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METHODOLOGIES AND APPLICATION

A fuzzy pragmatic DE–CSA hybrid approach for unbalanced radial distribution system planning with distributed generation

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Abstract

This paper presents a multi-objective planning approach for the optimal placement of distributed generation (DG) units in unbalanced radial distribution systems using a hybrid differential evolution (DE) and cuckoo search algorithm (CSA). In this planning optimization, the objective functions formulated are the minimization of: (i) total real power loss, (ii) maximum average voltage deviation index, (iii) total neutral current, and (iv) total cost. The total cost includes the cost of energy purchased from the grid and the capital investment and operational cost of DG units. These objective functions are aggregated using max–max and max–min analogies. Fuzzy set theory is used to model the uncertainties in load and generation of renewable DG units. Hence, these objective functions are found to be fuzzy sets. An appropriate defuzzification approach is used so as to compare and rank different solutions. A modified three-phase forward–backward sweep-based load flow algorithm including the DG model is used as the support subroutine of the proposed solution algorithm using the hybrid DE–CSA. The simulation results show that significant improvements in power loss, maximum average voltage deviation, system unbalance, and total annual energy cost are obtained due to the DG integration in unbalanced distribution networks. The results obtained with fuzzy-based modeling of load and generation are found to be superior as compared to the deterministic load and generation.

Keywords Unbalanced radial distribution system planning · Fuzzy set · Distributed generation · Differential evolution algorithm · Cuckoo search algorithm

List of symbols

NBR	Total number of branches/lines/feeder segments
NB	Total number of buses
NG	Total number of DG units
RM(.)	Removal function
Superscript (woDG)	Without DG
Superscript (wDG)	With DG
Superscript ∼	Fuzzy quantity
Superscript −	Phasor quantity
Superscript a, b, c	Phases a, b, c
$IL(I)$	Load (branch) current
V	Bus voltage
$P(Q)$	Active (reactive) power demand by the load

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1 Introduction

The optimal integration of distributed generation (DG) into distribution networks provides significant economical and operational benefits, such as the deferral in investment for building new lines, reduction in energy purchase from the grid, reduction in network power loss, improvement in bus voltage, peak load shaving, improvement in system stability and reliability (El-Khattam and Salama 2004; Bayod-Rújula 2009). A recent state-of-the-art review on the approaches for DG integration is available in Adefarati and Bansal (2016). Moreover, the practical distribution networks are usually unbalanced because of unequal loading among the phases and the high mutual inductance between the distribution lines which are seldom transposed. The proper placement of DG units can reduce the unbalancing of a network. Hence, the distributed generation allocation planning is a multi-objective optimization problem for the optimization of various objective functions under certain technical constraints.

There are various optimization techniques have been used (Abu-Mouti and El-Hawary 2011; Al Abri et al. 2013; Shaaban et al. 2013; Hejazi et al. 2013; Hung and Mithulananthan 2013; Kroposki et al. 2013; Doagou-Mojarrad et al. 2013; Sheng et al. 2015; Kim et al. 2014; Jabr and Pal 2009; Haghifam et al. 2008; Ramana et al. 2010; Hien et al. 2013; Niknam 2008; Ganguly and Samajpati 2015; Ganguly et al. 2013; Nasiraghdam and Jadid 2012; Soroudi and Ehsan 2011; Jamian et al. 2014; Sanjay et al. 2017; Gkaidatzis et al. 2017; Hassan et al. 2017; Kansal et al. 2017; Nguyen and Vo 2018; Coelho et al. 2018) in the literature to solve this planning optimization problem. This includes classical approaches such as analytical approaches (Hung and Mithulananthan 2013; Kroposki et al. 2013), mixed integer programming (Al Abri et al. 2013; Melgar Dominguez et al. 2018), optimal load flow (Moreti et al. 2018) and exhaustive search (Kim et al. 2014; Ramana et al. 2010), ordinal optimization approach (Jabr and Pal 2009), sensitivity analysis (Moreti et al. 2018), and metaheuristic algorithms such as genetic algorithm (GA) (Shaaban et al. 2013; Sheng et al. 2015; Haghifam et al. 2008; Ganguly and Samajpati 2015; Hassan et al. 2017), differential algorithm (DE) (Hejazi et al. 2013), hybrid shuffled frog leap algorithm and DE (Doagou-Mojarrad et al. 2013), particle swarm optimization (Hien et al. 2013; Kansal et al. 2017), hybrid particle swarm optimization (PSO) and ant colony optimization (ACO) (Niknam 2008; Gkaidatzis et al. 2017), adaptive genetic algorithm (AGA) (Ganguly and Samajpati 2015), modified non-dominated sorting GA (NSGA) (Soroudi and Ehsan 2011), gravitational search algorithm (Jamian et al. 2014), hybrid grey wolf optimizer (Sanjay et al. 2017), stochastic fractal search algorithm (SFSA) (Nguyen and Vo 2018), War Optimization (Coelho et al. 2018), hybrid teaching–learning-based optimization (Quadr et al. 2018). There are numerous objective functions formulated for the determination of optimal locations and sizes for DG units in distribution networks. These are:

(i) The minimization of system upgradation cost (Shaaban et al. 2013; Kim et al. 2014),
(ii) The cost of supply interruption (Shaaban et al. 2013),
(iii) The maximization of profit of a distribution company (Hejazi et al. 2013),
(iv) The minimization of power/energy loss (Shaaban et al. 2013; Hung and Mithulananthan 2013; Doagou-Mojarrad et al. 2013; Sheng et al. 2015; Kim et al. 2014; Jabr and Pal 2009; Haghifam et al. 2008; Ramana et al. 2010; Hien et al. 2013; Ganguly and Samajpati 2015; Ganguly et al. 2013; Jamian et al. 2014; Sanjay et al. 2017; Gkaidatzis et al. 2017; Hassan et al. 2017; Kansal et al. 2017; Coelho et al. 2018; Quadr et al. 2018),
(v) Maximizing benefit of DG integration in terms of reduced power loss, network upgrade deferral, environmental value, etc. (Kroposki et al. 2013),
(vi) Minimization of pollutant emission (Doagou-Mojarrad et al. 2013; Soroudi and Ehsan 2011; Melgar Dominguez et al. 2018),
(vii) Minimization of voltage deviation (Sheng et al. 2015; Ganguly and Samajpati 2015; Jamian et al. 2014; Sanjay et al. 2017; Quadr et al. 2018),
(viii) Maximization of voltage stability margin (Sheng et al. 2015; Quadr et al. 2018),
(ix) Minimization of cost of energy not supplied (Kim et al. 2014),
(x) Maximization DG penetration (Jabr and Pal 2009),
(xi) Minimization of investment and operational cost of DG units (Haghifam et al. 2008; Melgar Dominguez et al. 2018),
(xii) Maximization of network loadability due to the DG placement (Hien et al. 2013),
(xiii) Minimization of cost of power generation by DG units and by distribution companies (Niknam 2008),
(xiv) Minimization of total installation and operational cost and minimization of risk factor (Ganguly et al. 2013).

In most of the DG planning approaches, the distribution systems are assumed to be balanced (Abu-Mouti and El-Hawary 2011; Al Abri et al. 2013; Shaaban et al. 2013; Hejazi et al. 2013; Hung and Mithulananthan 2013; Kroposki et al. 2013; Doagou-Mojarrad et al. 2013; Sheng et al. 2015; Kim et al. 2014; Jabr and Pal 2009; Haghifam et al. 2008; Hien et al. 2013; Niknam 2008; Ganguly and Samajpati 2015; Ganguly et al. 2013; Nasiraghdam and Jadid 2012; Soroudi and Ehsan 2011; Jamian et al. 2014; Sanjay et al. 2017; Gkaidatzis et al. 2017; Hassan et al. 2017; Kansal et al. 2017; Nguyen and Vo 2018; Coelho et al. 2018; Quadr et al. 2018; Melgar Dominguez et al.

2018; Moreti et al. 2018). The planning of DG in unbalanced radial distribution systems has been reported only in Ramana et al. (2010). In most of the works, the planning has been done by considering the deterministic load demand, except in Ganguly and Samajpati (2015), in which the load and generation uncertainties are modeled by fuzzy set. In recent years, valuable researches have been carried out in the field of fuzzy set. In Amin et al. (2017), the concept of triangular linguistic hesitant fuzzy set and triangular linguistic hesitant fuzzy set and the concept of triangular cubic linguistic hesitant fuzzy sets are explained. The application of triangular cubic fuzzy numbers is explained in Fahmi et al. (2017a). In Fahmi et al. (2017b), the authors have proposed the cubic TOPSIS method and grey relational analysis set. The application of triangular cubic fuzzy hybrid aggregation concept is explained in Fahmi et al. (2018a). The use of triangular cubic linguistic hesitant fuzzy number in decision making is well explained in Fahmi et al. (2018b). In Fahmi et al. (2018c), the application of trapezoidal cubic fuzzy number Einstein hybrid weighted averaging operators is discussed. The concept of cubic fuzzy Einstein aggregation operators is described in Fahmi et al. (2018d). The authors in Al-Janabi (2017, 2018), Al-Janabi and Alwan (2017), Ali (2012), Al-Janabi et al. (2018) have proposed different pragmatic approaches for solving complex optimization problems. It is observed that integration of DG is only carried out in balanced distribution networks for load and generation uncertainties. However, in Samal et al. (2016), a planning approach for unbalanced distribution networks is reported. But, DG is not included in the planning model considering load and generation uncertainties. Hence, there is no work reported in the literature for the integration planning of DG in unbalanced networks considering load and generation uncertainties, as per the best knowledge of the authors.

In the proposed planning approach, the optimal number, locations, and sizes for DG units are determined by optimizing four objective functions. They are minimization of (i) power loss reduction index, (ii) maximum average voltage deviation index, (iii) neutral current reduction index, and (iv) cost reduction index. All these indices are ratio of the respective quantity with DG to that without DG. For example, the cost reduction index is a ratio of the cost of energy with DG to that without DG; the cost of energy with DG includes the energy purchase cost from the grid and the investment and operational cost of DG units. These objective functions are aggregated using two approaches: (a) fuzzy max–max analogy and (b) fuzzy min–max analogy. The results obtained with both the approaches are compared. The load and generation uncertainties are modeled by triangular fuzzy membership function (Ganguly and Samajpati 2015). A hybrid differential evolution and cuckoo search algorithm (DE–CSA) is used as a solution strategy for this planning optimization. In the proposed hybrid DE–CSA approach, the trial vector for crossover of the chromosomes is generated by following either the DE (Price et al. 2006) or the CSA (Yang and Deb 2009) scheme. A three-phase forward–backward load flow algorithm for unbalanced distribution systems including DG model is used as the support subroutine of the proposed planning approach. A 19-bus and a 25-bus unbalanced radial distribution networks are used to demonstrate the work. The contributions of this works can be summarized as:

- Formulation for a fuzzy multi-objective planning model for the integration of DG units in unbalanced radial distribution networks considering the uncertainties in load and generation
- Proposal of a hybrid DE–CSA as the solution strategy
- Performance comparison among DE, CSA, and hybrid DE–CSA

This paper is organized as follows: fuzzy multi-objective planning problem is described in Sect. 2. In Sect. 3, the proposed planning approach using hybrid DE–CSA is provided. Sections 4 and 5 provide the computer simulation results and conclusion of the work.

2 Fuzzy multi-objective planning problem

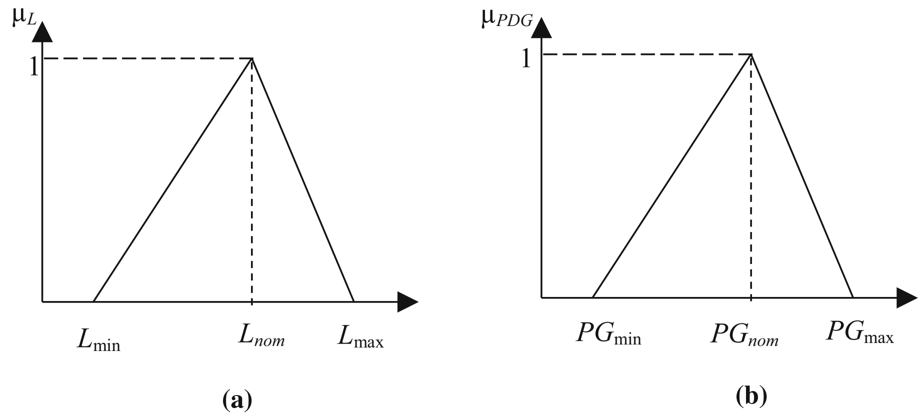
The section provides the formulation of the fuzzy multi-objective planning problem for the integration of DG units in unbalanced distribution networks considering load and generation uncertainties.

2.1 Modeling of load and generation uncertainties

The uncertainties in load demand and generation of DG units are modeled by triangular fuzzy membership function as in Ganguly and Samajpati (2015). Both the load demand in a distribution network and the power generation of the renewable DG units vary in different time of a day and in different seasons depending on the wind speed, solar radiation, etc. These variations do affect the bus voltage, current flowing through network branches, and power production. This may lead to violation of various technical constraints of a network. The triangular fuzzy membership functions used to represent the uncertainties associated with the load demand and the DG power generation are shown in Fig. 1.

The load demand is described as a fuzzy number, as shown in Fig. 1a, in which $L_{\min}$ and $L_{\max}$ are the lowest possible and the highest values of load demand. The load demand corresponding to the membership value 1, i.e.,

Fig. 1 Fuzzy representation of: **a** load demand and **b** DG power generation



L_{nom} specifies the value with the highest possibility of existence. Similarly, the power generated by the DG units is a fuzzy number, as represented in Fig. 1b, where $\text{PG}_{\min}$ and $\text{PG}_{\max}$ represent minimum and maximum DG power generation, respectively. The objective functions do appear as fuzzy numbers, since they are functions of the load demand and the power generation. Hence, this needs a defuzzification approach so as to compare/rank the solutions on the basis of the objective functions.

2.2 Defuzzification approach

The total distance criterion (TDC)-based defuzzification approach is used as described in Ganguly and Samajpati (2015). It finds out the average of the sum of areas under the left and right sides of the fuzzy membership function for a particular α-level. For a triangular fuzzy number, the removal $\{\text{RM}\ (\tilde{fn})\}$ for a fuzzy function corresponding to α-cut is obtained as:

$$\{\text{RM}(\tilde{fn})\} = (fn_{\alpha 1} + 2fn_2 + fn_{\alpha 2})/4 \tag{1}$$

where $[fn_{\alpha 1}, fn_{\alpha 2}]$ is the defuzzified value for the fuzzy function $\tilde{fn}$ obtained corresponding to α-cut and fn_2 is the point at which membership value attains unity.

2.3 Objective function formulation

Four objectives are aggregated in a multi-objective planning framework. They are: (i) power loss reduction index (ii) maximum average voltage deviation index, (iii) neutral current reduction index, and (iv) cost reduction index. The first two parameters/objective functions are important in energy efficiency and power quality of a power distribution network. It is a well-known fact that as the power system loss reduces the energy efficiency improves. The minimization of the second objective function improves the voltage profile of a network. The third objective function, i.e., neutral current reduction index is formulated so as to reduce system unbalance, since the most of the loads of a distribution network are of single-phase and unbalanced (different loading at different phases). When the neutral current which is the summation of three-phase current becomes higher, the system becomes highly unbalanced. Hence, minimization of neutral current reduces the system unbalance. The fourth objective, i.e., cost reduction index is used to minimize the cost of energy purchase of the utilities. These four objective functions fairly describe the optimization model. Moreover, these also articulate the benefits of DG integration in unbalanced distribution networks. These indices are mathematically expressed as:

(i) *Power loss reduction index (PLRI)* The power loss reduction index is defined as the ratio of maximum power loss in any branch with DG integration to the total network power loss without DG.

$$\text{PLRI} = \max\left\{\frac{\text{RM}(\tilde{PL}_i^{\text{wDG}})}{\text{RM}(T\tilde{P}L^{\text{woDG}})}\right\}_{i=1,\ldots,\text{NB}} \tag{2}$$

The power loss in a branch i is computed as evaluated in Samal et al. (2016).

Where TPL is the total power loss in kW.

(ii) *Maximum average voltage deviation index (MAVDI)* The average voltage deviation (AVD) is computed as:

$$\text{AVD}_i = \{V_{\text{sub}}^a - \text{RM}(\tilde{V}_i^a) + V_{\text{sub}}^b - \text{RM}(\tilde{V}_i^b) + V_{\text{sub}}^c - \text{RM}(\tilde{V}_i^c)\}/3 \tag{3}$$

The maximum AVD among all the buses is the ratio of the maximum AVD with DG integration to AVD without DG as given below.

$$\text{MAVDI} = \max\left\{\frac{\text{RM}\left(A\tilde{V}D_i^{\text{wDG}}\right)}{\text{RM}\left(A\tilde{V}D_i^{\text{woDG}}\right)}\right\}_{i=1,\ldots,\text{NB}} \tag{4}$$

In which V_{sub} represents the substation voltage; $\tilde{V}_i^a$, $\tilde{V}_i^b$, and $\tilde{V}_i^c$ denote the magnitudes of the phase voltage of phases a, b, and c, respectively.

(iii) *Neutral current reduction index (NCRI)* The total neutral current reduction index is defined as the ratio of the maximum neutral current in any branch due to the DG integration to the sum total of neutral current of the network without DG.

$$\mathrm{NCRI} = \max\left\{\frac{\mathrm{RM}\left(\tilde{N}C_i^{\mathrm{wDG}}\right)}{\mathrm{RM}\left(T\tilde{N}C^{\mathrm{woDG}}\right)}\right\}_{i=1,\ldots,\mathrm{NBR}} \tag{5}$$

$$\text{where,}\quad \mathrm{TNC} = \sum_{p\in a,b,c}\sum_{i=1}^{\mathrm{NBR}} I_i^p \tag{6}$$

where I_i^p represents branch current of phase p of the ith branch.

(iv) *Cost reduction index (CRI)* The cost reduction index is defined as the maximum ratio of the sum total of the investment and operational cost of any DG unit and the energy purchase cost from the grid to the energy purchase cost of the distribution network without DG.

$$\mathrm{CRI} = \max\left\{\frac{\mathrm{RM}\left(\tilde{C}_i^{\mathrm{wDG}}\right)}{\mathrm{RM}\left(\tilde{C}^{\mathrm{woDG}}\right)}\right\}_{i=1,\ldots,\mathrm{NG}} \tag{7}$$

$$\tilde{C} = \tilde{C}_{\mathrm{sub}} + \sum_{i=1}^{\mathrm{NG}} \tilde{C}_i \tag{8}$$

where C represents total cost of energy in a year which includes the cost of energy purchased from the grid and cost of energy produced by DG units (if any). This cost function consists of two parts. They are: (a) annual cost of energy purchased from the grid (C_{sub}) and (b) the capital investment and operational cost of DG units (C_i). Without DG, C_{sub} is computed as:

$$\tilde{C}_{\mathrm{sub}} = k_{\mathrm{sub}}\mathrm{LF}\sum_{i=1}^{\mathrm{NB}} \tilde{d}_i 8760 \tag{9}$$

where LF represents load factor of the system, d represents the load demand at ith bus in kW and k_{sub} represents cost of electric energy purchased from the grid in \$/kWh, respectively. With DG, it is computed as:

$$\tilde{C}_{\mathrm{sub}} = k_{\mathrm{sub}}\mathrm{LF}\sum_{i=1}^{\mathrm{NB}} \tilde{L}_i 8760 - \sum_{i=1}^{\mathrm{NG}}\left(\mathrm{CF}_i P\tilde{D}G_i dghr_i\right)365 \tag{10}$$

where CF_i represents the capacity factor of the ith DG unit; PG_i is the power generated by the ith DG unit; $dghr_i$ denotes the number of operating hours for the ith DG unit.

The capital investment and operational cost of DG units is computed as given below.

$$\tilde{C}_i = a_i + b_i\tilde{P}G_i \tag{11}$$

$$a = \frac{\text{Captial cost}(\$/\text{kW}) \times \text{Rated capacity} \times \text{Gr}}{\text{Life time(year)} \times 365 \times 24 \times \text{CF}} \tag{12}$$

where the price of DG power generation of unit i, is denoted as C_i (\$/kWh) (Nasiraghdam and Jadid 2012); Gr denotes the annual rate of benefit and CF represents the capacity factor of DG units. The term b_i is for the annual operation and maintenance cost for the ith DG unit.

Two approaches are used to aggregate all the objectives as:

Approach #1: *max–max analogy*:

$$\mathrm{fit}_1 = \max\{(\mathrm{PLRI}), (\mathrm{MAVDI}), (\mathrm{NCRI}), (\mathrm{CRI})\} \tag{13}$$

Approach #2: *min–max analogy*:

$$\mathrm{fit}_2 = \min\{(\mathrm{PLRI}), (\mathrm{MAVDI}), (\mathrm{NCRI}), (\mathrm{CRI})\} \tag{14}$$

The fitness function (*FT*) assigned to each chromosome representing a potential solution in the proposed DE–CSA is as follows:

$$\text{Maximize}\quad FT = 1/(1 + \mathrm{fit}) \tag{15}$$

This fitness function is maximized under the following constraints:

(i) *Voltage constraint* The voltage in each bus should lie within a given upper and lower limits.

$$V_s^{\min} \le \mathrm{RM}(\tilde{V}_s^{abc}) \le V_s^{\max} \tag{16}$$

(ii) *Thermal constraint* The current flowing through each branch must be less than the respective thermal limit of the conductor.

$$\mathrm{RM}(\tilde{I}_j^{abc}) \le I_j^{\max} \tag{17}$$

(iii) *DG power generation constraint*

$$\mathrm{PDG}_{\min} < \mathrm{RM}(P\tilde{D}G_i) < PDG_{\max} \tag{18}$$

3 Proposed planning approach using hybrid DE–CSA

The DG integration technique using hybrid DE–CSA consists of several subroutines, such as fuzzy three-phase load flow algorithm, an encoding/decoding technique for the chromosome of the hybrid DE–CSA, etc. These are described in detail in the following subsections.

3.1 Three-phase fuzzy forward–backward sweep load flow algorithm incorporating DG model

The three-phase forward–backward sweep load flow algorithm, as proposed in Samal and Ganguly (2015), is used in this work. It consists of two steps. In the first step, the backward sweep is executed to find out the branch currents. Firstly, the load current in each phase in each bus of an unbalanced radial distribution is calculated. Then, the forward sweep is executed to obtain the bus voltages. The load flow algorithm (Samal and Ganguly 2015) is modified by considering fuzzy load and generation model as in Ganguly et al. (2013).

3.1.1 Incorporation of DG model in load flow

The DG model is incorporated by modifying the active and reactive power demand at the bus at which a DG unit is placed, say, at bus i, as:

$$\begin{aligned} P_{D_{ip}}^{\mathrm{DG}} &= P_{D_{ip}}^{\mathrm{base}} - P_{ip}^{\mathrm{DG}} \\ Q_{D_{ip}}^{\mathrm{DG}} &= Q_{D_{ip}}^{\mathrm{base}} \pm Q_{ip}^{\mathrm{DG}} \end{aligned} \tag{19}$$

where $P_{D_{ip}}^{\mathrm{DG}}$ and $Q_{D_{ip}}^{\mathrm{DG}}$ are the active and reactive power demand for pth phase of ith bus with a DG unit and $P_{D_{ip}}^{\mathrm{base}}$ and $Q_{D_{jp}}^{\mathrm{base}}$ are the active and reactive power demand for pth phase of ith bus of the base-case network; P_{ip}^{DG} is the active power generated by the DG unit placed at pth phase of ith bus.

3.2 Proposed planning approach using the hybrid DE–CSA

A brief overview on DE and CSA is provided in the following subsections followed by the pseudocode of the planning approach using DE–CSA.

3.2.1 Differential evolution (DE) algorithm: an overview

DE is a meta-heuristic algorithm (Price et al. 2006) like GA. It performs with basic GA operator, such as selection, crossover, and mutation. It has several improved versions. They can be categorized using the notation: DE/λ/θ/κ; in which the method for the selection of the parent chromosome for crossover operation is indicated by λ, single or multi-point crossover is indicted by θ, and the crossover process to be followed is denoted by κ. In this work, DE/rand/1/bino is used. The bino indicates that the crossover operation is performed by a series of binomial experiments.

It starts searching for the best solution with some m-dimensional initial chromosomes which are randomly chosen. Then, they are iteratively generated according to the basic GA operation. The jth chromosome in iteration it is given by:

$$x_j(it) = (x_{j1}(it), x_{j2}(it), \ldots, x_{jn}(it)) \tag{20}$$

A vector is created in every iteration for mutation by using the vector difference from two randomly selected chromosomes. Then, trial vectors are generated for crossover and selection. The fitter chromosomes are selected for the next iteration. A brief discussion on mutation, crossover, and selection processes is provided below.

Mutation For a randomly chosen target chromosome, a vector is generated for mutation in iteration it as given below.

$$m_j(it+1) = x_{rn1}(it) + G(x_{rn2}(it) - x_{rn3}(it)) \tag{21}$$

where indices $rn1$, $rn2$, $rn3 \in [1, \eta_{\mathrm{pop}}]$ are generated randomly, $G \in [0, 2]$ is a scale factor, by which the mutation size is controlled, and η_{pop} is the size of the population.

Crossover For crossover, firstly, a trial chromosome is generated in iteration it as:

$$U_j(it) = (U_{j1}(it), U_{j2}(it), \ldots, U_{jn}(it)) \tag{22}$$

$$U_{jk}(it+1) = \{m_{jk}(it+1)\ \mathrm{rand}_{jk}[0,1] \le \mathrm{CR} \quad \text{or } k \ne k_{\mathrm{rnd}} \tag{23}$$

where CR is a parameter of DE in the range [0, 1], and k_{rnd} is a random integer number in the range of [1, η_{pop}] to ensure that the trial vector U_j can get at least one element from the mutant vector.

Selection The selection process is for selecting the fitter chromosome from the parent and the trial/child chromosome, and it is done as:

$$x_j(it+1) = \begin{cases} U_j(it+1)\ \mathrm{FTF}(U_j(it+1) > \mathrm{FTF}(U_j(it)) \\ x_j(t)\ \mathrm{FTF}(U_j(it+1) < \mathrm{FTF}(U_j(it)) \end{cases} \tag{24}$$

where FTF (.) is the fitness function to be maximized as given in Eq. (15).

3.2.2 Cuckoo search algorithm (CSA): an overview

Cuckoo search algorithm (CSA) was developed by Xin-She Yang and S. Deb by observing the intelligent egg laying strategy of cuckoos, which lay their eggs in a randomly chosen host nest for their survival. If the host bird identifies cuckoo eggs, it will either throw away their eggs or build a new nest somewhere else. The nest in the CSA algorithm is same as the population, which is used in particle swarm optimization. Each egg in the nest represents the possible

Begin

// η_{pop} = Population size

//*max_it* = Maximum iteration

Generate initial population for DE randomly using proposed encoding scheme

Decode the initial population and obtain the DG location and size for each chromosome and target vectors

Iteration=1

While *iter* <= *max_it*

  For i=1,…, η_{pop}

   Select rn_1, rn_2, rn_3 from the population such that ;
   obtain mutant vectors using equations (21);

   Generate a random number *r* between 0-1;

   If $r <$ CR

    Keep the trial chromosome *U* generated by DE using Eqs. (22)-(23);

   Else

    Generate trial chromosome *U* by CSA using Eqs. (25)-(26);

  End If

 End For

Determine the fuzzified objective function with the help of fuzzy distribution load flow so as to rank them using removal values, assign fitness to each chromosome

 Calculate *FT* for target chromosome and define as *fit*1;

 Calculate *FT* for trial chromosome and define as *fit*2;

 For i=1,…, η_{pop}

   If *fit*2>*fit*1

    Set the target chromosome r by the trial chromosome;

   Else

    Set the target chromosome by the previous target chromosome;

  End If

 End for

 Perform the load flow incorporating the DG units in respective locations;

 Find out the fittest chromosome from the target chromosomes for each iteration;

iter=*iter*+1;

End while

Obtain the best chromosome from the set of fittest chromosome;

End

Fig. 2 Pseudocodes for the proposed planning approach using the hybrid DE–CSA

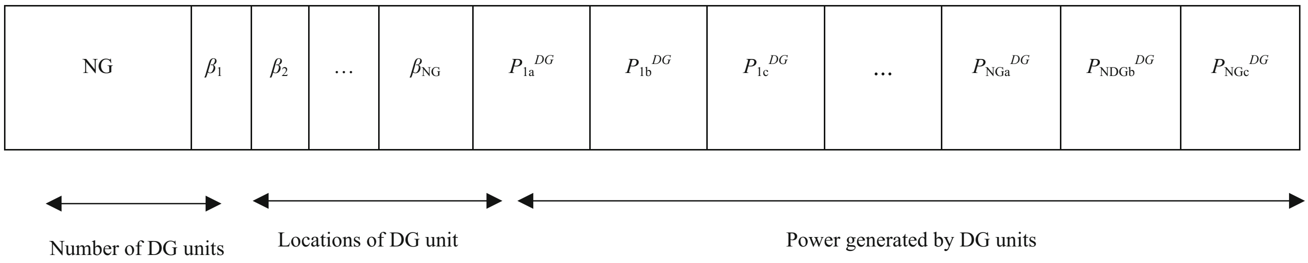


Fig. 3 Encoding strategy for a chromosome in DE–CSA

Table 1 Optimal parameters used in DE, CSA, and DE–CSA

Parameters	DE (Price et al. 2006)	CSA (Yang and Deb 2009)	DE–CSA
η_{pop}	100	100	100
max_it	150	150	150
Individual parameters	CR = 0.8	λ = 1	CR = 0.8, $\lambda = 1$
	G = 1.0	–	G = 1.0

solution or decision variable for the optimization problem. The CSA follows three rules (Yang and Deb 2009) as:

- Each cuckoo lays one egg at a time and abandons in a random nest;
- The better-quality eggs (good solutions) move to the next generations;
- A host bird can discover an alien egg with a probability p_a = [0, 1] and either builds a new nest at a new location or completely abandons its own nest or throws the eggs away.

CSA generates random host nest using levy flight for the new solution. The solution (x_i^{t+1}) is updated in iteration ($t + 1$) as:

$$x_i^{t+1} = x_i^t + \alpha \times \text{Levy}(\lambda) \tag{25}$$

$$\text{Levy}(\lambda) = \left| \frac{\Gamma(1+\lambda) \times \sin\left(\frac{\pi \times \lambda}{2}\right)}{\Gamma\left(\frac{1+\lambda}{2}\right) \times \lambda \times 2^{\frac{\lambda-1}{2}}} \right|^{\frac{1}{\lambda}} \tag{26}$$

where α [usually equal to 1 (Yang and Deb 2009)] and λ [lies (El-Khattam and Salama 2004; Adefarati and Bansal 2016)] are the parameters of CSA.

Table 2 Comparison of MET among DE, CSA, and DE–CSA for Case D planning with max–max approach for the 25-bus system

Algorithm	MET (s)
DE (Al-Janabi 2018)	304
CSA (Al-Janabi and Alwan 2017)	323
DE–CSA	215

3.2.3 Proposed planning approach: pseudocodes

In the proposed approach, unlike DE, the trial vector for each chromosome is generated by using the updating equations of both DE and CSA. The pseudocodes for the planning approach using hybrid DE–CSA is shown in Fig. 2.

3.3 Encoding/decoding strategy of the chromosomes

A chromosome for the hybrid DE–CSA represents a candidate solution which consists of the following three decision variables.

(i) The first one, i.e., NG represents the number of DG units connected to the system. In this work, maximum six DG units are considered.

(ii) The second variable (β) encodes the information of the location of DG units in a distribution network. The locations appearing in the first three entries are considered to be photovoltaic type, and rest are wind-turbine-type DG units.

(iii) The third decision variable represents DG power generation in each location.

where $P_{ia}^{\mathrm{DG}}, P_{ib}^{\mathrm{DG}}, P_{ic}^{\mathrm{DG}}$ are the DG capacities located in the three phases in ith bus and NG is the number of DG units.

A pictorial representation of a chromosome is shown in Fig. 3.

Since it is a type of direct encoding process, the decoding of a chromosome is straightforward. If the location/number is appearing as fractional number it is converted to its immediate integer number.

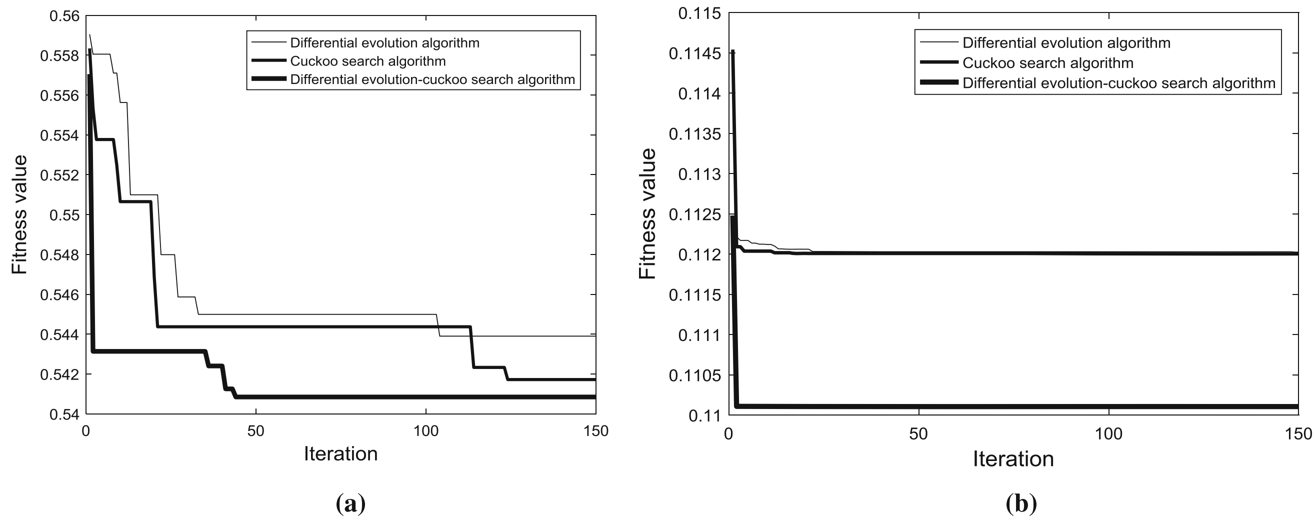


Fig. 4 Comparison of fitness value among DE–CSA, DE and CSA for a 19-bus system considering Case D using: **a** max–max and **b** min–max approach

4 Simulation study: results and discussion

The computer simulation study for the proposed planning approach is carried out in MATLAB R2012 environment using two test systems, i.e., 19-bus and 25-bus unbalanced radial distribution systems. The computer specification is Intel® Core™ i3-2330M processor with a speed of 2.2 GHz and RAM of 2 GB. The load and line data are available in Ramana et al. (2010) and Samal et al. (2016) for the 25-bus and 19-bus systems, respectively. The base voltage and base MVA are 11 kV, 1 MVA and 4.16 kV, 30 MVA for the 19-bus and for the 25-bus systems, respectively. The total active and reactive power demand for the 19-bus system are 365.94 kW and 177.27 kVAR, respectively. For the 25-bus system, they are 3240 kW and 2393 kVAR, respectively. The DE, CSA, and hybrid DE–CSA parameters are optimized by taking repetitive simulation runs, and the optimal parameters are shown in Table 1. The DG penetration level, i.e., the ratio of total DG active powers to total active power demand is considered to be 0.4 and 0.5 for 19-bus and 25 bus system, respectively. A hybrid renewable DG system comprising of photovoltaic (PV) and wind turbine (WT) units is considered in the planning. For a bus, maximum three DG units are to be placed in three different phases. The cost parameters of DG such as Gr, CF, and other parameters are taken from (Nasiraghdam and Jadid 2012). The maximum sizes of DG units are considered to be 30 kW and 400 kW for 19-bus and 25-bus system, respectively. The DG units are assumed to be operated at unity power factor. Four different planning optimization cases are used as in Ganguly and Samajpati (2015). They are:

- *Case A*: The load and generation are modeled by peak load demand and maximum generation, respectively.
- *Case B*: The load is modeled by fuzzy set and the generation is modeled by the maximum generation.
- *Case C*: The load is modeled by peak load demand and the generation is modeled by fuzzy set.
- *Case D*: Both the load and generation are modeled by fuzzy set.

For fuzzy modeling, the load demand $\widetilde{L}$ = (0.5, 1, 1.3) p.u. of the peak load demand and generation as (0.3, 1, 1.5) of the nominal generation are used.

It is observed that hybrid DE–CSA converges at a faster rate as compared to the DE and CSA. It seems that the algorithms are quickly converged or being trapped into local optimal with the *min–max* approach. However, no conclusion can be made from the result of single run of any heuristics-based algorithm. Thus, multiple simulation runs are carried out and the results are shown in the following subsection. Table 2 shows the comparison of mean execution time (MET) in seconds among DE, CSA, and DE–CSA for Case D planning with *max–max* for the 25-bus systems.

It can be observed from the above table that DE–CSA takes less execution time than DE and CSA for Case D planning with the *max–max* approach. A comparison of mean fitness values of the population as obtained with hybrid DE–CSA, DE, and CSA for the 19-bus system is shown in Fig. 4.

4.1 Results of Approach #1: max–max analogy

Firstly, quantitative performance comparison of the hybrid DE–CSA with DE and CSA with the results of 25 runs is

Table 3 Comparison of the results as obtained with DE–CSA, DE, and CSA for Case D planning for 19-bus and the 25-bus systems using the max–max approach

System	Solution strategy	TPL (kW)		MAVDI (p.u.)		TNC (p.u.)		*C* ($/yr)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
19 bus	DE–CSA	4.1621	0.0357	0.0221	0.0001	1.3601	0.0349	65,461.1	0.0004
	DE	4.3181	0.0364	0.0224	0.0005	1.3861	0.0354	66,557.8	0.0005
	CSA	4.3262	0.0454	0.0226	0.0011	1.3877	0.0359	66,894.1	0.0006
25 bus	DE–CSA	62.0917	0.3044	0.0345	0.0001	0.4578	0.0031	841,151	0.0005
	DE	67.0643	0.4638	0.0355	0.0003	0.4758	0.0032	883,188	0.0006
	CSA	67.2414	0.5165	0.0360	0.0011	0.4761	0.0033	883,961	0.0010

Table 4 Comparisons among the different objective functions solutions for different planning cases for 19-bus and the 25-bus systems using hybrid DE–CSA using the max–max approach

Objective function	19-bus system					25-bus system				
	Without DG	With DG				Without DG	With DG			
		Case A	Case B	Case C	Case D		Case A	Case B	Case C	Case D
TPL (kW)	13.470	4.8298	4.8302	4.8281	4.1621	150.12	70.7518	62.2578	71.0012	62.0917
MAVDI (p.u.)	0.0494	0.0244	0.0243	0.0244	0.0221	0.0689	0.0370	0.0348	0.0367	0.0345
TNC (p.u.)	2.384	1.4570	1.4556	1.4558	1.3601	0.6375	0.4839	0.4601	0.4845	0.4578
TC ($/yr)	116,685.09	71,331.7	71,324.2	71,295.6	65,461.1	1,033,119.36	908,847	845,678	892,391	841,151

shown in Table 3. The mean values of the objective function for the solutions obtained with the hybrid DE–CSA are found to be better than those obtained with DE and CSA. The results obtained with the hybrid DE–CSA are also found to be superior to those obtained with DE and CSA in view of the standard deviation of the solutions of 25 runs. Hence, hybrid DE–CSA is used as the solution strategy to show the performance comparison among different planning cases in Table 4. All the indices formulated as the objective functions are significantly improved with DG placement. The network is found to be relatively balanced with the DG placement because the neutral current is significantly reduced. The results obtained with the planning *Case D* are found to be better than those obtained with the planning *Cases A–C*. In Table 5, the locations, types, and sizes of the DG units for the best solutions as obtained with the hybrid DE–CSA are provided. It is found that the buses 9 and 10 are found to be the effective locations for the PV type of DG unit. Similarly, the buses 13 and 14 are effective locations for the WT type of DG integration.

Table 5 Comparison among location, type of DG, and power generated by DG in kW for the best solution obtained with the different planning cases with hybrid DE–CSA using the max–max operation

Distribution network	Case	Location	Type of DG	Power generated by DG units (kW)		
19 bus	A	13	PV	27.5	19.8	30.0
		14	WT	21.6	27.4	19.8
	B	13	PV	30.0	23.1	30.0
		14	WT	18.0	27.1	17.9
	C	10	PV	30.0	30.0	27.3
		14	WT	19.9	16.1	22.8
	D	10	PV	29.9	30.0	30.0
		14	WT	17.2	20.5	18.5
25 bus	A	9	PV	189.8	166.8	264.4
		13	WT	323.1	400.0	275.6
	B	10	PV	187.0	180.4	215.0
		13	WT	325.0	366.9	345.0
	C	10	PV	194.5	200.9	236.4
		13	WT	400.0	256.7	331.2
	D	11	PV	220.0	176.9	154.0
		13	WT	318.6	352.6	397.7

4.2 Results of Approach #2: min–max analogy

A similar simulation experiment is performed with *Approach* #2, i.e., min–max analogy. The comparative results among different algorithms and different planning cases are given in Tables 6 and 7, respectively. The results are slightly different as compared to those obtained with the Approach #1. But, they show similar trends as explained above. In Table 8, the locations, types, and sizes of the DG

Table 6 Comparison of the results as obtained with DE–CSA, DE, and CSA for Case D planning for 19-bus and the 25-bus systems using min–max approach

System	Solution strategy	TPL (kW)		MAVDI (p.u.)		TNC (p.u.)		TC ($/yr)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
19 bus	DE–CSA	4.1632	0.0358	0.0222	0.0001	1.3602	0.0351	65,477.3	0.0005
	DE	4.3198	0.0365	0.0225	0.0006	1.3869	0.0355	66,561.7	0.0006
	CSA	4.3271	0.0456	0.0227	0.0012	1.3881	0.0361	66,902.8	0.0007
25 bus	DE–CSA	63.0981	0.3048	0.0346	0.0001	0.4581	0.0032	841,155	0.0006
	DE	68.0348	0.4641	0.0357	0.0004	0.4761	0.0033	883,197	0.0007
	CSA	68.1358	0.5170	0.0361	0.0012	0.4764	0.0034	883,976	0.0011

Table 7 Comparisons among the different objective functions solutions for different planning cases for 19-bus and the 25-bus systems using hybrid DE–CSA using min–max approach

Objective function	19-bus system					25-bus system				
	Without DG	With DG				Without DG	With DG			
		Case A	Case B	Case C	Case D		Case A	Case B	Case C	Case D
TPL (kW)	13.470	4.8319	4.8316	4.8285	4.1632	150.12	70.8142	63.6412	71.0124	63.1651
MAVDI (p.u.)	0.0494	0.0245	0.0244	0.0245	0.0222	0.0689	0.0371	0.0349	0.0368	0.0346
TNC (p.u.)	2.384	1.4572	1.4559	1.4561	1.3602	0.6375	0.4840	0.4602	0.4847	0.4581
TC ($/yr)	116,685.09	71,336.5	71,328.6	71,298.5	65,477.3	1,033,119.36	908,851	845,684	892,402	841,155

Table 8 Comparison among location, type of DG, and power generated by DG in kW for the best solution obtained with the different planning cases with hybrid DE–CSA using the min–max approach

Distribution network	Case	Location	Type of DG	Power generated by DG units (kW)		
19 bus	A	10	PV	21.2	23.6	28.9
		14	WT	27.8	23.3	21.2
	B	13	PV	30.0	30.0	22.1
		14	WT	19.6	16.7	27.7
	C	10	PV	23.7	27.1	26.6
		14	WT	25.0	20.2	23.5
	D	10	PV	26.8	30.0	23.9
		14	WT	22.6	19.5	23.3
25 bus	A	10	PV	207.7	313.0	273.1
		14	WT	305.4	251.6	269.0
	B	10	PV	128.6	149.0	195.9
		14	WT	400.0	400.0	346.3
	C	10	PV	316.5	271.0	216.1
		13	WT	201.5	272.6	342.1
	D	9	PV	224.5	262.5	295.3
		13	WT	324.8	261.1	251.4

units for the best solutions as obtained with the hybrid DE–CSA are provided. The results show that the locations, sizes, types of DG units are different in various planning cases. Thus, it can be said that the optimal locations, types, and sizes of DG units vary with type of load and generation modeling. These are also found to be different as compared to those obtained with *Approach* #1. More number of locations are found to be the potential locations for DG integration in Approach #2. It is also observed that the best solution consists of DG units in all the three phases in a location with unequal sizes. This basically reduces the system unbalance.

4.3 Decision of results

From the above discussions, it is found that best solutions are obtained with max–max approach by using DE–CSA hybrid approach for Case D planning for both 19- and 25-bus unbalanced distribution systems. Furthermore, it is found that DE–CSA takes less execution time than DE and CSA for Case D planning with the max–max approach. It is also seen that with the application of only DE or CSA may lead to entrapment into local optima. However, the DE–CSA hybrid method provides more exploration and exploitation of the solutions around local optima so that better results can be found. Thus, the DE–CSA hybrid approach is found to be a superior optimization algorithm. The main limitations and advantages of the proposed approach are discussed below.

The main limitation of the pragmatic method is the variations in the final solutions in multiple simulation runs. However, the advantages of the proposed DE–CSA hybrid method are:

1. Better speed of convergence than DE and CSA.
2. Lesser execution time than DE and CSA.
3. Better final solution than DE and CSA.
4. Lower mean and standard deviations of the final results than DE and CSA.

5 Conclusion

In this paper, a planning approach has been proposed to determine the optimal locations, type, and sizes of DG units in unbalanced radial distribution systems. Firstly, a mathematical planning optimization model is formulated. It consists of four objective functions. They are minimization of the power loss, the maximum average voltage deviation, the total neutral current, and the total cost of the system which includes cost of energy purchased from the grid and the capital investment and operational cost of DG units. These objective functions are minimized so as to determine the locations, type, and sizes for DG units. Two types of renewable DG units, i.e., solar PV and wind turbine, are considered to be placed into distribution networks. The load demand and power generation uncertainties are modeled using fuzzy number. This yields all the objective functions to be fuzzy numbers. Hence, these are defuzzified so as to compare and rank different solutions. The solution strategy used is the hybrid DE–CSA, in which the trial vector for crossover of the chromosomes is generated by following either DE or CSA scheme. A forward–backward load flow algorithm including the DG model is used in the planning approach. The salient outcomes of the results obtained are:

- The proposed planning optimization approach using hybrid DE–CSA provides the locations, sizes, and type of DG units so as to obtain a distribution network with significantly reduced power loss and better voltage magnitude.
- The annual cost of energy is significantly reduced due to DG placement because the energy demand from the grid is significantly reduced.
- The network is also found to be relatively balanced with the DG allocation, since the neutral current is significantly reduced.
- For a particular type of DG unit, some particular locations are found to be suitable locations to get the best/optimal solution. But, these locations are found not to vary with the planning of different load and generation models.
- The best solution is found to have DG units in all the three phases in a location with unequal sizes.
- The optimal locations, types, and sizes of DG units are found to vary with type of load and generation modeling. The best result, however, is obtained with the planning with fuzzy load and generation. The results also depend on the type of aggregation of the objective function.
- The performance of the hybrid DE–CSA is found to be better and consistent as compared to individual algorithms of DE and CSA in terms of mean and standard deviation of the solution obtained with multiple runs.
- The hybrid DE–CSA is found to take lesser mean execution time than DE, and CSA.
- The hybrid DE–CSA method is found to be superior optimization algorithm than individual DE and CSA.

However, the theme of this approach is limited to the investment planning for DG integration. A coordinated investment planning and control can be a potential future direction of research.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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