_1 is a function of $2e^{-\left(\frac{4It}{It^{Max}}\right)^2}$; c_2 and c_3 are generated numbers randomly in the interval of [0, 1] [27].

(2) For setting parameter of SFO method, the day (d) and the sun (s) are selected to be 100 and 1, respectively, while the pollination (p) is chosen from 0.6 to 1 with a step of 0.2 [28].

(3) To run COA and ECOA methods, the number of coyotes in each pack (N_C) and the number of packs (N_P) should be pre-surveyed to select parameters appropriately. This is considered as a main disadvantage of these methods. In this study, the number of packs is investigated from 4 to 6 and it is combined with the number of coyotes in each pack from 4 to 6. The results have shown that the suitable parameters for position and capacity of DGs in the considered cases are 5 for both N_P and N_C. Thus, the population equals 25.

(4) In order to ensure a fair comparison as well as a complete convergence between the proposed method and the other methods, the maximum number of iterations for all networks has been investigated and chosen the appropriate values. In this study, for the 33-bus system, the proposed method (ECOA) is compared to others with the published iteration number from 30 to 60 for GA, PSO, GA/PSO, SA, BFOA and 150 iterations for BSOA. Besides, the proposed method has been compared with 3 implemented methods such as SSA, SFO and COA. The number of iterations for implemented methods is pre-investigated with different iteration number from 40 to 70 with the step of 10 iterations. Similarly, in the 69-bus system, the number of iterations for methods in previous studies such as GA, PSO, GA/PSO, SA, BFOA, HSA has been varied from 30 to 60. For the remaining methods such as SSA, SFO, COA and ECOA, the number of iterations is pre-surveyed from 50 to 80 and the step is 10 iterations. For 85-bus system, the survey results are selected from 60 to 100 with the step of 10 iterations for SSA, SFO, COA and ECOA. The results of the iteration selection survey have shown that the best results of implemented methods do not change when the number of iterations is greater than 50, 60 and 80 for 33-bus, 69-bus and 85-bus systems, respectively. In short, for the above implemented methods as SSA, SFO, COA and ECOA, the control parameters including population size (N_{ps}) and maximum number iteration ($\mathrm{It}^{\mathrm{Max}}$) for three distribution networks are chosen as follows:

+ $\mathrm{It}^{\mathrm{Max}}$ equals 50, 60 and 80 for 33, 69 and 85-bus IEEE radial distribution power network, respectively.
+ N_{ps} equals 30 for SSA and SFO methods in three the distribution networks.

Moreover, the multi-objective function as indicated in Eq. (5) needs three weighted coefficients ω_A,ω_B and ω_C associated with the total power loss, the voltage stability and the total operational cost, respectively. Those weight values reflect the importance of each component contributing on the optimization result of the multi-objective function. In order to determine the most appropriate values of three weighted coefficients:ω_A,ω_B and ω_C, we have tried many different settings for the coefficients where ω_A should be greater than ω_B and ω_C should be the smallest [41]. In this paper, to discover the most suitable values of the weight factors, we have installed a single DG in IEEE 33-bus radial distribution network and executed the optimization problem for DG's location and size through many attempts by using ECOA. As a result, different settings of the weight factors and corresponding values of the objective function F_{OF} (also equal fitness function) are shown in Table 2.

As shown in Table 2, the smallest objective function (F_{OF}) of 0.3576 can be obtained by using ω_A, ω_B and ω_C of 0.50, 0.40 and 0.10, respectively. This result is similar to the setting of the three weight factors referred in [41] where three values of 0.5, 0.4 and 0.1 were also found to make the best setting. Consequently, we have adopted the selection for all study cases in the paper.

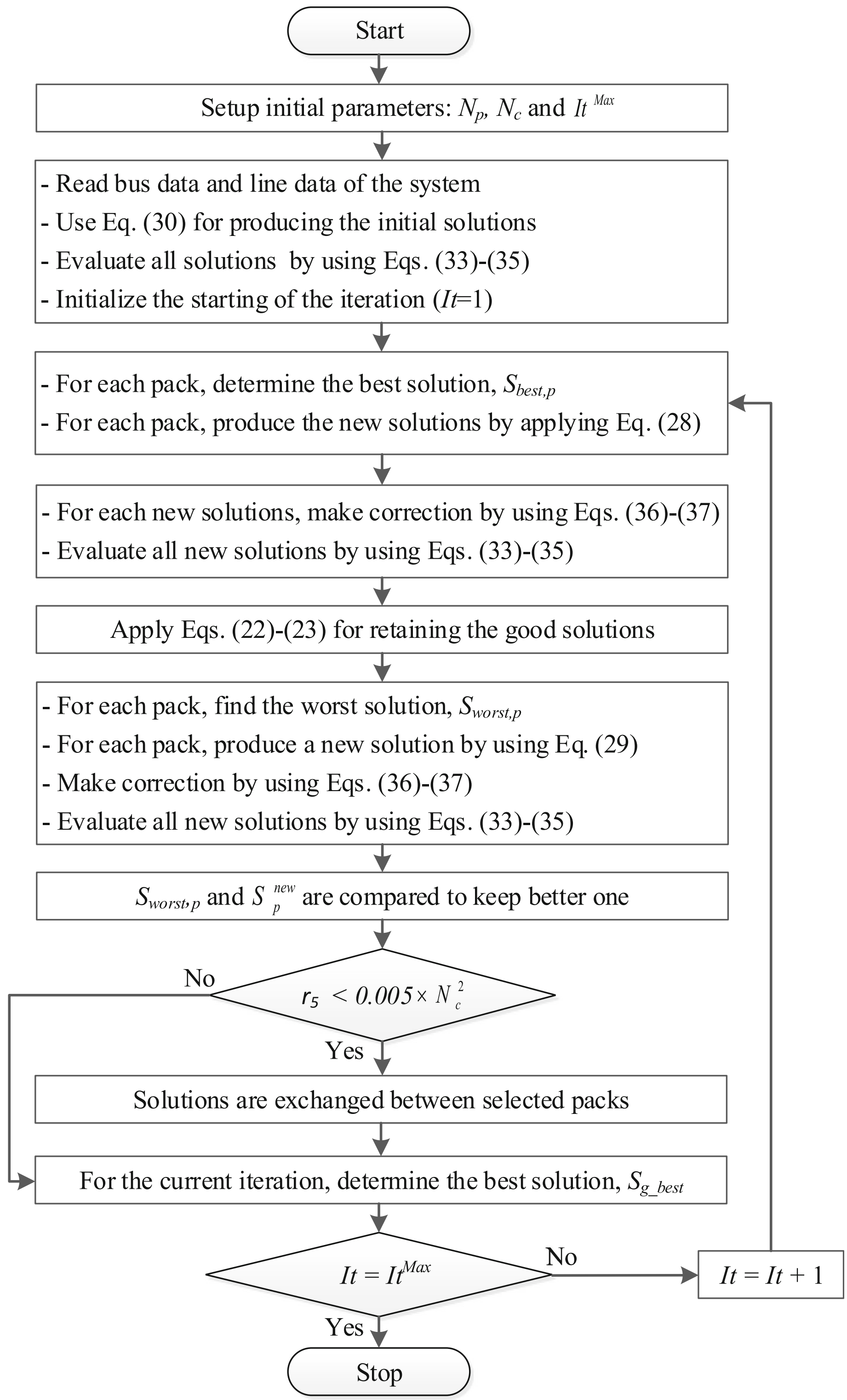


Fig. 3 The ECOA method's flowchart for solving the optimal location and sizing of DGs

5.1 Case 1: IEEE 33-bus radial distribution power network

In this section, three DGs are considered to be connected in IEEE 33-bus radial distribution network shown in Fig. 4 [42]. The position of each DG can be placed at one of 32 buses from Bus 2 to Bus 33 excluding Bus 1, which is in charge of the slack bus. For finding a promising solution, the sum of rated power of three DGs is limited from 10% to 80% of the total load demand, which is 3715.0 kW. In addition, the size of each DG is also constrained by the limit not higher 2000 kW.

Table 3 presents the best simulation results of the investigated methods as well as the referenced results from other existing methods for the same test system. As shown in Table 3, the total power loss and the smallest bus voltage without installing DGs are 211.0 kW and 0.9038 pu, respectively, while installing three DGs according to the solution determined by the proposed ECOA method reduces the total power losses dramatically to 74.6 kW and improves the smallest voltage significantly up to 0.9666 pu. This comparison shows that total power loss and voltage profile are actually improved if DGs can be properly connected in the distribution system.

As comparing the performance of the proposed method and other methods, it is hard to reach better solutions with better values for all three single objectives. In fact, this is a popular issue in solving multi-objective optimization problem including many different objectives. Thus, it should bring up appropriate comparison criteria for evaluating the performance. In the considered problem, the three criteria of the comparison should be pointed out as follows:

1. *Fitness function*: the fitness function is an evaluation function of obtained solutions. Basically, the fitness function is the sum of the multi-objective function and penalty terms. In case penalty terms are equal to zero, the fitness function and the multi-objective function are the same. Thus, a solution with the lower fitness value is definitely a better solution although three individual objective functions cannot be simultaneously smaller than those of other solutions.
2. *Control parameters*: the setting of control parameters, such as the population size and the maximum number of iterations, significantly influences the quality of optimal solutions. Therefore, those settings should be used as a comparison criterion and, for comparison purpose, we need merging two parameters, population and iterations, into the number of fitness function evaluations (N_{ffe}).
3. *Simulation time*: simulation time is also an important comparison criterion to prove potential search speed of methods. This criterion is applied to confirm one more time about the search speed of the proposed method. Basically, one method is run by setting lower value to N_{ffe}, the simulation time of the method will be shorter.

Table 2 The impact of different settings of the weight factors in obtained objective functions

ω_A	ω_B	ω_C	Objective function (F_{OF})
0.60	0.30	0.10	0.4020
0.55	0.35	0.10	0.3768
0.50	0.40	0.10	0.3576
0.60	0.25	0.15	0.4218
0.55	0.30	0.15	0.3965
0.50	0.35	0.15	0.3711

Based on the three comparison criteria, we can compare the performance of ECOA and other similar methods to verify the effectiveness of the proposed approach. According to the fitness function value (value of the multi-objective function), ECOA can make the best optimal result as compared to all other methods where ECOA's best solution gets 0.2581 but other compared results are higher, from 0.2583 to 0.3783. It means that the proposed method can find the better solution with lower fitness values from 0.0002 to 0.1201. According to the convergence speed based on the number of fitness function evaluations, the proposed method is one of the fastest methods with N_{ffe} = 1250 compared to other methods with N_{ffe} from 1500 to 5000. The shortest simulation time of the proposed ECOA method can confirm its faster search speed than COA, SFO and SSA. Other methods in previous studies have not shown the simulation time for comparison. However, the comparison of N_{ffe} also indicated the speed superiority of the proposed method over these methods. Consequently, it can conclude that the proposed ECOA method is superior to other methods in terms of higher quality solution and faster search implementation. Furthermore, to show the improvement level of the proposed method over other investigated ones, we visualize the performance of SFO, SSA, COA and ECOA in Fig. 5 showing the fitness functions of 50 trial runs and Fig. 6 presenting convergence curves for the best and worst runs of 50 trial runs. Clearly, the solution of ECOA at the 25th iteration can be shown a better quality than that of three other methods in the best trial run and the remaining solutions seem to fall into the local search area.

However, depending on the application purpose, each single objective of the multi-objective function can be analyzed individually for evaluating the contribution of the DGs installation in the distribution network. For example, we can consider the aspects about less total power losses, better maximum voltage deviation and less total operation cost, and then convert the values into the improvement level in percent by applying Eqs. (33) and (34). Therefore, Table 4 presents more details about the individual single objectives of ECOA and their improvements as compared to other methods' results. In three individual objectives of ECOA, it can get the better power loss and total operation cost, but it suffers from worse voltage improvement as

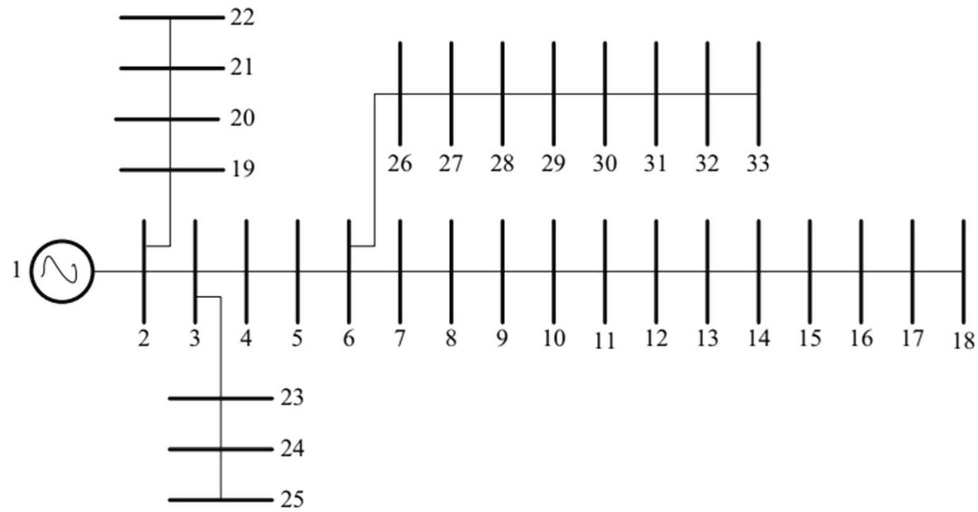


Fig. 4 The IEEE 33-bus distribution system

Table 3 The comparison of results obtained by the proposed ECOA and other methods

Method	TAPL (kW)	VDI (F_B)	TOC ($)	The best fitness (F_{OF})	It^{Max}	N_{ps}	N_{ffe}	Aver. time (s)
Without DG	211.0	0.0962	–	–	–	–	–	
GA [14]	106.3	0.0191	15,396.2	0.3419	60	50	3000	–
PSO [14]	105.4	0.0194	15,361.9	0.3401	40	40	1600	–
GA/PSO [14]	103.4	0.0192	15,353.6	0.3783	30	50	3000	–
SA [15]	82.0	0.0324	12,666.6	0.2755	50	30	1500	–
BFOA [22]	98.3	0.0355	9948.1	0.2784	50	100	5000	–
BSOA [20]	89.0	0.0446	8701.2	0.2757	150	13	1950	–
SSA	77.0	0.0345	11,660.2	0.2592	50	30	1500	1.504
SFO	75.9	0.0389	12,675.4	0.2639	50	30	1500	1.577
COA	76.0	0.0363	11,815.2	0.2583	50	25	1250	1.328
ECOA	74.6	0.0334	12,597.9	0.2581	50	25	1250	1.284

compared to GA [14], PSO [14], GA/PSO [14] and SA [15]. The proposed method can find less power loss than other methods from 6.83 kW to 31.1 kW as compared to SA [15] and GA [14]. Likewise, the corresponding values are the improvement level from 8.32% to 29.2568%. The operation cost of ECOA is also less than by from $297.50 to $3026.30 corresponding to the improvement level from 2.3487% to 19.6572%. But the proposed method cannot reach better maximum voltage deviation than the four methods and the improvement level is in negative range from − 1.5088% to − 0.1550%. As compared to COA, SSA, BFOA [22] and BSOA [20], the proposed ECOA approach can effectively reduce the total power loss from 1.4 kW to 14.7 kW and efficiently improve voltage from 0.0011 pu to 0.0107 pu, but the total operation cost of ECOA is higher than that of these mentioned methods. Accordingly, the improvement level of total power losses is from 1.8421 to 16.3515% and the voltage improvement level is from 0.1170 to 1.1199%. The comparison with SFO is the best observation for the ECOA's performance since three individual objectives of ECOA are better than those of SFO where the reduction in total power loss, the improvement of voltage level and the saving of operational cost are 1.30 kW, 0.0055 pu and $77.50, respectively. Similarly, the improvement level in percent of obtained results can be shown: the improvement level of power losses, the improvement level of voltage, and the improvement level of operational cost are 1.7128%, 0.5723%, and 0.6114%, respectively. As a result, the proposed method is actually more effective than the comparative methods and it can be seen as a strong method to solve the optimal location and capacity of DGs in the distribution system.

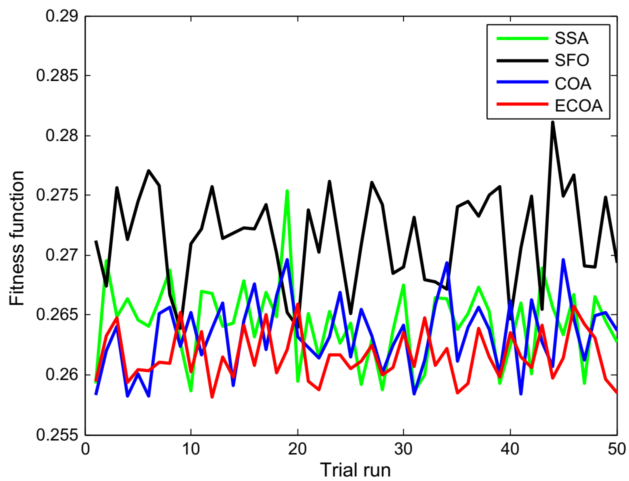


Fig. 5 The fitness function of 50 trial runs

$$\text{Saving of components} = \text{The value of a compared method} - \text{The value of ECOA} \tag{38}$$

$$\text{Improvement level}\,(\%) = \frac{\text{The value of a compared method} - \text{The value of ECOA}}{\text{The value of ECOA}} \times 100 \tag{39}$$

5.2 Case 2: IEEE 69-bus radial distribution network

In this case, three DGs are also considered for the integration to IEEE 69-bus radial distribution power network as Fig. 7 with the goal of determining location and sizing of DGs accordingly [6]. Similar to IEEE 33-bus system, the position of each DG will vary from Bus 2 to Bus 69 and the capacity will not exceed 2000 kW for each DG. Besides, the total capacity of three DGs will be constrained in the range from 10% to 80% of the total load, 3802.0 kW.

In Table 5, the collected results from the ECOA proposed method and other methods are compared together. Similar to the simulations of IEEE 33-bus distribution network, the total power loss can be reduced significantly when properly connecting DGs in IEEE 69-bus distribution network. Before DGs are connected, the total power loss is 224.5 kW. However, after connecting DGs according to the ECOA's solution, the power loss significantly decreases to 71.8 kW. In addition, the voltage profile also is improved positively where the lowest bus voltage without any DGs is 0.9092 pu, but it is significantly improved up to 0.9784 pu after properly integrating DGs in this system. This strongly demonstrates that the suitable installation of DGs in distribution networks not only minimizes total power loss but also improves the voltage stability.

Similar to the previous case, the simulations and the result analysis focus on comparing the fitness function and control parameters from various meta-heuristic methods to evaluate their effectiveness. As shown in Table 5, the fitness function found by ECOA is the lowest value with 0.2260, while other compared methods are in a range from 0.2264 to 0.2837. In addition, the number of fitness function evaluations of ECOA is only N_{ffe} = 1500, which is lower than that of the other methods varying from 1800 to 5000 excluding COA with N_{ffe} = 1500. Therefore, the optimal solution search speed and process data storage memory of the proposed method are actually better than other compared methods. In fact, the simulation time of the proposed method is the shortest among four implemented methods, whereas the time of other methods in previous studies has not been reported. Furthermore, to show the

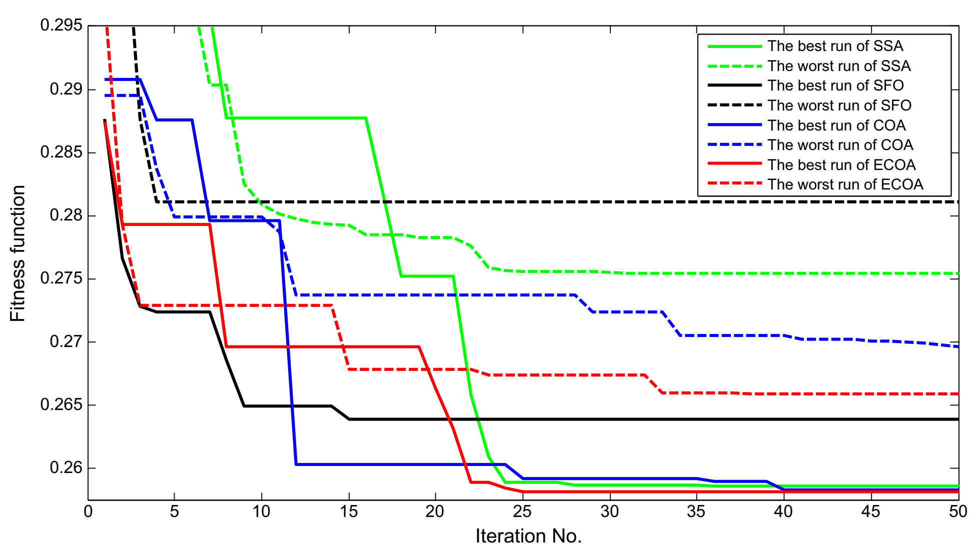


Fig. 6 The convergence curves for the best run and the worst run of 50 iterations

Table 4 Analysis of contribution of different methods to the 33-bus IEEE transmission power network thanks to the installation of DGs

Method	Saving TAPL (kW)	Better voltage (pu)	Saving TOC ($)	Saving fitness	Improvement level (%)			
					TAPL	Voltage	TOC	Fitness
GA [14]	31.1	− 0.0148	3026.3	0.0837	29.2568	− 1.5088	19.6572	24.4808
PSO [14]	30.15	− 0.0145	2992.8	0.0819	28.6189	− 1.4787	19.482	24.0812
GA/PSO [14]	28.2	− 0.0147	2984.5	0.1201	27.2727	− 1.4988	19.4384	31.7491
SA [15]	6.83	− 0.0015	297.5	0.0174	8.3262	− 0.155	2.3487	6.2965
BFOA [22]	14.7	0.0016	− 2421	0.0202	16.3515	0.4534	− 24.3363	7.2524
BSOA [20]	13.8	0.0107	− 3667.9	0.0175	15.5056	1.1199	− 42.154	6.3407
SSA	2.4	0.0011	− 937.7	0.0011	3.1169	0.117	− 8.0419	0.4244
SFO	1.3	0.0055	77.5	0.0058	1.7128	0.5723	0.6114	2.1978
COA	1.4	0.0029	− 782.7	0.0002	1.8421	0.3009	− 6.6245	0.0774
ECOA	–	–	–	–	–	–	–	–

improvement level of the proposed method over other investigated ones, we visualize the performance of SFO, SSA, COA and ECOA in Fig. 8 showing the fitness functions of 50 trial runs and Fig. 9 presenting convergence curves for the best and worst runs of 50 trial runs. The convergence curve of ECOA performed quite well when the best solution is found in the 42nd iteration in the best trial run, while other solutions are stuck in the local optimization with low performance.

However, to comprehensively evaluate the effectiveness of compared methods, the analysis of single objective functions is essential as presented in Table 6 where those values are calculated by applying Eqs. (33) and (34). As we can see in Table 6, the proposed method is more effective than GA [14], PSO [14], GA/PSO [14], SA [15] and BFOA [22] in reducing total power loss and saving operation cost. Specifically, it saves from 2.63 to 16.30 kW corresponding to improvement level from 3.4959 to 18.3352%. Besides, it can save from \$115.90 to \$4717.50 for the operation cost corresponding to the improvement level from 1.0790 to 30.7469%. However, in this particular case, the ECOA's ability in improving the voltage level is not as good as other compared methods where the lowest bus voltage is dropped from − 0.0154 pu to − 0.0112 pu corresponding to the voltage improvement level in percentages from − 1.5499 to − 0.2956%. By the comparison between ECOA and other methods, we can see that the proposed method is more effective for two of three individual objective functions. For example, the performance of ECOA is better than that of HSA, SSA, SFO and COA, by two individual objectives of reducing losses and improving voltage. In more details, its total power loss is lower than others from 0.70 kW to 14.17 kW corresponding from 0.9655 to 16.3305%. In addition, the lowest bus voltage of ECOA is greater than that of the compared methods from 0.0008 pu to 0.0112 pu which are converted to percentages of the improvement level from 0.0798 to 1.1582%. However, in terms of operation cost, ECOA is not a positive approach compared to other methods and the improvement values are negative varying from − 271.50 dollars to − 1414.20 dollars corresponding to the percentage from − 15.3529 to − 2.5535%.

5.3 Case 3: IEEE 85-bus radial distribution network

In this case, multi-objective function and single objective function are considered as two types of objective functions for an objective evaluation between the proposed method and other methods. For multiple objective functions, there are three DGs considered for installation in the system. For single objective function, the total power loss reduction is considered and only single DG is integrated into the system.

5.3.1 Multi-objective function

For the IEEE 85-bus radial distribution network as Fig. 10 [43], the multi-objective function is similar to the two considered systems above. Similarly, the total capacity of all DGs must not exceed 80% and not be less than 10% of the total loads, 2570.3 kW. In addition, the capacity of each DG is changed from 0 kW to 2000 kW and the search position is in the range from bus 2 to bus 85.

The proposed method (ECOA) is compared with implemented methods with three criteria in the multi-objective function as shown in Table 7. Clearly, the total power loss is drastically reduced from 316.1 to 152.5 kW after connecting suitable DGs to the distribution system. In addition, the lowest bus voltage is also significantly

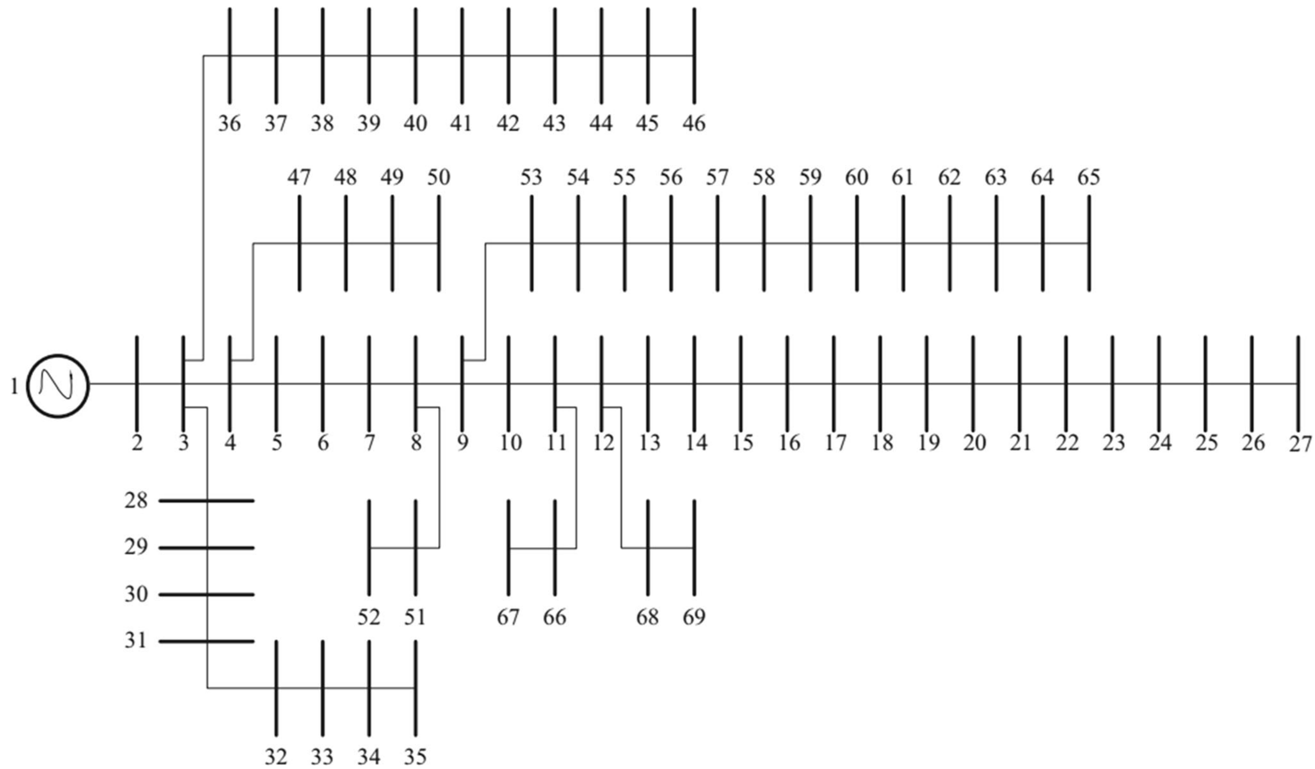


Fig. 7 The IEEE 69-bus distribution system

Table 5 The comparison of results obtained by the proposed ECOA and other methods

Method	TAPL (kW)	VDI (F_B)	TOC ($)	The best fitness (F_{OF})	$\mathrm{It}^{\mathrm{Max}}$	N_{ps}	N_{ffe}	Aver. Time (s)
Without DG	224.5	0.0908	–	–	–	–	–	–
GA [14]	89.0	0.0064	15,343.0	0.2837	60	50	3000	–
PSO [14]	83.2	0.0099	15,272.3	0.2692	40	40	1600	–
GA/PSO [14]	81.1	0.0075	15,264.4	0.2735	30	50	1500	–
SA [15]	77.1	0.0189	11,214.9	0.2399	50	30	1500	–
BFOA [22]	75.2	0.0192	10,741.4	0.2311	50	100	5000	–
HSA [21]	86.8	0.0330	9211.3	0.2535	60	30	1800	–
SSA	73.0	0.0236	10,617.8	0.2278	60	30	1800	4.244
SFO	72.7	0.0238	10,894.6	0.2288	60	30	1800	4.475
COA	72.5	0.0224	10,632.5	0.2264	60	25	1500	3.646
ECOA	71.8	0.0216	10,904.0	0.2260	60	25	1500	3.579

improved from 0.8713 pu to 0.9513 pu through this appropriate integration. Similar to the two considered systems above, for this system, DGs also have a positive impact and can bring many benefits when they are integrated into the system appropriately.

The best fitness result of ECOA is 0.3398 and lower than the compared methods from 0.008 to 0.051. This index shows the effectiveness of methods in solving the same optimization problem. In addition, the number of fitness function evaluation (N_{ffe}) of ECOA and COA is 2000, while SSA and SFO have the same value of 2400. The simulation time of ECOA is also the fastest among four methods. This proves that the proposed method can help to minimize the data processing process and enhance the search speed better than other methods.

In addition, the best fitness value of the proposed method and the compared methods in the 50 trial runs is shown in Fig. 11. Furthermore, Fig. 12 presents the

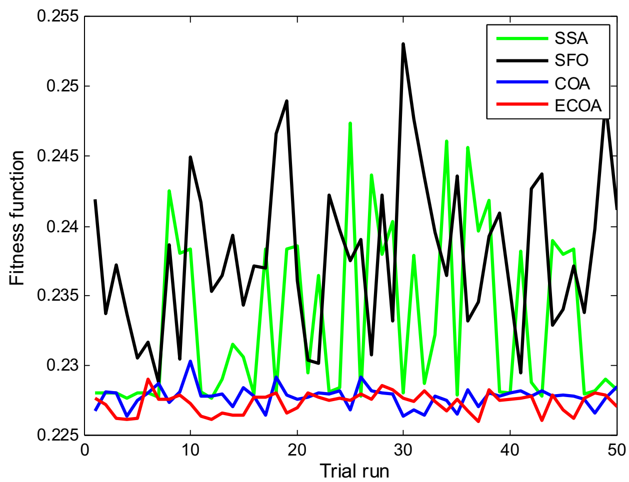


Fig. 8 The fitness function of 50 trial runs

convergence curves of the best and worst trial runs of implemented methods. The convergence characteristics of ECOA are quite good, and the best solution is found by ECOA at the 43rd iteration. Clearly, these figures show that ECOA finds better optimal solutions with more stability than other remaining methods.

However, for objective evaluation, the components in the multi-objective function are also necessary for consideration. Like Table 8, the proposed method (ECOA) is compared with SSA and SFO in the three values of the total power loss, voltage profile improvement and total operation cost. ECOA demonstrates its effectiveness when the solution outperforms the others. Specifically, ECOA can save from 0.4 kW to 1.1 kW corresponding to improvement level from 0.2616 to 0.7161%. For voltage profile improvement, it has improved for the weakest bus voltage from 0.0012 pu to 0.0013 pu, corresponding to 0.13–0.14% in the voltage improvement level. In addition, ECOA can save money from \$44.00 to \$352.50 corresponding to the improvement level from 0.4306 to 3.3486%. Along with the above two methods, ECOA is also compared with COA. In this case, ECOA helps to save total operation cost up to \$89.10, which corresponds to 0.8681% in the improvement level. Besides, it has also improved the voltage profile better than the COA with further enhancing the lowest bus voltage to 0.0013 pu and 0.14% of the improvement level.

Finally, according to the evaluation criteria, such as the fitness function, control parameters and simulation time, we can conclude that the proposed ECOA method is actually effective for solving optimization problems where its performance is superior to that of all other compared methods. Optimal solutions obtained by the proposed method and other ones are reported in Tables 10, 11 and 12 for the IEEE 33-bus network, IEEE 69-bus network and IEEE 85-bus network, respectively.

5.3.2 Single objective function

In this case, the proposed method is compared to other methods such as whale optimization algorithm (WOA) [44], combined power loss index-whale optimization algorithm (PLI-WOA) [45] and COA in a single objective function of minimizing total power loss on branches. The capacity of each DG is changed from 0 kW to 3000 kW, and the search position is within the limit of from bus 2 to bus 85. As comparing the ECOA to other published methods, the voltage constraints are extended from 0.9 pu to 1.1 pu and the surveyed iteration number is equal to the compared methods. As shown in Table 9, the ECOA method has reduced the total power loss significantly from 316.1 kW to 175.5 kW. Furthermore, voltage profile is also

Fig. 9 The convergence curves for the best run and the worst run in 60 iterations

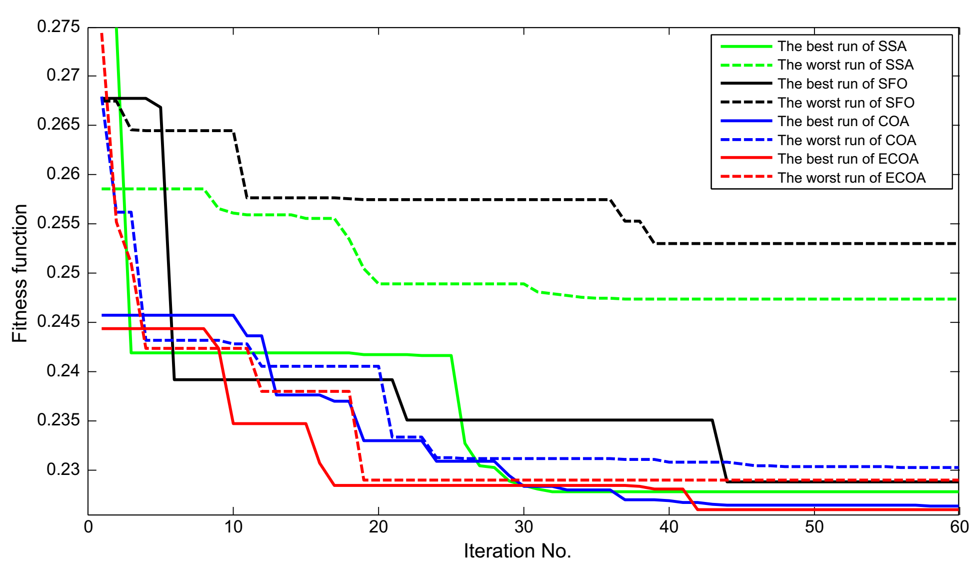


Table 6 Analysis of contribution of different methods to the 69-bus IEEE transmission power network thanks to the installation of DGs

Method	Saving TAPL (kW)	Better voltage (pu)	Saving TOC ($)	Saving fitness	Improvement level (%)			
					TAPL (kW)	Voltage (pu)	TOC ($)	Fitness
GA [14]	16.30	− 0.0154	4717.50	0.0574	18.3352	− 1.5499	30.7469	20.2143
PSO [14]	10.60	− 0.0119	4646.80	0.0428	12.7404	− 1.2019	30.4263	15.9138
GA/PSO [14]	8.50	− 0.0143	4653.10	0.0472	10.4809	− 1.4408	30.4550	17.2419
SA [15]	4.50	− 0.0029	589.40	0.0136	5.8366	− 0.2956	5.2555	5.6519
BFOA [22]	2.63	− 0.0112	115.90	0.0048	3.4959	− 1.1419	1.0790	2.0765
HAS [21]	14.17	0.0112	− 1414.20	0.0271	16.3305	1.1582	− 15.3529	10.7026
SSA	1.20	0.0020	− 286.20	0.0018	1.6438	0.2028	− 2.6955	0.7858
SFO	0.90	0.0022	− 9.40	0.0028	1.2380	0.2234	− 0.0863	1.2194
COA	0.70	0.0008	− 271.50	0.0004	0.9655	0.0798	− 2.5535	0.1723
ECOA	–	–	–	–	–	–	–	–

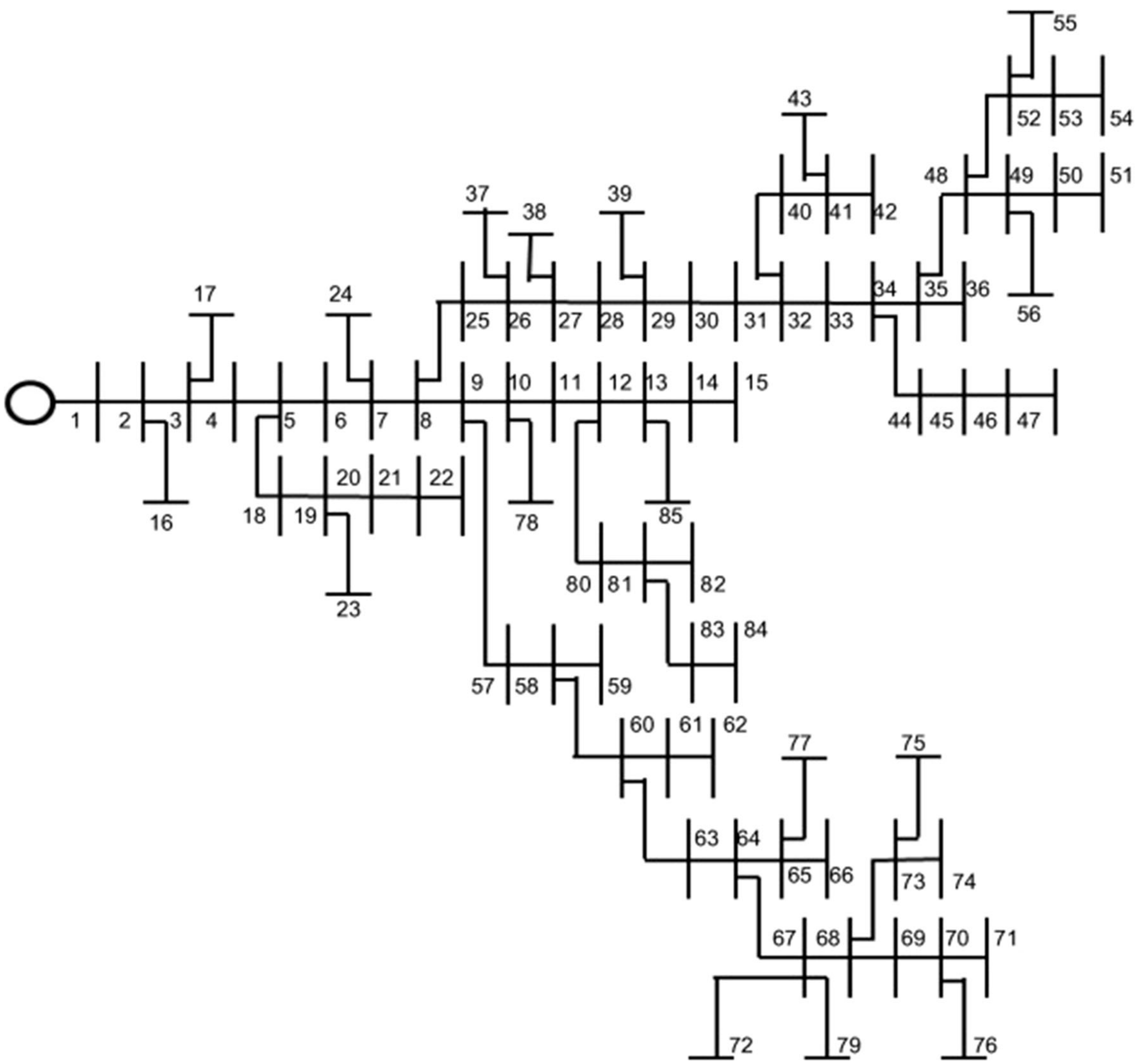


Fig. 10 The IEEE 85-bus distribution system

Table 7 The comparison of results obtained by the proposed ECOA and other methods

Method	TAPL (kW)	VDI (F_B)	TOC ($)	The best fitness (F_{OF})	It^{Max}	N_{ps}	N_{ffe}	Aver. time (s)
Without DG	316.1	0.1287	–	–	–	–	–	–
SSA	152.9	0.0500	10,218.2	0.3413	80	30	2400	8.534
SFO	153.6	0.0499	10,526.7	0.3449f	80	30	2400	8.820
COA	152.2	0.0500	10,263.3	0.3406	80	25	2000	7.442
ECOA	152.5	0.0487	10,174.2	0.3398	80	25	2000	7.347

drastically improved where the weakest bus voltage is increased from 0.8713 pu to 0.9282 pu. Clearly, the best solution proposed by ECOA and COA is the same and better than WOA and PLI-WOA. However, over 50 trial runs ECOA can find 44 the best solutions, but it is only 26 the best solutions for COA. This proves that ECOA is more stable than the COA and it has better performance than other methods.

5.4 Discussion on the improvement and contribution of ECOA

The proposed enhanced coyote optimization algorithm (ECOA) is developed by performing some modifications on conventional coyote optimization algorithm (COA). COA executes two times for solution update per iteration by using Eqs. (20) and (24). The whole population is newly updated in the first time corresponding to the generation of N_{ps} new solutions, while only one solution is produced for each solution pack in the second time corresponding to the generation of N_p new solutions. Thus, the effectiveness of COA is mainly based on Eqs. (20) and (24) where Eq. (20) has more significant impact than Eq. (24). However, the main disadvantages are found in the two formulas and the

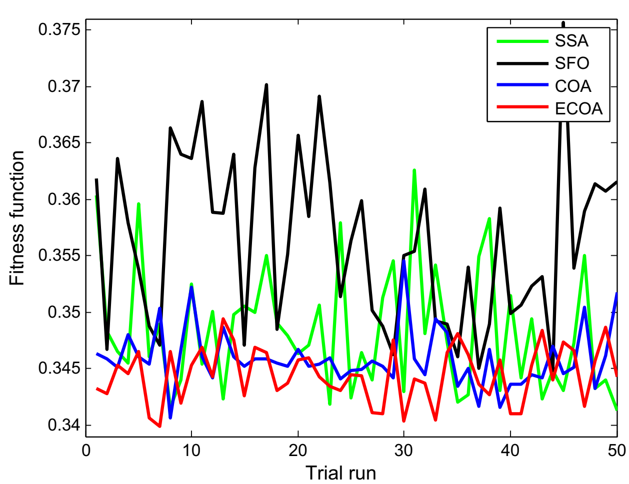


Fig. 11 The fitness function of 50 trial runs

solutions of overcoming the disadvantages are to form the real efficiency of the proposed ECOA method. Equation (28) is proposed to reach high efficiency for the first update; meanwhile, Eq. (29) is proposed to replace the less effectiveness of the second update of COA. The two proposed formulas have changed search spaces of COA into other search spaces.

In the first update, COA selects a central solution for updating the new solutions in each pack. As explaining in [26], a central tendency or a central social condition of all coyotes can lead to creating higher quality new solutions. In other words, based on this central solution, each coyote could produce a new solution better than the current solution in the searching area. However, in various optimization problems, the central solution seems not to be a positive selection. Similarly, in this study, we found that the use of central variables to produce new solutions in Eq. (20) is really ineffective. In terms of natural and mathematical phenomena, the trend of finding better solutions is not clearly related to the central social condition. In some cases of the Benchmark optimization functions [26], there are central variables of "zero value" making this method effective. However, it should be noted that in the cases, the "zero value" solution (or central solution) is a useful item because it lies between the lower and the upper bound of variables. However, this does not fit to all optimization problems because in general good solutions do not locate around the central solution.

In the second update, the three random conditions in Eq. (24) show the huge impact of randomization on the newly produced solutions. There are three ways to produce new control parameters in which $CV_{k,r1,p}$ and $CV_{k,r2,p}$ in the first and the second ways are the control variables randomly chosen from the first solution and the second solution in the pth pack, whereas $CV_{k,rd}$ in the third way is the kth control variable which is randomly generated in the range of $\left[CV_k^{min}, CV_k^{max}\right]$. Clearly, the combination of the three randomizations cannot lead to an effective solution with high quality excluding the diversification of generated control variables. So, the randomization technique should

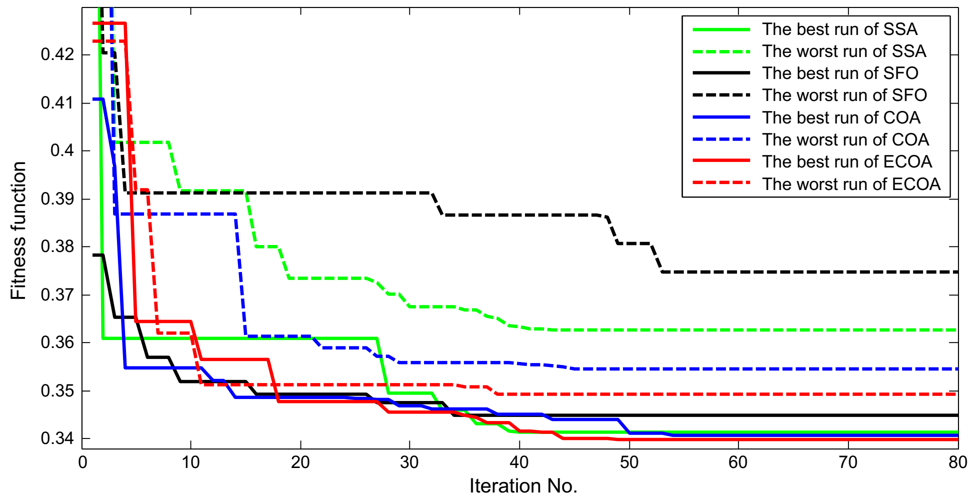


Fig. 12 The convergence curves for the best run and the worst run in 80 iterations

Table 8 Analysis of contribution of different methods to the 85-bus IEEE transmission power network thanks to the installation of DGs

Method	Saving TAPL (kW)	Better voltage (pu)	Saving TOC ($)	Saving fitness	Improvement level (%)			
					TAPL (kW)	Voltage (pu)	TOC ($)	Fitness
SSA	0.4	0.0013	44.00	0.0015	0.2616	0.14	0.4306	0.4395
SFO	1.1	0.0012	352.50	0.0051	0.7161	0.13	3.3486	1.4787
COA	− 0.3	0.0013	89.10	0.0008	− 0.1971	0.14	0.8681	0.2348
ECOA	–	–	–	–	–	–	–	–

Table 9 The comparison of results obtained of single DG by the proposed ECOA and other methods

Method	TAPL (kW)	Worst voltage (pu)	Location—capacity	It^{Max}	N_{ps}	The number of runs finding the best solution	The improvement of TAPL (%)
Without DG	316.1	0.8713	–	–	–	–	44.4796
WOA [44]	224.0	0.9109	Bus: 55—size: 0.9463 MW	50	50	–	21.6518
PLI-WOA [45]	227.1	0.9101	Bus: 54—size: 0.9101 MW	50	50	–	22.7213
COA	175.5	0.9282	Bus: 08—size: 2.3743 MW	50	25	26	0.0000
ECOA	175.5	0.9282	Bus: 08—size: 2.3743 MW	50	25	44	–

be abandoned and replaced with a more promising technique by using Eq. (29).

In summary, the modifications on the first and the second update techniques of COA can eliminate the following existing main drawbacks

1. Not to produce tendency solution in the first update. The process of finding the tendency solution is complicated and time consuming. So, the elimination of the solution can shorten the computation steps and reduce simulation time.
2. Eliminate the randomization combination and avoid the huge impact of the randomization. The randomization technique is time consuming and ineffective. So, the replacement of the second update can support ECOA to find more promising solutions and reduce computation steps and simulation time.

The two existing main drawbacks of COA are also the two main contributions of the proposed ECOA that can be seen clearly by observing the results shown in tables and figures. The best fitness function of 50 trial runs for three study networks with 33, 69 and 85 nodes indicated ECOA is always more effective than COA and approximately all 50 runs of ECOA can reach better fitness function. The improvement of ECOA over COA is, respectively, 0.0774%, 0.1723% and 0.2348% for the 33-, 69- and 85-bus distribution networks. Clearly, the improvement is more significant for larger-scale system. In particular, for the largest system with 85 nodes and single objective function, ECOA can find the best solution 46 times for 50 runs, whereas COA only finds the best solution 26 times. In addition, average simulation time for each run is also reported in Tables 3, 5 and 7 for COA, the proposed ECOA and other implemented methods including SSA and SFO. The simulation time of other methods in previous studies has not been reported for comparison. The simulation time of COA and the proposed ECOA is respectively 1.328 and 1.284 seconds for the 33-bus system, 3.646 and 3.579 seconds for the 69-bus system, and 7.442 and 7.347 for the 85-bus system. The time comparison can show the faster search of ECOA. Although the time reduction is not significant, the proposed method can reach less fitness function than COA for approximately all study cases.

Finally, through statistically analyzing the experiment results in three standard power systems, i.e., IEEE 33-, 69- and 85-bus radial distribution networks, we can withdraw some general comments about the performance of the proposed ECOA approach and the paper's contributions as follows:

1. Clarity: analyzing the experiment results we can conclude that properly integrating DGs in the power distribution networks really improves the network's operation in all considerable aspects, such as reduction in the power losses, improvement of the voltage stability and minimization of the operational cost. The proposed ECOA method can be effectively solved the optimal location and size of DGs in the power distribution networks where the general multi-objective function is the combination of three individual objectives.
2. Originality: COA inspired from the natural behaviors of coyotes is a new meta-heuristic algorithm which has just been published in 2018. Thus, this paper is the first research applying COA and the proposed ECOA methods for the multi-objective optimization problem of solving the optimal location and size of DGs in the power distribution networks.
3. Superiority: compared to other recently similar methods, the proposed ECOA method is superior in terms of higher quality solution, faster search implementation and shorter simulation time. According to the general multi-objective function (fitness function value) consisting of three individual objectives, ECOA can find the best optimal result. Similarly, according to the convergence speed based on the number of fitness function evaluations and simulation time, ECOA is the fastest methods.
4. Novelty: the proposed ECOA method is developed with two essential modifying ideas to overcome the disadvantages of the original COA which are slow convergent to low-quality solutions. The first one is replacing the central solution by the best current solution that is the most dominant quality solution of a group. Thus, creating a new solution using the best current solution obviously is a positive and effective way better than using the central solution. The second idea is proposing a new solution generation technique that can reduce the number of computation steps and process time thanks to avoiding the randomization-based conditions.

6 Conclusion

In this paper, a multi-objective problem with three single functions including power loss reduction, voltage deviation index and total operation cost has been solved by the application of SSA, SFO, COA and the proposed ECOA. Location and capacity of DGs in the 33-bus, 69-bus and 85-bus radial distribution systems have been found for determining the multi-objective function and implementing comparison. The comparison criteria have been applied to evaluate the proposed method including the fitness function, control parameters and simulation time. The proposed ECOA method was superior to COA, SSA and SFO in terms of using smaller control parameters, taking shorter simulation time but finding much better fitness function. As compared to COA, SSA and SFO, the improvement of the best solution from the proposed method was, respectively, 0.0774%, 0.4244% and 2.1978% for the 33-bus system, 0.1723%, 0.7858%, and 1.2194% for the 69-bus system, and 0.2348%, 0.4395% and 1.4787% for the 85-bus system. The comparisons with other previous methods have indicated the significant improvement of the proposed method. The improvement was up to 31.7491%, 20.2143% and 22.7213% for the three employed test systems, respectively. Furthermore, the proposed method has been much faster than these previous methods because it has been run with smaller number of fitness function evaluations than these previous methods. As a result, the proposed method could be used as a powerful method for the multi-objective problem. In the future, ECOA will be tried for larger and more complex networks with many devices already connected on the grid such as capacitor banks, voltage regulators, switches and filters. For more details, ECOA will be considered to apply for solving optimization problems in the co-simulation between MATLAB and OpenDSS software in complex multi-phase unbalanced networks under variable load conditions. Obviously, ECOA promises to be an effective algorithm with high stability and reliability in solving various optimization problems.

Compliance with ethical standards

Conflict of interest Our paper has no conflict of interest with any other individuals or parties. We have also not received any funding support for this research.

Appendix

See Tables 10, 11 and 12.

Table 10 The best location and capacity of DGs found by the proposed method and other methods for the IEEE 33-bus distribution network

Method	Optimal solution	TAPL (kW)	Minimum bus voltage (pu)	TOC ($)
GA [14]	Bus: 11—size: 1.5000 MW	106.3	0.9809	15,396.2
	Bus: 29—size: 0.4228 MW			
	Bus: 30—size: 1.0714 MW			
PSO [14]	Bus: 08—size: 1.1768 MW	105.4	0.9806	15,361.9
	Bus: 13—size: 0.9816 MW			
	Bus: 32—size: 0.8297 MW			
GA/PSO [14]	Bus: 11—size: 0.9250 MW	103.4	0.9808	15,353.6
	Bus: 16—size: 0.8630 MW			
	Bus: 32—size: 1.2000 MW			
SA [15]	Bus: 06—size: 1.1124 MW	82.0	0.9676	12,666.6
	Bus: 18—size: 0.4874 MW			
	Bus: 30—size: 0.8679 MW			
BSOA [20]	Bus: 13—size: 0.6320 MW	89.0	0.9554	8701.2
	Bus: 28—size: 0.4860 MW			
	Bus: 31—size: 0.550 MW			
BFOA [22]	Bus: 17—size: 0.6335 MW	98.3	0.9645	9948.1
	Bus: 18—size: 0.0908 MW			
	Bus: 33—size: 0.9470 MW			
SSA	Bus: 13—size: 0.8423 MW	77.0	0.9655	11,660.2
	Bus: 25—size: 0.5910 MW			
	Bus: 31—size: 0.8371 MW			
SFO	Bus: 15—size: 0.6950 MW	75.9	0.9611	12,675.4
	Bus: 24—size: 0.8915 MW			
	Bus: 30—size: 0.8878 MW			
COA	Bus: 14—size: 0.7096 MW	76.0	0.9637	11,815.2
	Bus: 25—size: 0.5954 MW			
	Bus: 30—size: 0.9972 MW			
ECOA	Bus: 14—size: 0.7376 MW	74.6	0.9666	12,597.9
	Bus: 25—size: 0.6518 MW			
	Bus: 30—size: 1.0705 MW			

Table 11 The best location and capacity of DGs found by the proposed method and other methods for the IEEE 69-bus distribution network

Method	Optimal solution	TAPL (kW)	Minimum bus voltage (pu)	TOC ($)
GA [14]	Bus: 21—size: 0.9297 MW	89.0	0.9936	15,343.0
	Bus: 62—size: 1.0752 MW			
	Bus: 64—size: 0.9925 MW			
PSO [14]	Bus: 17—size: 0.9925 MW	83.2	0.9901	15,272.3
	Bus: 61—size: 1.1998 MW			
	Bus: 63—size: 0.7956 MW			
GA/PSO [14]	Bus: 21—size: 0.9105 MW	81.1	0.9925	15,264.4
	Bus: 61—size: 1.1926 MW			
	Bus: 63—size: 0.8849 MW			
SA [15]	Bus: 18—size: 0.4204 MW	77.1	0.9811	11,214.9
	Bus: 60—size: 1.3311 MW			
	Bus: 65—size: 0.4298 MW			
HSA [21]	Bus: 63—size: 1.3024 MW	86.8	0.9670	9211.3
	Bus: 64—size: 0.3690 MW			
	Bus: 65—size: 0.1018 MW			
BFOA [22]	Bus: 27—size: 0.2954 MW	75.2	0.9808	10,741.4
	Bus: 61—size: 1.3451 MW			
	Bus: 65—size: 0.4476 MW			
SSA	Bus: 17—size: 0.3358 MW	73.0	0.9764	10,617.8
	Bus: 61—size: 1.6581 MW			
	Bus: 64—size: 0.0713 MW			
SFO	Bus: 19—size: 0.3583 MW	72.7	0.9762	10,894.6
	Bus: 50—size: 0.0300 MW			
	Bus: 61—size: 1.7323 MW			
COA	Bus: 19—size: 0.3439 MW	72.5	0.9776	10,632.5
	Bus: 61—size: 1.4388 MW			
	Bus: 64—size: 0.2858 MW			
ECOA	Bus: 18—size: 0.4001 MW	71.8	0.9784	10,904.0

Table 12 The best location and capacity of DGs found by the proposed method and other methods for the IEEE 85-bus distribution network

Method	Optimal solution	TAPL (kW)	Minimum bus voltage (pu)	TOC ($)
SSA	Bus: 10—size: 0.5086 MW	152.9	0.9500	10,218.2
	Bus: 72—size: 0.5733 MW			
	Bus: 34—size: 0.8394 MW			
SFO	Bus: 32—size: 1.0592 MW	153.6	0.9501	10,526.7
	Bus: 12—size: 0.3546 MW			
	Bus: 72—size: 0.5686 MW			
COA	Bus: 67—size: 0.6779 MW	152.2	0.9500	10,263.3
	Bus: 34—size: 0.8312 MW			
	Bus: 80—size: 0.4219 MW			
ECOA	Bus: 67—size: 0.6354 MW	152.5	0.9513	10,174.2

References

1. Dogansahin K, Kekezoglu B, Yumurtaci R, Erdinc O, Catalao JPS (2018) Maximum permissible integration capacity of renewable DG units based on system loads. Energies 11(1):255. https://doi.org/10.3390/en11010255
2. Ramavat SR, Jaiswal SP, Goel N, Shrivastava V (2019) Optimal location and sizing of DG in distribution system and its cost–benefit analysis. In: Applications of artificial intelligence techniques in engineering. Springer, Singapore, pp 103–112. https://doi.org/10.1007/978-981-13-1819-1_11
3. Morshidi MN, Musirin I, Rahim SRA, Adzman MR, Hussain MH (2018) Whale Optimal Algorithm based technique for distributed generation installation in distribution system. Bull Electr Eng Inform 7(3):442–449. https://doi.org/10.11591/eei.v7i31276

4. Ismael SM, Aleem SHEA, Abdelaziz AY (2018) Optimal sizing and placement of distributed generation in Egyptian radial distribution systems using crow search algorithm. In: 2018 international conference on innovative trends in computer engineering IEEE, pp 332–337. https://doi.org/10.1109/ITCE.2018.8316646
5. Prakash DB, Lakshminarayana C (2018) Multiple DG placements in radial distribution system for multi objectives using Whale Optimization Algorithm. Alex Eng J 57(4):2797–2806. https://doi.org/10.1016/j.aej.2017.11.003
6. Duong MQ, Pham TD, Nguyen TT, Doan AT, Tran HV (2019) Determination of optimal location and sizing of solar photovoltaic distribution generation units in radial distribution systems. Energies 12(1):174. https://doi.org/10.3390/en12010174
7. Bansal A, Singh S (2016) Optimal allocation and sizing of distributed generation for power loss reduction. https://doi.org/10.1049/cp.2016.1116
8. EL-Sayed SK (2017) Optimal location and sizing of distributed generation for minimizing power loss using simulated annealing algorithm. J Electr Electron Eng 5(3):104–110. https://doi.org/10.11648/j.jeee.20170503.14
9. Dixit M, Kundu P, Jariwala HR (2016) Optimal placement and sizing of DG in Distribution system using Artificial Bee Colony Algorithm. In: 2016 IEEE 6th international conference on power systems ICPS, pp 1–6. IEEE. https://doi.org/10.1109/ICPES.2016.7584010
10. Kashyap M, Mittal A, Kansal S (2019) Optimal placement of distributed generation using genetic algorithm approach. In: Proceeding of the second international conference on microelectronics, computing and communication systems. Springer, pp 587–597. https://doi.org/10.1007/978-981-10-8234-4_47
11. Sulistyowati R, Riawan DC, Ashari M (2016) PV farm placement and sizing using GA for area development plan of distribution network. In: 2016 international seminar on intelligent technology and its applications IEEE, pp 509–514. https://doi.org/10.1109/ISITIA.2016.7828712
12. Mahesh K, Nallagownden PAL, Elamvazuthu IAL (2015) Optimal placement and sizing of DG in distribution system using accelerated PSO for power loss minimization. In: 2015 IEEE conference on energy conversion. IEEE, pp 193–198. https://doi.org/10.1109/CENCON.2015.7409538
13. Zongo OA, Oonsivilai A (2017) Optimal placement of distributed generator for power loss minimization and voltage stability improvement. Energy Proc 138:134–139. https://doi.org/10.1016/j.egypro.2017.10.080
14. Moradi MH, Abedini M (2012) A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems. Int J Electr Power Energy Syst 34(1):66–74. https://doi.org/10.1016/j.ijepes.2011.08.023
15. Injeti SK, Kumar NP (2013) A novel approach to identify optimal access point and capacity of multiple DGs in a small, medium and large scale radial distribution systems. Int J Electr Power Energy Syst 45(1):142–151. https://doi.org/10.1016/j.ijepes.2012.08.043
16. Rashmi D, Amol K (2018) Optimal placement and sizing of Distributed Generator in Distribution system using Artificial Bee Colony Algorithm. In: 2018 IEEE global conference on wireless computing and networking. IEEE, pp 178–181. https://doi.org/10.1109/GCWCN.2018.8668633
17. Mohandas N, Balamurugan R, Lakshminarasimman L (2015) Optimal location and sizing of real power DG units to improve the voltage stability in the distribution system using ABC algorithm united with chaos. Int J Electr Power Energy Syst 66:41–52. https://doi.org/10.1016/j.ijepes.2014.10.033
18. Othman MM, El-Khattam W, Hegazy YG, Abdelaziz AY (2014) Optimal placement and sizing of distributed generators in unbalanced distribution systems using supervised big bang-big crunch method. IEEE Trans Power Syst 30(2):911–919. https://doi.org/10.1109/TPWRS.2014.2331364
19. Gupta S, Saxena A, Soni BP (2015) Optimal placement strategy of distributed generators based on radial basis function neural network in distribution networks. Pro Comput Sci 57:249–257. https://doi.org/10.1016/j.procs.2015.07.478
20. El-Fergany A (2015) Optimal allocation of multi-type distributed generators using backtracking search optimization algorithm. Int J Electr Power Energy Syst 64:1197–1205. https://doi.org/10.1016/j.ijepes.2014.09.020
21. Rao RS, Ravindra K, Satish K, Narasimham SVL (2012) Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation. IEEE Trans Power Syst 28(1):317–325. https://doi.org/10.1109/TPWRS.2012.2197227
22. Devabalaji KR, Ravi K (2015) Optimal size and siting of multiple DG and DSTATCOM in radial distribution system using Bacterial Foraging Optimization Algorithm. Ain Shams Eng J. https://doi.org/10.1016/j.asej.2015.07.002
23. Ameli A, Bahrami S, Khazaeli F, Haghifam MR (2014) A multiobjective particle swarm optimization for sizing and placement of DGs from DG owner's and distribution company's viewpoints. IEEE Trans Power Deliv 29(4):1831–1840. https://doi.org/10.1109/TPWRD.2014.2300845
24. Phonrattanasak P (2010) Optimal placement of DG using multiobjective particle swarm optimization. In: 2010 international conference on mechanical and electrical technology. IEEE, pp 342–346. https://doi.org/10.1109/ICMET.2010.5598377
25. Abdel-Akher M, Ali AA, Eid AM, El-Kishky H (2011) Optimal size and location of distributed generation unit for voltage stability enhancement. In: 2011 IEEE energy conversion congress and exposition IEEE, pp 104–108. https://doi.org/10.1109/ECCE.2011.6063755
26. Pierezan J, Coelho LDS (2018) Coyote optimization algorithm: a new metaheuristic for global optimization problems. In: 2018 IEEE congress on evolutionary computation IEEE, pp 1–8. https://doi.org/10.1109/CEC.2018.8477769
27. Mirjalili S, Gandomi AH, Mirjalili SZ, Saremi S, Faris H, Mirjalili SM (2017) Salp Swarm Algorithm: a bio-inspired optimizer for engineering design problems. Adv Eng Softw 114:163–191. https://doi.org/10.1016/j.advengsoft.2017.07.002
28. Gomes GF, da Cunha SS, Ancelotti AC (2019) A sunflower optimization (SFO) algorithm applied to damage identification on laminated composite plates. Eng Comput 35(2):619–626. https://doi.org/10.1007/s00366-018-0620-8
29. Suresh MCV, Belwin EJ (2018) Optimal DG placement for benefit maximization in distribution networks by using Dragonfly algorithm. Renew Wind Water Solar 5(1):4. https://doi.org/10.1186/s40807-018-0050-7
30. Uniyal A, Kumar A (2018) Optimal distributed generation placement with multiple objectives considering probabilistic load. Proc Comput Sci 125:382–388. https://doi.org/10.1016/j.procs.2017.12.050
31. Sarkar K, Pang C, Yang L (2017) Optimal location for single and multiple DG based on Vulnerability Index in smart distribution system. In: 2017 power and energy society general meeting IEEE, pp 1–5. https://doi.org/10.1109/pesgn.2017.8274476
32. Shamugapriyan J, Karuppiah N, Muthubalaji S, Tamulselvi S (2018) Optimum placement of multi type DG units for loss reduction in a radial distribution system considering the distributed generation suitability index using evolutionary algorithms. Bull Pol Acad Sci Technol Sci 66(3):345–354. https://doi.org/10.24425/123441
33. Prakash R, Sujatha BC (2016) Optimal placement and sizing of DG for power loss minimization and VSI improvement using bat

algorithm. In: 2016 national power systems conference IEEE, pp 1–6. https://doi.org/10.1109/NPSC.2016.7858964
34. Nweke JN, Ekwue AO, Ejiogu EC (2016) Optimal location of distributed generation on the Nigerian power system. Niger J Technol 35(2):398–403. https://doi.org/10.4314/njt.v35i2.22
35. Aman MM, Jasmon GB, Bakar AHA, Mokhlis H (2014) A new approach for optimum simultaneous multi-DG distributed generation units placement and sizing based on maximization of system load ability using HPSO (hybrid particle swarm optimization) algorithm. Energy 66:202–215. https://doi.org/10.1016/j.energy.2013.12.037
36. Saha S, Mukherjee V (2016) Optimal placement and sizing of DGs in RDS using chaos embedded SOS algorithm. IET Gener Transm Distrib 10(14):3671–3680. https://doi.org/10.1049/iet-gtd.2016.0151
37. Lü Q, Liao X, Li H, Huang T (2020) A Nesterov-like gradient tracking algorithm for distributed optimization over directed networks. IEEE Trans Syst Man Cybern Syst. https://doi.org/10.1109/tsmc.2019.2960770
38. Lü Q, Li H, Wang Z, Han Q, Ge W (2019) Performing linear convergence for distributed constrained optimisation over time-varying directed unbalanced networks. IET Control Theory Appl 13(17):2800–2810. https://doi.org/10.1049/iet-cta.2018.6026
39. Teng HJ, Chang YC (2007) Backward/forward sweep-base harmonic analysis method for distribution systems. IEEE Trans Power Deliv 22(3):1665–1672. https://doi.org/10.1109/tpwrd.2007.899523
40. Mahmoud HP, Behnam IM (2020) Optimization of power system problems: methods, algorithms and MATLAB codes. Springer, Basel
41. Mohamed IA, Kowsalya M (2014) Optimal size and siting of multiple distributed generators in distribution system using bacterial foraging optimization. Swarm Evolut Comput 57:58–65. https://doi.org/10.1016/j.swevo.2013.12.001
42. Vita V (2017) Development of a decision-making algorithm for the optimum size and placement of distributed generation units in distribution networks. Energies 10(9):1433. https://doi.org/10.3390/en10091433
43. Prakash DB, Lakshminarayana C (2017) Optimal siting of capacitors in radial distribution network using whale optimization algorithm. Alex Eng J 56(4):499–509. https://doi.org/10.1016/j.aej.2016.10.002
44. Reddy PDP, Reddy VCV, Manohar GT (2017) Whale optimization algorithm for optimal sizing of renewable resources for loss reduction in distribution systems. Renew Wind Water Solar 4(3):1–13. https://doi.org/10.1186/s40807-017-0040-1
45. Reddy PDP, Reddy VCV, Manohar GT (2017) Optimal renewable resources placement in distribution networks by combined power loss index and whale optimization algorithms. J Electr Syst Inf Technol. https://doi.org/10.1016/j.jesit.2017.05.006