How does the civilized gravitational search algorithm solve the optimal DG placement?

SAMAN HOSSEINI-HEMATI[1], **SHAHRAM KARIMI**[1,*], AND **GHOLAM HOSSEIN SHEISI**[1]

[1] *Electrical Engineering Department, Engineering Faculty, Razi University, Kermanshah, Iran*
[*] *Corresponding author: shahramkarimi@razi.ac.ir*

Manuscript received 29 March, 2020; revised 05 September, 2020, accepted 20 September, 2020. Paper no. JEMT-2003-1234.

This study addresses Civilized Gravitational Search Algorithm (CGSA) as a new mass intelligence optimization algorithm for solving optimal single and multiple DG placement problems in distribution networks. The proposed technique utilizes the modified search procedure of Society Civilization Algorithm (SCA) combining with Newtonian laws of GSA. It mainly consists of two steps. The first step provides a candidate list for DG allocation based on active power loss minimization and the second one searches simultaneously the optimal DG size(s) and location(s) using Self-Adoptive Learning (SAL) strategy. In order to verify the capabilities and effectiveness of the suggested approach, all simulations are conducted through IEEE 33- and 69-bus distribution grids. Moreover, 23 standard functions are examined to verify the stability of the proposed algorithm on different low- and high-dimensional functions. Comparisons demonstrate the superior performance of the presented method to provide better solution quality with a fast convergence characteristic.

keywords: *Optimal DG placement, Distribution network, Civilized gravitational search algorithm, Real power loss minimization.*

http://dx.doi.org/10.22109/jemt.2020.224858.1234

NOMENCLATURE

Abbreviation

BGA Binary Genetic Algorithm
CGSA Civilized Gravitational Search Algorithm
CL Civilized Leader
DG Distributed Generation
DGP Distributed Generation Placement
DISCO Distribution Company
FWA Fireworks Algorithm
GA Genetic Algorithm
GSA Gravitational Search Algorithm
HSA Harmony Search Algorithm
L Light
N Nominal
NA Not Available
ODGP Optimal Distributed Generation Placement
P Peak
PSO Particle Swarm Optimization
RGA Refined Genetic Algorithm
RWS Roulette Wheel Selection
SAL Self-Adoptive Learning
SCA Society Civilization Algorithm
Std Standard deviation
SL Society Leader
SM Society Member
WOA Whale Optimization Algorithm

Nomenclature

P_{loss} Total real power losses
$P_{loss,L}$ Real power loss of light load level
$P_{loss,N}$ Real power loss of nominal load level
$P_{loss,P}$ Real power loss of peak load level
R_i Resistance of the ith branch
$|I_i|$ Current magnitude in branch i
BR Set of branches
E_{loss} Annual energy loss
D_L Duration of light load level
D_N Duration of nominal load level
D_P Duration of peak load level
P_{g_i} Real power production of the ith bus
Q_{g_i} Reactive power production of the ith bus
P_{d_i} Active power demand of the ith bus
Q_{d_i} Reactive power demand of the ith bus
P_{DG_i} Real power production of DG at bus i

$|V_i|$ Voltage magnitude of the ith bus
δ_{ij} Phase angle between two buses i and j
G_{ij} Conductance of line i-j
B_{ij} Susceptance of line i-j
N_b Number of nodes
min Lower limit
max Upper limit
Loc DG location
X_i Position of the ith mass
x_i^d dth component of X
N Number of masses
$(.)^T$ Transposition of $(\cdot)$
$F_{ij}^d(t)$ Gravitational force between two masses i and j in the dth dimension at time t
$G(t)$ Gravitational constant at time t
G_0 Initial value of gravitational constant
$Iteration_{\max}$ Maximum iterations
t Time, iteration
ϑ A constant value
$R_{ij}(t)$ Euclidian distance between two masses i and j at time t
K_{best} Number of good agents
K_0 Initial value
$rand$ A random number within interval
M_{ii} Inertial mass of the ith agent
$v_i^d(t)$ Velocity of mass i in the dth dimension at time t
$a_i^d(t)$ Acceleration of mass i in the dth dimension at time t
$fit_i(t)$ Fitness value of agent i at time t
N_S Number of SLs
N_{DG} Number of DGs
S Society
M_{best}^{CL} The best searched CL saved until now
M_{best}^{SL} The best searched SL saved until now
γ_{CL} Acceleration factor for CL
γ_{SL} Acceleration factor for SL
γ_{SM} Acceleration factor for SM
$initial$ Initial value
$final$ Final value
$N_{DG-Candidate}$ Number of candidate buses
$\Pr ob_{Loc}$ Probability of a candidate location
θ Learning factor
AP_{Loc_i} Accumulator for the ith location
wf Weight factor

1. INTRODUCTION

The electrical distribution network as the final link between customers and bulk power network is becoming more complex and large leading to poor voltage regulation as well as higher real losses [1]. Based on estimations, 13% of the electrical power generations are lost in electrical power losses form in the distribution grids [2]. In fact, due to a high R/X ratio and operating at low voltage and high current (in comparison to the high voltage systems), distribution networks suffer from high active power losses (low efficiency) and poor voltage profile [3]. Moreover, at heavy loads, the power losses can even be more significant. These flows deteriorate the voltage profile and can result in a high voltage drop in some sections of the distribution network [4]. So, DISCOs attempt to optimize the operation by minimizing the power losses which lead to the voltage improvement at different nodes. In order to achieve this goal, applying some new technologies like DGs is attracting more attentions. DGs can reduce the total power losses; enhance the voltage and also the system efficiency; as well as increase the remained capacities of lines. To assure the technical benefits of DG utilization, DISCO needs to determine the optimal site and size of them at different load profiles [5]. It should be noted that inappropriate allocation of DG leads to additional power losses which can sometimes endanger the network operation [6], [7]. Hence, the optimal DG placement in electrical distribution systems is always a major concern of DISCOs.

The DGs penetration in distribution systems has recently been increased due to their considerable advances and their positive environmental and operational impacts. Many researchers proposed different methods to optimally find both size and location of the DG units. Reference [1] reviewed different optimization methods and models applied to the ODGP. As it was indicated in [1], the main objective functions of ODGP which should be optimized include: the cost, power loss, voltage magnitude, average interruption index, DG capacity, profit, and voltage limit load ability.

Ref. [8] combined GA and tabu search approach to solve ODGP. In [9], an analytical method based on the loss formulation has been utilized. In other words, [9] formulated a loss sensitivity factor using exact power loss formula to limit the solution space and to find the optimal size of DGs. A similar approach has been used in [6], [10]–[12] to search the optimal sites for DG installation. In [10], an integration of GA and branch exchange has been suggested to solve DG allocation problem. This reference minimized the energy losses subject to different constraints regarding to the bus, line, and DG units.

Ref. [11] applied HSA to search the optimal DG size. In [12], [13], DG allocation for optimizing the total real losses using PSO has been reported. Another approach based on ant colony search has been introduced in [14] to seek the DG sizes and buses. Paper [15] documented GA and PSO combination to optimize the power losses, voltage regulation as well as stability of radial distribution networks. In [4] a similar method has been introduced for multiple DG placement. In [16], grey wolf optimizer has been proposed for ODGP problem considering two DGs in a distribution grid. Ref. [17] used the voltage stability index to find the optimal buses and then implemented the FWA to search the optimal size of DG minimizing total power losses. Paper [18] applied hybrid big bang-big crunch algorithm optimizing different objectives like power losses, voltage stability, emission, etc. In [19], a hybrid evolutionary technique has been utilized for the optimal placement and sizing of DG investigating various DG technologies. Ref. [20] introduced techno-economic and environmental method for ODGP. Ref [3] solved the mentioned problem minimizing various objectives by multi-objective opposition based chaotic differential evolution.

Most of the reviewed papers employ the node sensitivity analysis (e.g. [6], [9]–[12]) to find the candidate buses. In other words, they select only top few buses to make a bus priority list to restrict the solution space. However, providing this list based on sensitivity approach is not foolproof, as the sensitivity factors are normally computed for the base case condition. Moreover, applying this method may eliminate some potential buses that would actually form part of a sub-optimal or even an optimal solution. In the meantime, employing a powerful optimization algorithm to solve ODGP problem is essential as the most of the reported approaches cannot always converge to the global optimum or near-global optimal solution because of the special structure of the mentioned subject. Moreover, some approaches like [10], [11], [17], [18], [21] combined DG allocation with other problems like capacitor allocation and reconfiguration and they did not directly focus on DG allocation.

In 2009, based on the Newtonian laws, a powerful search method has been introduced, namely GSA [22]. This technique has successfully been examined on different complex problems and the reported results proved its high efficiency and enough flexibility to raise abilities of both exploitation and exploration. Due to these, a civilized version of it, namely CGSA, is proposed to handle the real world ODGP considering the linked difficulties and as authors of this paper know, CGSA has not been suggested, presented, and evaluated on this problem at all.

In this work, a novel optimization technique based on the suggested CGSA is proposed for ODGP. The proposed CGSA civilizes the GSA by applying the modified search procedure of SCA. The proposed optimization algorithm only focuses on DG allocation problem and has two main steps. The first step provides a list of candidate buses (not a bus priority list; unlike the reported methods) for DG installation and the second one through a proposed probabilistic way, namely SAL strategy, simultaneously finds the optimal placement and sizing of DG(s).

The main trait of the CGSA is linked to its potential in searching an optimal solution of DGP in distribution systems. This provides necessary motivations to achieve more technical benefits such as lower power loss, improvement of voltage profile, better annual energy loss reduction, etc. by finding better optimum (DG site(s) and size(s)) than other presented techniques along with acceptable convergence characteristics. In other words, the suggested method can yield a good solution quality and better operating points without convergence problems. Hence, performances of various techniques are mainly evaluated based on the mentioned technical benefits which can be achieved in finding the global solution (or a near optimal one).

Rest of the paper is organized as: Second section presents the formulation of ODGP. Mathematical structure of CGSA and the proposed SAL strategy to search the optimal locations of DGs are introduced in third section. In Section 4, the introduced optimization algorithm based on CGSA to solve ODGP problem and its relevant steps are summarized. The optimization results for single and multiple ODGP problems are presented and compared to some optimization algorithms in Section 5. The final section draws conclusions.

2. ODGP FORMULATION

Benefits of DGs can be enhanced if they are allocated in an accurate manner. Hence, ODGP problem is formulated in this section considering the following assumptions [11], [17], [21]:
1) Distribution network is a balanced system.
2) DGs are operated with unity power factor.
3) Substation bus is not considered for DG placement.

A. Objective function

In this work, optimization of total real power losses is considered as the main objective as follows:

$$\min P_{loss} = \sum_{i \in BR} R_i \left| I_i \right|^2 \tag{1}$$

Moreover, the annual energy loss as another objective is minimized as:

$$\min E_{loss} = P_{loss,L} D_L + P_{loss,N} D_N + P_{loss,P} D_P \tag{2}$$

B. Problem constraints

The main constraints of the ODGP problem can be formulated as follows:
a)Power balance equations
The real power balance equation considering DG unit as (3) and reactive power balance equation as (4) are two equality constraints for the ith node.

$$P_{g_i} + P_{DG_i} - P_{d_i} = |V_i| \sum_{j=1}^{N_b} \left| V_j \right| (G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij})) \tag{3}$$

$$Q_{g_i} - Q_{d_i} = |V_i| \sum_{j=1}^{N_b} \left| V_j \right| (G_{ij} \sin(\delta_{ij}) - B_{ij} \cos(\delta_{ij})) \tag{4}$$

b) Voltage constraint
The voltage limits are stated as below:

$$|V_i|_{\min} \leq |V_i| \leq |V_i|_{\max}; i = 1, ..., N_b \tag{5}$$

c) Branch thermal constraints
Line thermal limits can be formulated as (6) to ensure that the current flow through each branch is less than the rated ampacity of each branch.

$$|I_i| \leq |I_i|_{\max}; i \in BR \tag{6}$$

d)DG capacity limit
The real power generation by the ith DG must satisfy the following constraint.

$$P_{DG_{\min}} \leq P_{DG_i} \leq P_{DG_{\max}}; i = 1, ..., N_b \tag{7}$$

e) Total capacity limit of DGs
The total real power output of all DGs should be limited to the total demands of the network as follows:

$$\sum_{i=1}^{N_{DG}} P_{DG_i} \leq \sum_{i=1}^{N_b} P_{d_i} \tag{8}$$

f) DG location constraint
The following constraint should be applied to prevent selecting a candidate node for two or more DG placements.

$$Loc_i \neq Loc_j; i, j = 1, ..., N_{DG} \tag{9}$$

3. MATHEMATICAL STRUCTURE OF CGSA

In this section, the main GSA structure is mathematically presented and then the suggested modifications are presented to form the CGSA.

A. GSA

GSA is a powerful optimization algorithm which was found in 2009 [22]. Newtonian laws of gravitation and motion form this algorithm and it can handle highly non-convex and nonlinear optimization problems as demonstrated in [22], [23]. So far, different modifications have been applied to this algorithm and some of them can be found in [24], [25]. Therefore, the principles of GSA are briefly presented here.

In GSA, the position of the ith mass is stated as (10) which shows a possible solution.

$$X_i = \left[x_i^1, ..., x_i^d, ..., x_i^n\right]^T; i = 1, 2, ..., N \quad (10)$$

The gravitational force between two masses i and j in the dth dimension at time t can be formulated as follows:

$$F_{ij}^d(t) = G(t) \times \frac{M_i(t)M_j(t)}{R_{ij}(t) + \varepsilon} \times (x_j^d(t) - x_i^d(t)) \quad (11)$$

where

$$G(t) = G_0 \exp(\frac{-\vartheta t}{Iteration_{\max}}); R_{ij}(t) = \left\|X_i(t), X_j(t)\right\|_2 \quad (12)$$

and where the search accuracy is controlled by the gravitational constant $G(t)$ which is exponentially decreased.

It should be mentioned that, in (11), $R_{ij}(t)$ provides better performance than $R_{ij}^2(t)$ (unlike the law of gravity which says that F_{ij}^d is inversely proportional to $R_{ij}^2(t)$) [22], [24], [25]. Moreover, (11) indicates that F_{ij}^d is highest when the masses are heavier and their distance is short. Also, the gravity acts without any delay between separated masses [22].

Equation (13) represents the total force F_i^d applied by the ith mass. It reduces the number of agents during optimization process and allows to more search the whole search space and avoid finding a local minimum. In addition, the exploitation power fades during optimization process. Moreover, K_{best} solutions corresponding to heavier ones (good agents) just apply their force to other agents to enhance the GSA performance. It linearly decreased from K_0.

$$F_i^d(t) = \sum_{\substack{j \in K_{best} \\ j \neq i}}^{N} rand_j \times F_{ij}^d(t) \quad (13)$$

Acceleration of mass i at time t in the dth dimension can be calculated using Newton's law of motion as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \quad (14)$$

M_{ii} as the inertial mass resists to change its motion state. Thus, a large inertial mass (a good solution) accelerates more slowly than a lighter mass (a bad solution) and vice versa. Hence, heavier agents (better solutions) slowly move and attract all other agents according to (13) considering (11).

In GSA, the velocity at iteration $(t + 1)$ as well as its new position in the dth dimension are expressed as (15) and (16), respectively.

$$v_i^d(t + 1) = rand_i \times v_i^d(t) + a_i^d(t) \quad (15)$$

$$x_i^d(t + 1) = x_i^d(t) + v_i^d(t + 1) \quad (16)$$

Finally, the updated agent i at time t is calculated as below:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)}; M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \quad (17)$$

where

$$best(t) = \min_{j \in \{1,..., N\}} fit_j(t); worst(t) = \max_{j \in \{1,..., N\}} fit_j(t) \quad (18)$$

B. Applying modified SCA search procedure to GSA

In this subsection, the search procedure of SCA [26] is modified and integrated with GSA to form the suggested CGSA. Firstly, all masses should be divided into various societies and different leaders. Among N masses, the best N_s masses are designated as SL so that each society has its own SL. Therefore, other masses $(N - N_S)$ are SMs. Moreover, the best mass among all masses (which is one of the SLs) is selected as CL. The ith SM belongs to the jth society, if R_{ij} (between SL and SM) is minimal. Each SM should update its position by chasing respective SL and each SL updates its position by chasing CL (the best among SLs). Finally, CL guides its society and all other SLs. These concepts along with gravitational laws are depicted in Fig. 1. Accordingly, in this paper, all masses are ranked from the best to worst solutions and GSA movement as (16) is modified considering the acceleration factors and movement strategies of SCA as follows:

a) The updated position of CL is calculated as ($i = 1$ and $s = 1$):

$$\begin{aligned} x_{i,s}^d(t + 1) = x_{i,s}^d(t) + v_{i,s}^d(t + 1) + \gamma_{CL}(t) \times rand \\ \times (M_{best}^{CL} - x_{i,s}^d(t)) \end{aligned} \quad (19)$$

where M_{best}^{CL} represents the best searched CL saved until now; $\gamma_{CL}(t)$ is acceleration factor as:

$$\gamma_{CL}(t) = \gamma_{CL,initial} + \frac{\gamma_{CL,final} - \gamma_{CL,initial}}{Iteration_{\max}} \times t \quad (20)$$

b)The updated position of the ith SL related to the sth socity is stated as ($i = 2, ..., N_S$ and $s = 2, ..., N_S$):

$$\begin{aligned} x_{i,s}^d(t + 1) = x_{i,s}^d(t) + v_{i,s}^d(t + 1) + \gamma_{SL1}(t) \times rand \\ \times (M_{best}^{SL}(t) - x_{i,s}^d(t)) + \gamma_{SL2}(t) \times rand \\ \times (M_{best}^{CL}(t) - x_{i,s}^d(t)) \end{aligned} \quad (21)$$

where $M_{best}^{CL}(t)$ is the best searched SL saved until now; $\gamma_{SL1}(t)$ and $\gamma_{SL2}(t)$ are acceleration factors and are linearly changed as Eq. (20); In this work, the best position among SLs is also considered to improve the search ability.

c)The updated position of the ith SM related to the sth socity is presented as ($i = N_S + 1, ..., N$ and $s = 1, ..., N_S$):

$$\begin{aligned} x_{i,s}^d(t + 1) = x_{i,s}^d(t) + v_{i,s}^d(t + 1) + \gamma_{SM}(t) \times rand \\ \times (M_{best,s}^{SL}(t) - x_{i,s}^d(t)) \end{aligned} \quad (22)$$

where $\gamma_{SM}(t)$ is linearly changed as Eq. (20).

It should be noted that due to the evaluating the objective function, designation of CL, SLs, and SMs may be changed in each iteration. Moreover, based on the experiment results, the $\gamma(t)$ affects the search quality and convergence of the suggested algorithm, so that if γ is high, it prematurely results in searching a local minimum and on the contrary, if it is low, it leads in straying agents around the solution space. Due to this, γ should be increased in each iteration.

C. The proposed SAL strategy for DG placement in CGSA

In this subsection, SAL strategy is proposed to select the best DG locations among DG candidate nodes (see Section 4). Suppose that, there are $N_{DG-Candidate}$ candidate buses. In SAL approach, the more profitable DG locations than others are listed in a probabilistic manner at any iteration. So, a probability value can be applied to each of candidate locations (candidate buses). It

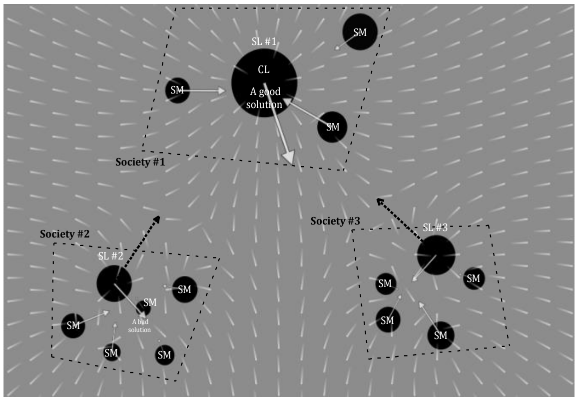

Fig. 1. The concept of the gravitational force between masses combined with the search procedure of SCA

depends on the ability of that location in providing better agents based on an adaptively mechanism. The probability of each candidate location (i.e. $Prob_{Loc}$) in the candidate list is calculated as follows:

$$\Pr ob_{Loc_i} = (1-\theta) \times \Pr ob_{Loc_i} + \frac{\theta \times AP_{Loc_i}}{Iteration_{\max}} \\ ; i = 1, ..., N_{DG-Candidate} \tag{23}$$

where θ can be chosen as $\theta = 0.142$ [27]; also, a weight factor (i.e. $wf_i = \frac{\log(N_{DG-Candidate}-j+1)}{\log(1)+...+\log(N_{DG-Candidate})}$) can be assigned for the jth best location with $j = 1, ..., N_{DG-Candidate}$. It makes better bus selection through assigning the larger weights. Finally, the normalized probabilities for each location can be calculated as:

$$\Pr ob_{Loc_i} = \frac{\Pr ob_{Loc_i}}{\sum_{i=1}^{N_{DG-Candidate}} \Pr ob_{Loc_i}} ; i = 1, ..., N_{DG-Candidate} \tag{24}$$

The appropriate method to select N_{DG} locations (buses) is presented in Section 4.

D. Differences between GSA and CGSA

- In both algorithms, the optimization process is formed through the movement of masses in the solution space; but their movement strategies and the search procedures are different.

- Both of the mentioned techniques use of the ability of information-transferring; but, this feature is more important in CGSA. Because, it improves the solutions diversity and so avoids searching a local optimum solution by changing designation of CL, SLs, and SMs.

- In these algorithms, the updating mechanism is on the basis of the solution quality and fitness value during updating process. In fact, the force is proportional to the fitness value and so, all agents in their influence area of the force can clearly see the solution space near themselves. But, in CGSA, this procedure is mainly performed in each society and CL indirectly affects all SMs (through SLs). In fact, the concept of influence area of the force is more highlighted.

- In the original GSA the direction of each mass is computed using the overall force of all other agents; but, CGSA divides masses into various societies and different leaders and uses the best position obtained so far and finally applies acceleration coefficients to them to improve the quality of solutions.

4. CGSA-BASED ODGP PROBLEM

The proposed CGSA-based ODGP has two main steps as follows: **Step 1 (selection of candidate locations).** The estimation of candidate buses in Step 1 helps significantly reduce the solution space for the ODGP step (i.e. Step 2). To find a list of candidate nodes (not a priority list), a test DG is subsequently set at each bus of the distribution system and then Step 2 is implemented (neglecting Sub-step 2.2). One node that causes the minimum objective function value (here, it is P_{loss}) due to the placed DG, is stored in the candidate list. Also, before searching the next candidate node, a DG is placed in the found location. So, the next optimal bus is explored in the same manner considering the found DG(s). This process is kept as long as there is no significant change in the objective function. Fig. 2 illustrates this process and its sub-steps are as follows:
Sub-step 1.1. Set. $N_{DG-Candidate} = 0$.
Sub-step 1.2. Set *i=2* (suppose that node 1 is substation bus).
Sub-step 1.3. *i=i+1* .
Sub-step 1.4. Place a test DG at bus *i*. It is important to note that $N_{DG-Candidate} = 0$ means that there is no candidate bus yet. But, $N_{DG-Candidate} \neq 0$ means that there are $N_{DG-Candidate}$ nodes. In this condition, Eq. (9) should be satisfied to prevent placement of two or more DGs in the found buses (candidate list).
Sub-step 1.5. Run Step 2 neglecting Sub-step 2.2. Candidate bus locations are generated based on the proposed CGSA.
Sub-step 1.6. Store the obtained results like P_{loss}, DG location, etc.
Sub-step 1.7. If $i = N_b$ (i.e. all buses were checked), then go to Sub-step 1.8. Otherwise, repeat Sub-steps 1.3–1.6.
Sub-step 1.8. Find the minimum of P_{loss} from the saved results and then extract the respective bus.
Sub-step 1.9. Place a DG in the found node and $N_{DG-Candidate} = N_{DG-Candidate} + 1$.
Sub-step 1.10. If there is a significant change in P_{loss} (than the saved last P_{loss} related to the last candidate bus (not all nodes)), then go to Sub-step 1.2. Otherwise, go to Sub-step 1.11.
Sub-step 1.11. Print the DG candidate nodes (candidate list).

Step 2 (optimal DG allocation). This step decides about the optimal sizing and siting of DG(s) to be installed in the distribution grid using the proposed CGSA based on a probabilistic way (i.e. SAL strategy). Fig. 3 illustrates the suggested method and its various sub-steps are as below: *Sub-step 2.1.* Set the parameters of the CGSA, i.e. G_0, N, K_0, ϑ, $\gamma_{CL,initial}$, $\gamma_{CL,final}$, $\gamma_{SL1,initial}$, $\gamma_{SL1,final}$, $\gamma_{SL2,initial}$, $\gamma_{SL2,final}$, $\gamma_{SM,initial}$, $\gamma_{SM,final}$, $Iteration_{\max}$, N_{DG}, and initial values of $Prob_{Loc}$ and AP_{Loc} Note that, Step 1 determined $N_{DG-Candidate}$.
Sub-step 2.2. Using the RWS (for more information, see [27]), N_{DG} nodes (considering Eq. (9)) from $N_{DG-Candidate}$ candidates are selected according to their probabilities calculated through Eq. (24) considering Eq. (23).
Sub-step 2.3. Set initial independent variables within their limits (that is DG outputs) as initial positions of agents.
Sub-step 2.4. Determine the state variables through running the load flow program. They must satisfy all inequalities. If a dependent variable does not meet the limitations, remove the corresponding agent and then re-initialize it.
Sub-step 2.5. Evaluate the objective function for all masses.
Sub-step 2.6. Update *G(t)*, *best(t)*, *worst(t)*, and $M_i(t)$ for each

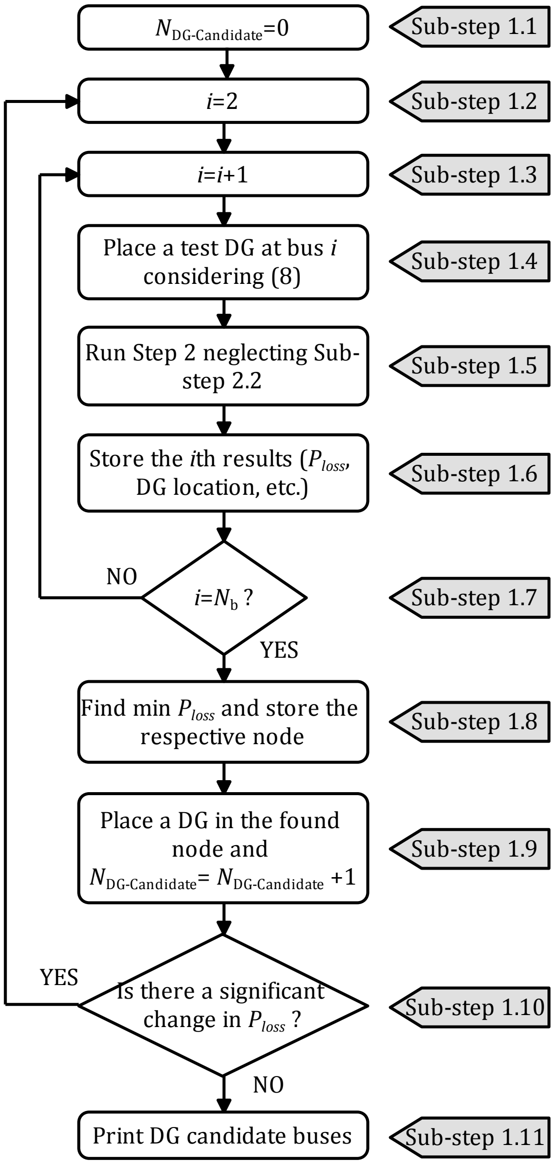

Fig. 2. Selection of candidate buses based on the proposed CGSA

set of agents. Moreover, compute Eq. (13) for all masses. Then, calculate the accelerations and velocities using Eq. (14) and Eq. (15), respectively. Finally, calculate Eq. (19)–Eq. (22) to update all mass positions.
Sub-step 2.7. Check that all independent variables satisfy their boundaries and set the violated constraints at their limit.
Sub-step 2.8. If $t \leq Iteration_{\max}$, then repeat Sub-steps 2.2–2.7. Otherwise, go to Sub-step 2.9.
Sub-step 2.9. Print the final results.

5. SIMULATION RESULTS

The proposed ODGP based on the CGSA is evaluated on IEEE 33- and 69-bus distribution networks and the found results in terms of convergence speed and solution quality over 30 independent runs are compared to different optimization techniques. For both systems, the annual load profiles are assumed to be as

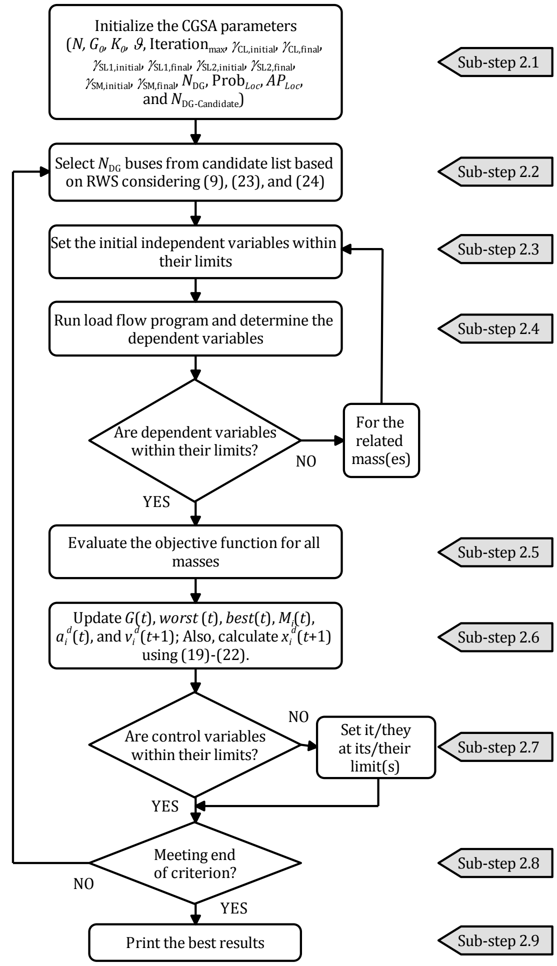

Fig. 3. Flowchart of the proposed CGSA-based ODGP

Table 1 [17, 28].

Moreover, based on [11], for each distribution system, $P_{DG_{\min}} = 0$ and $P_{DG_{\max}} = 2$ MW are considered at a single node. Also, the voltage limits of both networks are set at $|V|_{\min} = 0.9$ pu and $|V|_{\max} = 1.05$ pu [29, 30]. Based on our studies in Step 1 and as reported in [11, 17, 31], due to the reduction of improvement of power losses by increasing the DG sites, the maximum number of DGs for the given distribution networks is restricted to three (i.e. $N_{DG} \leq 3$) for all load levels. Therefore, for both systems, two cases including $N_{DG} = 1$ (single DG allocation) and $N_{DG} = 3$ (multiple DG allocation) are analyzed.
Also, 23 standard functions are selected to evaluate the performance of the CGSA and the final results are compared with different techniques.
Note that, the best quality solutions and convergence characteristics of the proposed CGSA are achieved through the optimum setting of various parameters. So, various trails for a given power network can be executed to get the best settings. Hence, the parameters (for power systems only) are selected as $G_0 = 10$, $\delta = 1000$, $N = K_0 = 20$, $Iteration_{\max} = 50$, $\gamma_{CL,initial} = 0.5$, $\gamma_{CL,final} = 1$, $\gamma_{SL1,initial} = 0.5$, $\gamma_{SL1,final} = 1$, $\gamma_{SL2,initial} = 1.5$, $\gamma_{SL2,final} = 3.5$, $\gamma_{SM,initial} = 1.5$, $\gamma_{SM,final} = 0.5$, $Prob_{Loc} = 1/N_{DG-Candidate}$, and $AP_{Loc_i} = 0$ with $i = 1, ..., N_{DG-Candidate}$. Also, parameters of GSA are illustrated in Appendix A. Moreover, the proposed approach is programmed in MATLAB envi-

Table 1. Load profiles [17, 18].

Load profile	Load level (%)	Duration (hr)
L	50	2000
N	100	5260
P	160	1500

Table 4. Initial conditions of IEEE 33-bus distribution system.

Load profile	Total active demand (MW)	Total reactive demand (MVAR)	P_{loss}(kW)	$\|V_{\min}\|$
L	1.8575	1.15	47.0708	0.9583
N	3.715	2.3	202.6771	0.9131
P	5.944	3.68	575.3616	0.8528

ronment and implemented on an Intel Pentium CPU, 2.0 GHz with 3GB RAM, PC.

A. Standard functions

These functions have a lot of local minima and are listed in Table 2. Some of functions like $f_8 - f_{13}$ are noted as the most difficult benchmark functions to optimize; because increasing the dimension exponentially grows the number of their local optimums [32, 33]. In order to optimize them, the CGSA parameters are as: $N = K_0 = 50$, $Iteration_{\max} = 500$, $\gamma_{CL,initial} = 0.5$, $\gamma_{CL,final} = 1$, $\gamma_{SL1,initial} = 0.5$, $\gamma_{SL1,final} = 1$, $\gamma_{SL2,initial} = 1.5$, $\gamma_{SL2,final} = 3.5$, $\gamma_{SM,initial} = 1.5$, $\gamma_{SM,final} = 0.5$ for all functions. Moreover, $G_0 = 0.01$, $\vartheta = 6$ for f_1 and f_2; $G_0 = 3$, $\vartheta = 0.6$ for f_3; $G_0 = 0.3$, $\vartheta = 6$ for f_4;$G_0 = 0.03$, $\vartheta = 60$ for f_{5-23}.
Table 3 compares the obtained results by GA [32], FWA [34], HSA [35], GSA, and the proposed CGSA (over 30 independent runs) in terms of mean and standard deviation. These show the ability of each technique in searching near-global optima and at the same time escaping from poor local ones. Accordingly, Table 3 demonstrates that the CGSA found significantly better results than other presented techniques for all evaluated functions. But based on this table, it can also be found that only for function f_8 the mean found by the GA is better than that searched by the CGSA.

B. IEEE 33-bus distribution network

The system data are taken from [29]. Initial conditions of IEEE 33-bus distribution system for various load levels are tabulated in Table 4.

The results of Step 1 are illustrated in Fig. 4. Based on this figure, the candidate buses are 7, 30, 13, 25, 24, and 21. Moreover, as demonstrated here, there is no significant change in P_{loss} for more test DGs. So, $N_{DG-Candidate} = 6$.

Case 1 ($N_{DG} = 1$). The best results found by the CGSA for both power and annual energy losses are compared with GSA and WOA [36] in Table 5 for different load profiles. This table clearly reflects that the proposed CGSA can reach to a better optimum than GSA and WOA. In other words, when the power loss is minimized, CGSA can reduce the total power losses to 25.1896 kW (i.e. 46.49% for 1.1919 MW DG at bus 7), 107.9709 kW (i.e. 46.73% for 2.0000 MW DG at bus 7), and 329.8554 kW (i.e. 42.67% for 2.0000 MW DG at bus 30) for L, N, and P demands, respectively. When the annual energy loss is optimized, DG location remains fixed at bus 7 for all load levels and CGSA reduces the total power losses to 25.1896 kW (i.e. 46.49% for 1.1919 MW DG), 107.9709 kW (i.e. 46.73% for 2.0000 MW DG), and 352.3140 kW (i.e. 38.77% for 2.0000 MW DG) for L, N, and

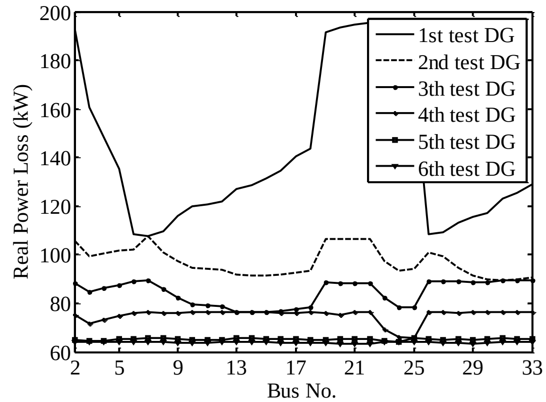

Fig. 4. Results of Step 1 for IEEE 33-bus distribution system

P demands, respectively. As it can be seen, DG installation at bus 7 for profile P cannot reduce the power loss as much as optimal location at bus 30. Also, the minimum voltages for various load profiles obtained by the suggested method are better than those found by GSA and WOA. Moreover, the annual energy loss reduction due to the use of WOA, GSA, CGSA (based on the power loss minimization) and CGSA (based on the annual energy loss minimization) are about 42, 42, 45 and 43% respectively. This means that the maximum annual energy loss reduction is achievable when the DG sites for all load levels can optimally be determined. It is important to note that reference [36] has not provided the results of ODGP for profiles L and P and so its annual energy loss reduction is calculated based on load level N and 8760 hr. Table 5 demonstrates that the first candidate bus is not certainly the best DG location for all load levels; because, the DG location has been changed for the peak load level (for P_{loss} minimization). Hence, even for one DG allocation, an optimization technique (here, CGSA) should be employed to guarantee the best solution (DG site and size).
Table 6 compares the mean and standard deviation of solutions as well as the effective runtimes (define as the average time to converge [37]) of three presented algorithms for load profile N and power loss optimization. This table shows the stability of the proposed technique in searching the optimal solution with lower effective runtime. The voltage profiles for different load levels using CGSA (for P_{loss} minimization) are depicted in Fig. 5. It demonstrates that the voltage profiles are improved for all demand levels.
Case 2 ($N_{DG} = 3$). Table 7 compares the best results found by HSA [11], GA [11], BGA [21], RGA [11], FWA [17], GSA, and the proposed algorithm. Accordingly, CGSA provides the best solution for all load profiles in terms of minimum power losses (maximum improvement), enhancement of the worst voltage, and a better annual energy loss reduction. In fact, the proposed method for both objectives has improved (than the base case) the power losses and the minimum bus voltages by 63.15% and 2.75%, 64.72% and 6.09%, and 66.94% and 11.34% for profiles L, N, and P, respectively. Moreover, the maximum annual energy loss reduction (among other presented algorithms) can be reached to 65.59% using the suggested CGSA. It is worth to note that when P_{loss} is minimized, the DGs are optimally located at unique buses for all load levels and optimizing the annual energy loss results in the same buses for DGs (and also the same results). Moreover, it can be seen that in comparison with Case 1 (one DG allocation), the total power loss is reduced by about 36%

Table 2. Standard benchmark functions.

Function name	Function	n	R^n	$f_{\min}$ $[x_1, \ldots, x_n]$
Sphere	$f_1 = \sum_{i=1}^{n} x_i^2$	30	$[-100, 100]^n$	0 $[0, 0, \ldots, 0]$
Schewefel 2.22	$f_2 = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	30	$[-10, 10]^n$	0 $[0, 0, \ldots, 0]$
Schewefel 1.2	$f_3 = \sum_{i=1}^{n} \left(\sum_{j=1}^{i} x_j \right)^2$	30	$[-100, 100]^n$	0 $[0, 0, \ldots, 0]$
Schewefel 2.21	$f_4 = \max \{\lvert x_i \rvert, 1 \le i \le n\}$	30	$[-100, 100]^n$	0 $[0, 0, \ldots, 0]$
Rosenbrock	$f_5 = \sum_{i=1}^{n-1} \left[100 \left(x_{i+1} - x_i^2 \right)^2 + (x_i - 1)^2 \right]$	30	$[-30, 30]^n$	0 $[1, 1, \ldots, 1]$
Step	$f_6 = \sum_{i=1}^{n} ([x_i + 0.5])^2$	30	$[-100, 100]^n$	0 $[0, 0, \ldots, 0]$
Noise	$f_7 = \sum_{i=1}^{n} i x_i^4 + rand\,[0,\ 1)$	30	$[-1.28, 1.28]^n$	0 $[0, 0, \ldots, 0]$
Schwefel 2.26	$f_8 = \sum_{i=1}^{n} -x_i \sin \sqrt{\lvert x_i \rvert}$	30	$[-500, 500]^n$	≈ -12569.5 $[420.97, \ldots, 420.97]$
Rastrigin	$f_9 = \sum_{i=1}^{n} \left[x_i^2 - 10 \cos (2\pi x_i) + 10 \right]$	30	$[-5.12, 5.12]^n$	0 $[0, 0, \ldots, 0]$
Ackley	$f_{10} = -20 \exp \left(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2} \right) - \exp \left(\frac{1}{n} \sum_{i=1}^{n} \cos(2\pi x_i) \right) + 20 + e$	30	$[-32, 32]^n$	0 $[0, 0, \ldots, 0]$
Griewank	$f_{11} = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos \left(\frac{x_i}{\sqrt{i}} \right) + 1$	30	$[-600, 600]^n$	0 $[0, 0, \ldots, 0]$
Penalized	$f_{12} = \frac{\pi}{n} \left\{ 10 \sin (\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2 \left[1 + 10 \sin^2 (\pi y_{i+1}) \right] + (y_n - 1)^2 \right\}$ $+ \sum_{i=1}^{n} u (x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i + 1}{4}$ $u (x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	30	$[-50, 50]^n$	0 $[1, 1, \ldots, 1]$
Penalized 2	$f_{13} = 0.1 \left\{ \begin{array}{l} \sin^2 (3\pi x_1) + \sum_{i=1}^{n} (x_i - 1)^2 \left[1 + \sin^2 (3\pi x_i + 1) \right] \\ + (x_n - 1)^2 \left[1 + \sin^2 (2\pi x_n) \right] \end{array} \right\}$ $+ \sum_{i=1}^{n} u (x_i, 5, 100, 4)$	30	$[-50, 50]^n$	0 $[1, 1, \ldots, 1]$
Shekel's Foxholes	$f_{14} = \left(\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^{2} \left(x_i - a_{ij} \right)^6} \right)^{-1}$	2	$[-65.53, 65.53]^n$	≈ 0.998 $[-32, \ldots, 32]$
Kowalik	$f_{15} = \sum_{i=1}^{11} \left[a_i - \frac{x_1 \left(b_i^2 + b_i x_2 \right)}{b_i^2 + b_i x_3 + x_4} \right]^2$	4	$[-5, 5]^n$	≈ 0.0003075 $[0.193, 0.191, 0.123, 0.136]$
Six-hump Camel-Back	$f_{16} = 4x_1^2 - 2.1x_1^4 + \frac{1}{3} x_1^6 + x_1 x_2 - 4x_2^2 + 4x_2^4$	2	$[-5, 5]^n$	≈ -1.031628 $[0.0898, -0.7126]$ $[-0.0898, 0.7126]$
Branin RCOS	$f_{17} = \left(x_2 - \frac{5.1}{4\pi^2} x_1^2 + \frac{5}{\pi} x_1 - 6 \right)^2 + 10 \left(1 - \frac{1}{8\pi} \right) \cos (x_1) + 10$	2	$[-5, 10] \times [0, 15]$	≈ 0.3978 $[-3.142, 12.275]$ $[-3.142, 2.275]$ $[-9.425, 2.425]$
Goldstein-Price	$f_{18} = \left[1 + (x_1 + x_2 + 1)^2 \left(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1 x_2 + 3x_2^2 \right) \right]$ $\times \left[30 + (2x_1 - 3x_2) \times \left(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1 x_2 + 27x_2^2 \right) \right]$	2	$[-5, 5]^n$	3 $[0, -1]$
Hartman-3	$f_{19} = -\sum_{i=1}^{4} c_i \exp \left(-\sum_{j=1}^{3} a_{ij} \left(x_j - p_{ij} \right)^2 \right)$	3	$[0, 1]^n$	≈ -3.87 $[0.114, 0.556, 0.852]$
Hartman-6	$f_{20} = -\sum_{i=1}^{4} c_i \exp \left(-\sum_{j=1}^{6} a_{ij} \left(x_j - p_{ij} \right)^2 \right)$	6	$[0, 1]^n$	≈ -3.32 $\begin{bmatrix} 0.201, 0.15, 0.447, \\ 0.275, 0.311, 0.657 \end{bmatrix}$
Shekel-5	$f_{21} = -\sum_{i=1}^{5} \left[(X - a_i) (X - a_i)^T + c_i \right]^{-1}$	4	$[0, 10]^n$	$\approx -1/c_i$ $\approx a_i$ $i = 1, \ldots, n$
Shekel-7	$f_{22} = -\sum_{i=1}^{7} \left[(X - a_i) (X - a_i)^T + c_i \right]^{-1}$	4	$[0, 10]^n$	$\approx -1/c_i$ $\approx a_i$ $i = 1, \ldots, n$
Shekel-10	$f_{23} = -\sum_{i=1}^{10} \left[(X - a_i) (X - a_i)^T + c_i \right]^{-1}$	4	$[0, 10]^n$	$\approx -1/c_i$ $\approx a_i$ $i = 1, \ldots, n$

(average) and the worst voltage is improved by about 3.5% (average). Also, the quality solution of various analyzed approaches in terms of mean and standard deviation of the P_{loss} and the effective runtimes are presented in Table 8. This table reflects the superior performance of the suggested method in providing a better solution. Fig. 6 shows the voltage profile for different load levels and power loss optimization using CGSA. According to this figure, all voltage profiles are significantly improved. Moreover, power flow through the network branches and their limits (for load level P and power loss optimization) are depicted in Fig. 7. It can be seen that before DG installation, more power flows through some lines due to load growth while after DG installation, the line limits have been satisfied. Fig. 8 depicts the convergence behavior of GSA and the proposed algorithm. This figure shows the superior performance of the suggested method. In other words, it quickly searches the optimal site and size of DGs. From the mentioned and compared results, it can be concluded that employing CGSA leads to the better results and outperforms several reported approaches.

Table 3. Comparison of different technique means and standard deviations for benchmark functions.

Functions	GA [32]		FWA [34]		HSA [35]		GSA		Proposed, CGSA	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
f_1	3.1711	1.6621	5.01	0.901	113.38	NA	$7.9365*10^{-18}$	$3.3007*10^{-19}$	$4.2659*10^{-23}$	$2.9801*10^{-24}$
f_2	0.5771	0.1306	0.917	0.149	14.83	NA	$2.2554*10^{-15}$	$1.9724*10^{-15}$	$1.0786*10^{-18}$	$6.3722*10^{-19}$
f_3	9749.915	2594.959	62.3	14.5	3.06	NA	$1.9094*10^{-5}$	$5.2031*10^{-5}$	$1.6577*10^{-7}$	$4.9826*10^{-8}$
f_4	7.961	1.5063	0.955	$6.79*10^{-2}$	2.53	NA	$1.6627*10^{-17}$	$2.3145*10^{-16}$	$9.2359*10^{-29}$	$5.9036*10^{-29}$
f_5	338.5616	361.497	218	257	21.8	NA	$5.9908*10^{-4}$	$1.2315*10^{-4}$	$4.7653*10^{-7}$	$2.9530*10^{-7}$
f_6	3.697	1.9517	3.87	0.999	NA	NA	$\ll 10^{-300}$	$\ll 10^{-300}$	$\ll 10^{-300}$	$\ll 10^{-300}$
f_7	0.1045	$3.6217*10^{-2}$	$1.83*10^{-2}$	$1.36*10^{-2}$	3000	NA	$2.5092*10^{-2}$	$1.4374*10^{-3}$	$1.1289*10^{-3}$	$1.0046*10^{-3}$
f_8	-12566.1	2.1088	NA	NA	NA	NA	-2845.31	4.8171	-10793.4	1.0937
f_9	0.6509	0.3594	127	20.2	9.25	NA	$6.6156*10^{-10}$	$1.1134*10^{-11}$	$1.8316*10^{-12}$	$2.9271*10^{-12}$
f_{10}	0.8678	0.2805	1.16	0.172	2.75	NA	$4.2301*10^{-9}$	$3.3235*10^{-9}$	$7.0118*10^{-17}$	$2.2699*10^{-17}$
f_{11}	1.0038	$6.7545*10^{-2}$	1.03	$2.21*10^{-2}$	68.69	NA	$9.6917*10^{-29}$	$2.9253*10^{-29}$	$\ll 10^{-300}$	$\ll 10^{-300}$
f_{12}	$4.3572*10^{-2}$	$5.0579*10^{-2}$	11.2	2.77	$9.6*10^{-6}$	NA	$1.2505*10^{-2}$	$9.5819*10^{-4}$	$9.2379*10^{-3}$	$3.3053*10^{-8}$
f_{13}	0.1681	$7.0681*10^{-2}$	0.818	0.239	$9.6*10^{-5}$	NA	$7.9131*10^{-2}$	$3.8199*10^{-3}$	$9.8945*10^{-3}$	$1.5119*10^{-5}$
f_{14}	0.9989	$4.4333*10^{-3}$	NA	NA	NA	NA	1.703	0.0832	0.9981	$2.0471*10^{-7}$
f_{15}	$7.0878*10^{-3}$	$7.8549*10^{-3}$	NA	NA	NA	NA	$5.6728*10^{-3}$	$3.8862*10^{-3}$	$1.1473*10^{-3}$	$7.9255*10^{-4}$
f_{16}	-1.0298	$3.1314*10^{-3}$	NA	NA	NA	NA	-1.0316	$6.7103*10^{-6}$	-1.0316	$3.6129*10^{-8}$
f_{17}	0.404	$1.0385*10^{-2}$	NA	NA	NA	NA	0.3999	$1.2850*10^{-4}$	0.3979	$1.1266*10^{-5}$
f_{18}	7.5027	10.3978	NA	NA	NA	NA	3	$5.7629*10^{-4}$	3	$9.3728*10^{-6}$
f_{19}	-3.8624	$6.2841*10^{-4}$	NA	NA	NA	NA	-3.8641	$9.1476*10^{-4}$	-3.8673	$2.7563*10^{-4}$
f_{20}	-3.2627	$6.0398*10^{-2}$	NA	NA	NA	NA	-3.3043	$2.6125*10^{-3}$	-3.3182	$4.4029*10^{-4}$
f_{21}	-5.1653	2.9254	NA	NA	NA	NA	-5.895	0.1852	-7.9538	$3.5147*10^{-3}$
f_{22}	-5.4432	3.2778	NA	NA	NA	NA	-8.5291	$7.4788*10^{-2}$	-10.3934	$9.0805*10^{-3}$
f_{23}	-4.9108	3.4871	NA	NA	NA	NA	-7.2644	$9.8669*10^{-2}$	-10.5335	$1.7351*10^{-2}$

Table 5. Results of different techniques for $N_{DG} = 1$– IEEE 33-bus test system.

Technique	Load profile	DG size in MW (DG Bus)	$\lvert V_{\min}\rvert$(at bus)	P_{loss} (kW)	ΔP_{loss}(%)	Annual energy loss reduction (%)
WOA [36]	L	-	-	-	-	41.95[a]
	N	1.5500 (30)	0.9364 (18)	117.6473	41.95	
	P	-	-	-	-	
GSA	L	1.1360 (7)	0.9756 (18)	25.2362	46.39	41.56
	N	1.7000 (7)	0.9407 (18)	113.4993	44	
	P	1.5120 (30)	0.8790 (18)	356.6607	38.01	
Proposed, CGSA (based on min P_{loss})	L	1.1919 (7)	0.9764 (18)	25.1896	46.49	45
	N	2.0000 (7)	0.9454 (18)	107.9709	46.73	
	P	2.0000 (30)	0.8866[b] (18)	329.8554	42.67	
Proposed, CGSA (based on min E_{loss})	L	1.1919 (7)	0.9764 (18)	25.1896	46.49	43.32
	N	2.0000 (7)	0.9454 (18)	107.9709	46.73	
	P	2.0000 (7)	0.8889[b] (18)	352.314	38.77	

[a] These values are only calculated based on 8760 hr and normal load level. [b] There is not any feasible solution satisfying voltage constraint.

Table 7. Results of different techniques for $N_{DG} = 3$–IEEE 33-bus test system.

Technique	Load profile	DG size in MW (DG Bus)	$\lvert V_{\min}\rvert$(at bus)	P_{loss} (kW)	ΔP_{loss}(%)	Annual energy loss reduction (%)
HSA [11]	L	0.1303 (18), 0.1777 (17), 0.5029 (33)	0.9831 (30)[c]	23.29	50.5	53.19
	N	0.1070 (18), 0.5724 (17), 1.0462 (33)	0.9670 (29)[c]	96.76	52.26	
	P	0.1939 (18), 0.9108 (17), 1.6115 (33)	0.9437 (30)[c]	260.97	54.63	
GA [11]	L	-	-	-	-	50.61[b]
	N	1.6044[a]	0.9605 (NA)	100.1	50.6	
	P	-	-	-	-	
BGA [21]	L	-	-	-	-	53.01[b]
	N	0.750 (11), 0.250 (18), 0.500 (33)	0.9528 (31)[c]	95.2281	53.01	
	P	-	-	-	-	
RGA [11]	L	-	-	-	-	51.84[b]
	N	1.7770[a]	0.9687 (NA)	97.6	51.84	
	P	-	-	-	-	
FWA [17]	L	0.2948 (14), 0.0947 (18), 0.5072 (32)	0.9844 (30)[c]	21.37	54.58	57.18
	N	0.5897 (14), 0.1895 (18), 1.0146 (32)	0.9680 (30)[c]	88.68	56.24	
	P	0.9441 (14), 0.3013 (18), 1.6784 (32)	0.9484 (29)[c]	238.07	58.57	
GSA	L	0.3663 (13), 0.4188 (30), 0.2545 (25)	0.9798 (33)	18.7971	60.07	64.43
	N	0.6689 (13), 1.1234 (30), 0.7393 (25)	0.9655 (18)	73.3481	63.81	
	P	1.6738 (13), 1.4620 (30), 1.8973 (24)	0.9468 (33)	197.455	65.68	
Proposed, CGSA (based on min P_{loss})	L	0.3942 (13), 0.5221 (24), 0.5314 (30)	0.9847 (33)	17.3465	63.15	65.59
	N	0.7851 (13), 1.0938 (24), 1.0591 (30)	0.9687 (33)	71.4989	64.72	
	P	1.2777 (13), 1.7771 (24), 1.7244 (30)	0.9495 (33)	190.2429	66.94	
Proposed, CGSA (based on min E_{loss})	L	0.3942 (13), 0.5221 (24), 0.5314 (30)	0.9847 (33)	17.3465	63.15	65.59
	N	0.7851 (13), 1.0938 (24), 1.0591 (30)	0.9687 (33)	71.4989	64.72	
	P	1.2777 (13), 1.7771 (24), 1.7244 (30)	0.9495 (33)	190.2429	66.94	

[a] Only, total size has been reported. [b] These values are calculated based on 8760 hr. [c] It was obtained based on the reported results.

Table 6. Comparison of quality solution of different techniques based on P_{loss}– profile N-N_{DG} = 1–IEEE 33-bus test system.

Technique	Minimum	Mean	Standard deviation	Effective Runtime[a] (s)
WOA [36]	117.6473	NA	NA	NA
GSA	113.4993	115.5643	1.6286	3.89
Proposed, CGSA	107.9709	108.2427	0.2381	2.51

[a] It defines as the average time to converge (for more information, see [37]).

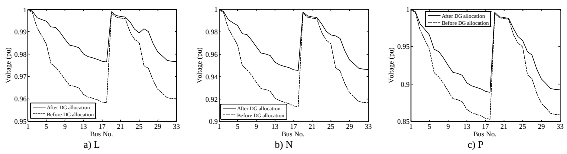

Fig. 5. Voltage profile of IEEE 33-bus test system for different load profiles (CGSA–Power loss minimization–N_{DG} = 1)

Table 8. Comparison of quality solution of different techniques based on P_{loss} profile N- N_{DG} = 3–IEEE 33-bus test system.

Technique	Minimum	Mean	Standard deviation	Effective run-time (s)
HSA [11]	96.76	NA	NA	NA
GA [11]	100.1	NA	NA	NA
BGA [21]	95.2281	NA	NA	NA
RGA [11]	97.6	NA	NA	NA
FWA [17]	88.68	NA	NA	NA
GSA	73.3481	78.6395	4.3641	11.38
Proposed, CGSA	71.4989	71.5336	0.0045	5.83

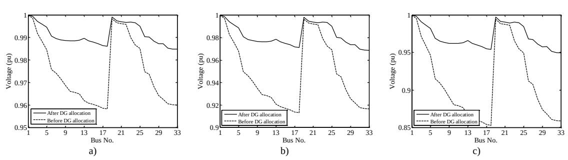

Fig. 6. Voltage profile of IEEE 33-bus test system for different load profiles (CGSA–Power loss minimization–N_{DG} = 3)

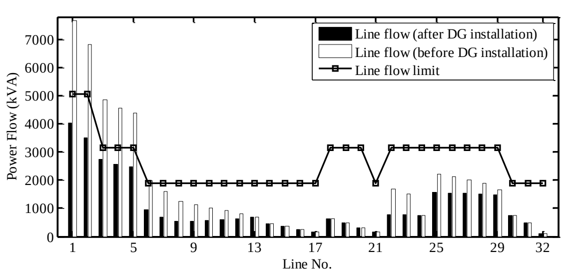

Fig. 7. Power flow through the branches of IEEE 33-bus test system for profile P and power loss minimization using CGSA

C. IEEE 69-bus distribution network

The initial conditions (base case) of 69-bus distribution system for all load profiles are illustrated in Table 9. Network's line and load data are adopted from [38]. Results of Step 1 (Fig. 9) show that buses 61, 17, 11, 50, 64, and 9 are the candidate nodes. So, $N_{DG-Candidate}$=6.

Case 1 (N_{DG} = 1). The optimal solution of DG allocation in terms of DG size and site, the worst bus voltage, the power loss and its improvement, as well as annual energy loss reduction obtained by the proposed CGSA are compared with those

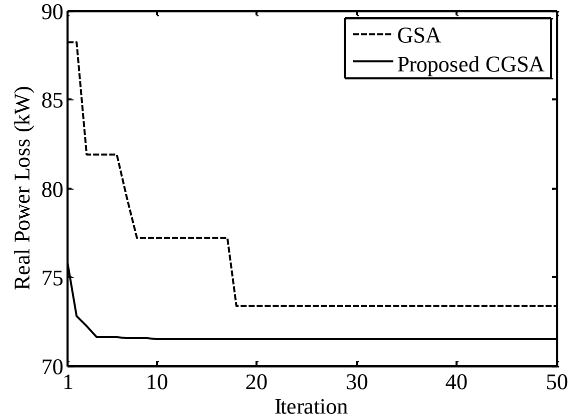

Fig. 8. Convergence behavior of different techniques (IEEE 33-bus distribution system–Nominal demand–Power loss minimization–N_{DG} = 3)

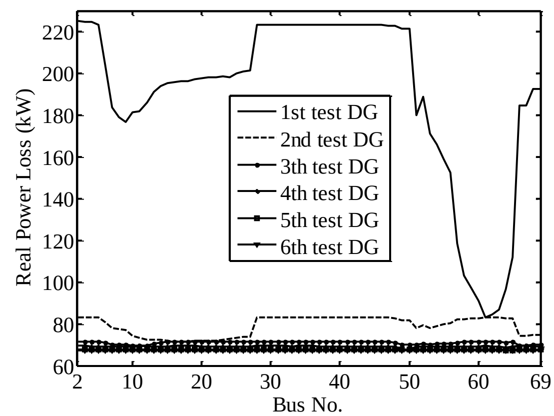

Fig. 9. Results of Step 1 for IEEE 69-bus distribution system

Table 9. Initial conditions of IEEE 69-bus distribution system.

Load profile	Total active demand (MW)	Total reactive demand (MVAR)	P_{loss} (kW)	$\|V_{\min}\|$
L	1.8959	1.3471	51.5093	0.9567
N	3.7919	2.6943	224.9521	0.9092
P	6.067	4.3109	652.3736	0.8445

searched by GSA and WOA [39] in Table 10. According to this table, the results of CGSA for both power and annual energy loss optimizations are same and the proposed algorithm can reduce the total power losses to 20.2854, 83.0689, and 262.2723 kW for profiles L, N, and P, respectively. This means that CGSA improves the power losses by about 61, 63, and 60%, respectively. Moreover, the annual energy loss reduction can be reached to 61.55% which is better than the results of GSA. It should be noted that for WOA this is calculated based on the load level N and 8760 hr. In other words, this reference has not presented the results of profiles L and P and due to this, its annual energy loss reduction has reached to 63%. If the obtained power loss reduction of CGSA is compared to that of WOA for profile N, it is clear that CGSA has provided more power loss reduction. Table 11 compares the solution quality found by different optimization methods for profile N and power loss optimization. This

Table 11. Comparison of quality solution of different techniques based on P_{loss}– profile N–N_{DG} = 1–IEEE 69-bus test system.

Technique	Minimum	Mean	Standard deviation	Effective runtime (s)
GSA	83.1927	83.5024	0.071	82.22[a]
Proposed, CGSA	83.0689	83.0859	0.0044	12.69

[a] In general, GSA convergence to its optimal solutions after 40th iteration; neglecting the small differences between their optimal and near optimal solutions, this runtime is 21.53 s.

table demonstrates the robustness of the proposed algorithm in finding the optimal solution. Moreover, this table indicates that CGSA needs a lower average CPU time to converge to the optimal solution. The voltage profiles after DG allocation for different load levels using the suggested method are compared with the base cases in Fig. 10 (for P_{loss} minimization). It is clear that the voltage profiles have been improved.

Case 2 (N_{DG} = 3). The best DG sites and sizes found by CGSA are compared with HSA [11], GA [11], RGA [11], FWA [17], and GSA in Table 12. Moreover, this table reflects the minimum bus voltages, power losses and their improvements, and annual loss reductions. Also, Table 13 illustrates the mean and standard deviation of the obtained solutions by various techniques and the related runtimes for load level N. Accordingly, the suggested algorithm is robustness and proposes three DGs as (for power loss minimization): 0.2663 MW at bus 17, 0.8812 MW at bus 61, and 0.3297 MW at bus 50 for light load level; 0.6226 MW at bus 11, 0.3546 MW at bus 17, and 1.7067 MW at bus 61 for nominal load profile; and finally, 1.8884 MW at bus 61, 1.0038 MW at bus 64, and 0.9166 MW at bus 17 for peak load level. These DGs reduce the total power losses by 66.65%, 69.15%, and 71.08% for the mentioned load profiles, respectively. This leads to 70% annual energy loss reduction approximately. For annual energy loss optimization, the DGs are at buses 61, 17 and 64 for all load levels and totally 1.1249 MW, 2.3371 MW and 3.8088 MW are installed for load profiles L, N and P, respectively. Table 12 clearly shows that in the case of minimizing the power loss, the maximum power loss and annual energy loss reductions are obtained while the locations of DGs vary for each load profile. On the other hand, solution of annual energy loss optimization is close to the searched solution of power loss minimization. Figs. 11(a), (b), and (c) show the voltage profile based on power loss optimization for load levels L, N, and P, respectively. It is evident that the voltage profiles are improved significantly, so that the worst voltages are 0.9895, 0.9790, and 0.9715 pu, respectively. Apparent power flows through all lines for peak load level and power loss minimization are illustrated in Fig. 12. This figure indicates that the proposed CGSA can satisfy the line thermal constraints when the distribution network is under the maximum stress while without DG installation, the load on some branches goes beyond their capacities. The convergence characteristic of GSA and the suggested algorithm for the nominal load level are depicted in Fig. 13. It is clear that the CGSA is quickly converged to the best solution.

APPENDIX A

GSA parameters are as $G_0 = 100, \vartheta = 100$, $N = K_0 = 20$, and $Iteration_{\max} = 50$.

6. CONCLUSION

In this study, a new ODGP method based on a novel optimization technique, namely CGSA, was proposed. This method had

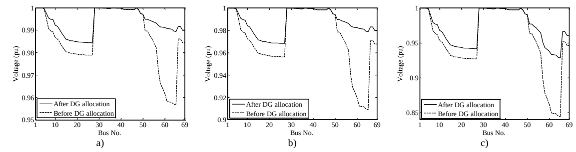

Fig. 10. Voltage profile of IEEE 69-bus distribution system for different load profiles (CGSA–Power loss minimization–N_{DG} = 1)

Table 13. Comparison of quality solution of different techniques based on P_{loss}– profile N–N_{DG} = 3–IEEE 69-bus test system.

Technique	Minimum	Mean	Standard deviation	Effective runtime (s)
HSA [11]	86.77	NA	NA	NA
GA [11]	88.5	NA	NA	NA
RGA [11]	87.65	NA	NA	NA
FWA [17]	77.85	NA	NA	NA
GSA	74.5482	77.3849	1.9104	96.78
Proposed, CGSA	69.4006	70.0384	0.1865	15.39

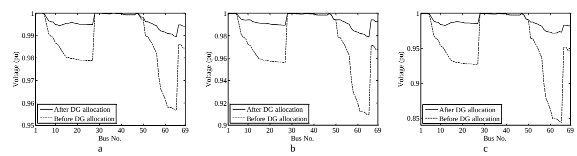

Fig. 11. Voltage profile of IEEE 69-bus distribution system for different load profiles (CGSA–Power loss minimization–N_{DG} = 3)

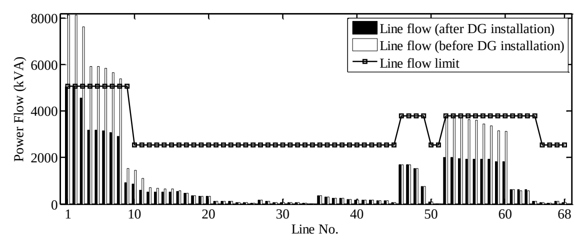

Fig. 12. Power flow through the branches of IEEE 69-bus test system for profile P and power loss minimization using CGSA

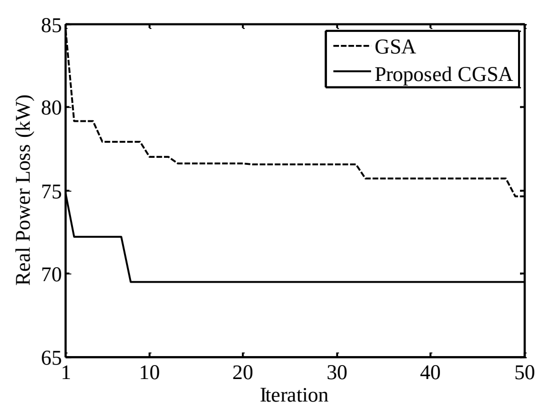

Fig. 13. Convergence behavior of different techniques (IEEE 69-bus distribution system–Nominal demand–Power loss minimization–N_{DG} = 3)

Table 10. Results of different techniques for $N_{DG} = 1$–IEEE 69-bus test system.

Technique	Load profile	DG size in MW (DG Bus)	$\|V_{\min}\|$(at bus)	P_{loss} (kW)	ΔP_{loss} (%)	Annual energy loss reduction (%)
WOA [39]	L	-	-	-	-	63.00[a]
	N	1.8728 (61)	0.9683 (27)	83.2279	63	
	P	-	-	-	-	
GSA	L	1.4016 (61)	0.9871 (27)	27.9221	45.79	60.56
	N	1.9308 (61)	0.9687 (27)	83.1927	63.02	
	P	1.9513 (61)	0.9286 (65)	266.4973	59.15	
Proposed, CGSA (based on min P_{loss})	L	0.9218 (61)	0.9844 (27)	20.2854	60.62	61.55
	N	1.8688 (61)	0.9683 (27)	83.0689	63.07	
	P	2.0000 (61)	0.9286 (65)	262.2723	59.8	
Proposed, CGSA (based on min E_{loss})	L	0.9218 (61)	0.9844 (27)	20.2854	60.62	61.55
	N	1.8688 (61)	0.9683 (27)	83.0689	63.07	
	P	2.0000 (61)	0.9286 (65)	262.2723	59.8	

[a] These values are only calculated based on 8760 hr and normal load level.

Table 12. Results of different techniques for $N_{DG} = 3$–IEEE 69-bus test system

Technique	Load profile	DG size in MW (DG Bus)	$\|V_{\min}\|$(at bus)	P_{loss} (kW)	ΔP_{loss}(%)	Annual energy loss reduction (%)
HSA [11]	L	0.2579 (65), 0.1280 (64), 0.5857 (63)	0.9846 (27)[c]	21.92	57.53	62.64
	N	0.1018 (65), 0.3690 (64), 1.3024 (63)	0.9677 (27)[c]	86.77	61.43	
	P	0.1589 (65), 0.8308 (64), 1.9710 (63)	0.9478 (27)[c]	230.61	64.66	
GA [11]	L	-	-	-	-	60.66[b]
	N	1.9471[a]	0.9687 (NA)	88.5	60.66	
	P	-	-	-	-	
RGA [11]	L	-	-	-	-	61.04[b]
	N	1.7868[a]	0.9678 (NA)	87.65	61.04	
	P	-	-	-	-	
FWA [17]	L	0.2067 (65), 0.5903 (61), 0.1076 (27)	0.9871 (62)[c]	19.05	60.08	66.56
	N	0.4085 (65), 1.1986 (61), 0.2258 (27)	0.9740 (62)[c]	77.85	65.39	
	P	0.6537 (65), 1.9177 (61), 0.3613 (27)	0.9568 (62)[c]	206.49	68.35	
GSA	L	0.6232 (11), 0.2369 (50), 0.7316 (61)	0.9864 (65)	18.3223	64.43	67.69
	N	2.0000 (61), 0.6869 (9), 0.2254 (17)	0.9824 (27)	74.5482	66.86	
	P	2.0000 (11), 1.1063(61), 2.0000(61)	0.9739 (27)	202.0191	69.03	
Proposed, CGSA (based on min P_{loss})	L	0.2663 (17), 0.8812 (61), 0.3297 (50)	0.9895 (65)	17.1785	66.65	69.87
	N	0.6226 (11), 0.3546 (17), 1.7067 (61)	0.9790 (65)	69.4006	69.15	
	P	1.8884 (61), 1.0038 (64), 0.9166 (17)	0.9715 (61)	188.6846	71.08	
Proposed, CGSA (based on min E_{loss})	L	0.7517 (61), 0.2846 (17), 0.0886 (64)	0.9887 (65)	17.499	66.03	69.36
	N	1.2321 (61), 0.5752 (17), 0.5298 (64)	0.9814 (61)	71.4724	68.23	
	P	1.8881 (61), 0.9169 (17), 1.0038 (64)	0.9715 (61)	188.6859	71.07	

[a] Only, total size has been reported. [b] These values are calculated based on 8760 hr. [c] It was obtained based on the reported results.

two main steps. Step one selected the candidate locations (candidate list), and step two (using CGSA) provided the best DG size(s) and site(s). The suggested CGSA civilized GSA considering SAL strategy. In fact, it combined GSA with the modified search strategies (movements) of SCA to find the best size of DG(s) and simultaneously applied SAL strategy to select the best DG location(s). The effectiveness and efficiency of the proposed algorithm to provide a better quality solution were tested on two various test systems including IEEE 33-bus and 69-bus radial distribution grids and also 23 benchmark functions. Moreover, two cases (i.e. $N_{DG} = 1$ and $N_{DG} = 3$) and two objectives (i.e. P_{loss} and E_{loss}) for each network were investigated. The found solutions were compared to those of different method such as WOA, GA, RGA, BGA, HSA, FWA, and GSA. The results clearly depicted the stability and superior performance of the suggested technique in solving this type of problems (non-convex, nonlinear, and complex one due to the nodal power balance equations) as well as providing a better quality solution with a good convergence speed in comparison with other presented methods. Furthermore, the suggested algorithm is robustness and can search lower active power losses (for IEEE 33-bus distribution system about 46% for one installed DG and 65% for three installed DGs; these are respectively 60% and 70% for IEEE 69-bus distribution network) by proposing the best DG location(s) and size(s). This resulted in maximum annual energy loss reduction (up to 66% for IEEE 33-bus system and 70% for IEEE 69-bus network) and a better minimum bus voltage while satisfying line capacity constraints. Furthermore, the found solutions demonstrated that minimizing P_{loss} eventuates in better results while optimizing E_{loss} can propose the fixed DG site(s) for all load levels. Consequently, it is necessary to make discrimination for real-life application based on the robustness, i.e. the capability of providing a good solution quality without convergence problems.

REFERENCES

1. F. Jabari, S. Asadi, and S. Seyed-barhagh, "A Novel Forward-Backward Sweep Based Optimal DG Placement Approach in Radial Distribution Systems," Optim. Power Syst. Probl., vol. 262, no. 1, pp. 49–61, 2020.
2. K. R. Devabalaj, K. Ravi, and D. P. Kothari, "Optimal location and sizing of capacitor placement in radial distribution system using bacterial foraging optimization algorithm," Int. J. Electr. Power Energy Syst., vol. 71, pp. 383–390, 2015.
3. S. Kumar, K. Mandal, and N. Chakraborty, "Optimal DG placement by multi-objective opposition based chaotic differential evolution for techno-economic analysis," Appl. Soft Comput., vol. 78, pp. 70–83, 2019.
4. M. . Sujatha, V. Roja, and T. . Prasad, "Multiple DG Placement and Sizing in Radial Distribution System Using Genetic Algorithm and Particle Swarm Optimization," Comput. Intell. Big Data Anal., pp. 21–36, 2019.
5. M. . Lalitha and O. Hemakesavulu, "Effect of Load Model and Load Level on DG Placement by Crow Search Algorithm," Emerg. Trends Electr. Commun. Inf. Technol., vol. 569, pp. 185–198, 2020.
6. D. Rama Prabha, T. Jayabarathi, R. Umamageswari, and S. Saranya,

"Optimal location and sizing of distributed generation unit using intelligent water drop algorithm," Sustain. Energy Technol. Assessments, vol. 11, pp. 106–113, 2015.
7. C. . Prasad, K. Subbaramaiah, and P. Sujatha, "Cost–benefit analysis for optimal DG placement in distribution systems by using elephant herding optimization algorithm," Renewables Wind. Water, Sol., vol. 6, no. 2, 2019.
8. M. Gandomkar, M. Vakilian, and M. Ehsan, "A genetic–based tabu search algorithm for optimal DG allocation in distribution networks," Electr. Power Components Syst., vol. 33, no. 12, pp. 1351–1362, 2005.
9. N. Acharya, P. Mahat, and N. Mithulananthan, "An analytical approach for DG allocation in primary distribution network," Int. J. Electr. Power Energy Syst., vol. 28, no. 10, pp. 669–678, 2006.
10. H. R. Esmaeilian and R. Fadaeinedjad, "Energy loss minimization in distribution systems utilizing an enhanced reconfiguration method integrating distributed generation," IEEE Syst. J., vol. 9, no. 4, pp. 1430–1439, 2015.
11. R. Srinivasa Rao, K. Ravindra, K. Satish, and S. V. L. Narasimham, "Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation," IEEE Trans. Power Syst., vol. 28, no. 1, pp. 317–325, 2013.
12. S. Kansal, B. B. R. Sai, B. Tyagi, and V. Kumar, "Optimal placement of distributed generation in distribution networks," Int. J. Eng. Sci. Technol., vol. 3, no. 3, pp. 47–55, 2011.
13. B. Sookananta, W. Kuanprab, and S. Hanak, "Determination of the optimal location and sizing of distributed generation using particle swarm optimization," in International Conference on Electrical Engineering/Electronics Computer Telecommunications and Information Technology (ECTI-CON), 2010, pp. 818–822.
14. B. Sookananta, P. Utaton, and R. Khongsila, "Determination of the optimal location and sizing of distributed generation using ant colony search," in International Conference on Electrical Engineering/Electronics Computer Telecommunications and Information Technology (ECTI-CON), 2010, pp. 814–817.
15. M. H. Moradi and M. Abedini, "A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems," Int. J. Electr. Power Energy Syst., vol. 34, no. 1, pp. 66–74, 2012.
16. U. Sultana, A. B. Khairuddin, A. S. Mokhtar, N. Zareen, and B. Sultana, "Grey wolf optimizer based placement and sizing of multiple distributed generation in the distribution system," Energy, vol. 111, pp. 525–536, 2016.
17. A. Mohamed Imran, M. Kowsalya, and D. P. Kothari, "A novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution networks," Int. J. Electr. Power Energy Syst., vol. 63, pp. 461–472, 2014.
18. M. Sedighizadeh, M. Esmaili, and M. Esmaeili, "Application of the hybrid big bang-big crunch algorithm to optimal reconfiguration and distributed generation power allocation in distribution systems," Energy, vol. 76, pp. 920–930, 2014.
19. H. Doagou-Mojarrad, G. B. Gharehpetian, H. Rastegar, and J. Olamaei, "Optimal placement and sizing of DG (distributed generation) units in distribution networks by novel hybrid evolutionary algorithm," Energy, vol. 54, pp. 129–138, 2013.
20. S. S. Tanwar and D. K. Khatod, "Techno-economic and environmental approach for optimal placement and sizing of renewable DGs in distribution system," Energy, vol. 127, pp. 52–67, 2017.
21. S. Golshannavaz, "Optimal simultaneous siting and sizing of DGs and capacitors considering reconfiguration in smart automated distribution systems," J. Intell. Fuzzy Syst., vol. 27, no. 4, pp. 1719–1729, 2014.
22. E. Rashedi, H. Nezamabadi-pour, and S. Saryazdi, "GSA: a gravitational search algorithm," Inf. Sci. (Ny)., vol. 179, no. 13, pp. 2232–2248, 2009.
23. A. Bhattacharya and P. K. Roy, "Solution of multi-objective optimal power flow using gravitational search algorithm," IET Gener. Transm. Distrib., vol. 6, no. 8, pp. 751–763, 2012.
24. S. Ghavidel, J. Aghaei, K. M. Muttaqi, and A. Heidari, "Renewable energy management in a remote area using modified gravitational search algorithm," Energy, vol. 97, pp. 391–399, 2016.
25. M. R. Narimani, A. Azizi Vahed, R. Azizipanah-Abarghooee, and M. Javidsharifi, "Enhanced gravitational search algorithm for multi-objective distribution feeder reconfiguration considering reliability, loss and operational cost," IET Gener. Transm. Distrib., vol. 8, no. 1, pp. 55–69, 2013.
26. T. Ray and K. M. Liew, "Society and civilization: an optimization algorithm based on the simulation of social behavior," IEEE Trans. Evol. Comput., vol. 7, no. 4, pp. 386–396, 2003.
27. Y. Wang, B. Li, T. Weise, J. Wang, B. Yuan, and Q. Tian, "Self-adaptive learning based particle swarm optimization," Inf. Sci. (Ny)., vol. 181, no. 20, pp. 4515–4538, 2011.
28. D. Das, "Optimal placement of capacitors in radial distribution system using a Fuzzy-GA method," Int. J. Electr. Power Energy Syst., vol. 30, no. 6–7, pp. 361–367, 2008.
29. M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," IEEE Trans. Power Deliv., vol. 4, no. 2, pp. 1401–1407, 1989.
30. A. F. A.Kadir, A. Mohamed, H. Shareef, and M. Z. C.Wanik, "Optimal placement and sizing of distributed generations in distribution systems for minimizing losses and THD_v using evolutionary programming," Turkish J. Electr. Eng. Comput. Sci., vol. 21, pp. 2269–2282, 2013.
31. K. D. Mistry and R. Roy, "Enhancement of loading capacity of distribution system through distributed generator placement considering techno-economic benefits with load growth," Int. J. Electr. Power Energy Syst., vol. 54, pp. 505–515, 2014.
32. S. He, Q. H. Wu, and J. R. Saunders, "Group search optimizer: an optimization algorithm inspired by animal searching behavior," IEEE Trans. Evol. Comput., vol. 13, no. 5, pp. 973–990, 2009.
33. Y. Sun, X. Wang, Y. Chen, and Z. Liu, "A modified whale optimization algorithm for large-scale global optimization problems," Expert Syst. Appl., vol. 114, pp. 563–577, 2018.
34. B. Zhang, M. Zhang, and Y.-J. Zheng, "Improving enhanced fireworks algorithm with new gaussian explosion and population selection strategies," in International Conference in Swarm Intelligence, 2014, pp. 53–63.
35. G.-G. Wang, A. H. Gandomi, X. Zhao, and H. C. E. Chu, "Hybridizing harmony search algorithm with cuckoo search for global numerical optimization," Soft Comput., vol. 20, no. 1, pp. 273–285, 2016.
36. S. Ang and U. Leeton, "Optimal placement and size of distributed generation in radial distribution system using whale optimization algorithm," Suranaree J. Sci. Technol., vol. 26, no. 1, pp. 1–12, 2019.
37. H. D. M. Braz and B. A. Souza, "Distribution network reconfiguration using genetic algorithms with sequential encoding: subtractive and additive approaches," IEEE Trans. Power Syst., vol. 26, no. 2, pp. 582–593, 2011.
38. J. S. Savier and D. Das, "Impact of network reconfiguration on loss allocation of radial distribution systems," IEEE Trans. Power Deliv., vol. 22, no. 4, pp. 2473–2480, 2007.
39. P. D.P.Reddy, V. C. V.Reddy, and T. G.Manohar, "Whale optimization algorithm for optimal sizing of renewable resources for loss reduction in distribution systems," Renewables Wind. Water, Sol., vol. 4, no. 3, pp. 1–13, 2017.