# PLANNING OF UNBALANCED RADIAL DISTRIBUTION SYSTEMS WITH DISTRIBUTED GENERATIONS CONSIDERING UNCERTAINTY USING HYBRID DE-CS ALGORITHM

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***Abstract:*** *This work presents a planning approach of distributed generating units for unbalanced radial distribution systems using a hybrid differential evolution algorithm (DE) and Cuckoo search algorithm (CSA) so as to determine the optimal distributed generation (DG) location(s) and power allocation. Four objective functions are formulated in the planning problem. They are the minimization of: (i) total real power loss, (ii) maximum average voltage deviation, (iii) total neutral current, and (iv) total system cost. These objectives are optimized under the constraints of minimum and maximum voltage limits for each bus voltage and thermal limit of each line. A modified three phase forward-backward sweep based load flow algorithm is employed as a supplementary tool for the evaluation of these objective functions. The simulation results obtained with the 19-bus and 25-bus unbalanced radial distribution systems show that significant improvement in power loss, maximum average voltage deviation, and total system cost can be achieved with simultaneous optimization for DG location(s) and power generation. The performance of hybrid DE-CSA is found to be better and consistent as compared to some other meta-heuristic algorithms studied here.*

***Key words****: Unbalanced radial distribution systems, three phase load flow, distributed generation, differential evolution algorithm.*

## 1. Introduction

Nowadays distributed generation (DG) are gaining popularity over traditional power generating units due to several advantages in view of economy and operation [1]. The economic benefits are deferral in cost of investment for building new lines, reduction in wholesale price by supplying power to the grid. The operational benefits are the power loss reduction, the voltage profile improvement, the peak load shaving, improvement in system stability and reliability [1, 2] . However, improper DG allocation may lead to increase in system loss, cost and violation of various technical constraints. But, optimal allocation and proper sizing of DGs can reduce network power loss, investment cost, and improvement in power quality and voltage profile of the system. Generally distributed generation planning is complex mathematical problem which requires simultaneous optimization of various objective functions such as minimization of the fuel cost, the power loss and bus voltage deviation, etc.

Various optimization techniques have been used [3–13] in the literature to solve the distributed generation planning problem. They are based on analytical approach [7, 8], voltage index method [4], numerical approach [12], restoration approach [11] and meta-heuristic optimization [5, 6, 9, 10, 13, 15, 17]. Meta-heuristic-based are genetic algorithm (GA) [5, 10, 13, 17], differential algorithm (DE) [6], hybrid shuffled frog leap algorithm and DE [9], particle swarm optimization (PSO) and ant colony optimization (ACO) [16], adaptive genetic algorithm (AGA) [17]. Modified NSGA [20], and gravitational search algorithm [21]. The objectives considered in the literature for the distributed generation planning are the minimization of system upgrade cost, cost of the energy loss and the interruption cost [5], the maximization of profit of a distribution Company [6], the minimization of power loss [7], maximizing system value [8], minimization of total power loss, cost of electrical energy and total pollutant emission [9 ,20], minimization of line loss, voltage deviation and voltage stability margin [10], minimization of cost of energy not supplied and cost of energy loss [11], loss minimization and DG capacity maximization [12], minimization of cost and over/under voltage of buses [13], reactive power minimization [15] and cost of power generation by DGs and distribution companies [16], minimization of total installation and operational cost, and minimization of risk factor [18], power loss and maximum voltage deviation minimization[17], and power loss minimization [18,21], and voltage profile improvement [21].

In most of the DG planning approaches, the distribution systems are considered to be balanced [1-13], [15–24]. The optimal allocation of DG considering load and generation uncertainties for balanced distribution systems is presented in [17]. However, no work is reported in the literature for planning of DG in unbalanced radial distribution systems considering load and generation uncertainties.

The objective functions are the total power loss,[1] maximum average voltage deviation, total neutral current and total system cost. A hybrid Differential evolution (DE) and Cuckoo search algorithm (CSA) is adopted as the solution strategy for minimizing these objective functions to obtain optimal DG locations and power generation. For the evaluation of each objective, a forward-backward load flow algorithm is developed. The proposed approach is demonstrated on the 19-bus and 25-bus unbalanced radial distribution systems. Multiple simulation runs are taken, and the results are compared with Differential evolution algorithm (DE) [22], and cuckoo search algorithm (CSA) [23]. The performance of hybrid DE-CSA is found to be better among them. The contributions of this works are summarized as:

- Application of a hybrid Differential evolution and Cuckoo Search based planning algorithm for DG power allocation and sizing considering uncertainty of load and generation;
- Comprehensive performance comparison of Hybrid DE-CSA with DE and CSA.

This paper is organized as follows: Fuzzy-based modelling of load and generation uncertainties is described in section 2. Problem Formulation is presented in section 3. In Section 4, the implementation of proposed planning approach using Hybrid DE-CSA is described. The simulation results are presented in section 5. Section 6 concludes the paper.

## 2. Fuzzy based Modelling of Load and Generation Uncertainties

In this work, the variation in load demand and generation power are expressed by triangular fuzzy numbers [18]. The load variation in distribution network is random in nature and also the power generated by DG is considered to be uncertain due to variation in wind speed and solar radiation. This variation affects the bus voltage, current flowing through branches and cost of power production which may lead to violation of various technical and economic constraints of a system. In this approach, the variation in load and power generation are modelled using fuzzy quantities [18].

The uncertainties associated with the load demand and the DG power generation are represented as fuzzy numbers [18] as shown in Fig. 1.

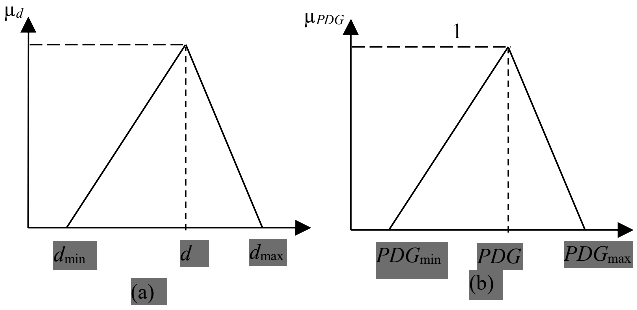



Fig. 1. Fuzzy representation of load demand (a) and power generated by DG (b)

The load demand is described as a fuzzy number $\tilde{d} = (d_{\min}, d, d_{\max})$ as shown in Fig.1 (a), $d_{\min}$ is the lowest value of load demand, $d_{\max}$ is the highest value of load demand, and $d$ corresponds to the load demand at which membership value attains value 1 (i.e. load demand with highest possibility of existence). Similarly, the power generated by DG is a fuzzy number $\tilde{PDG} = (PDG_{\min}, PDG, PDG_{\max})$ as represented in Fig. 1(b), where $PDG_{\min}$ represents minimum DG power generation, $PDG_{\max}$ maximum DG power generation, and $PDG$ shows highest possibility of existence for power generated by DG. The objective function is also a fuzzy number as it contains the load demand and the DG power generation as variables.

### 2.1 Defuzzification approach

In order to compare and rank among several solutions with fuzzy objective functions, a total distance criterion (TDC) based defuzzification technique [24] is used, as they provide better representation of a fuzzy set in comparison to other techniques such as mean of maxima and center of gravity. TDC finds out the average of the sum of areas under the left and right sides of the fuzzy membership function for a particular $\alpha$-level. Mathematically for a triangular fuzzy number, the removal $\{RM(\tilde{fn})\}$ of a fuzzy objective function for a $\alpha$-cut obtained as:

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

Where, $[fn_{\alpha 1}, fn_{\alpha 2}]$ is the defuzzified value for the objective function $\tilde{fn}$ obtained from $\alpha$-cut [17], and $fn_2$ is the point at which membership value attains unity.

## 3. Problem Formulation

The objective of this planning problem is the minimization of various objective functions subject to some technical constraints. These objective functions are described below.

(i) *Total Power Loss reduction index (TPLRI):* The total power loss of a system is expressed as follows

$$\tilde{TPLRI} = \frac{\tilde{TPL}^{with\_DG}}{\tilde{TPL}^{without\_DG}} \quad (2)$$

$$TPL = \sum_{p=a}^{c}\sum_{j=1}^{NBR}\left(V_{SN_j}^{p} - V_{RN_j}^{p}\right).I_{SN_jRN_j}^{p} \quad (3)$$

Where, $TPL$ is the total power loss in kW and $I_j^p$ and are the current and resistance of phase $p$ of the $j^{th}$ feeder segment, respectively.

(ii) *Maximum average voltage deviation index (MAVDI):* The maximum average voltage deviation index is formulated according to Eq. (4)

$$\tilde{MAVDI} = \frac{\max((V_{sub} - \tilde{V}_i^{a^{with\_DG}} + V_{sub} - \tilde{V}_i^{b^{with\_DG}} + V_{sub} - \tilde{V}_i^{c^{with\_DG}})/3)}{\max((V_{sub} - \tilde{V}_i^{a^{without\_DG}} + V_{sub} - \tilde{V}_i^{b^{without\_DG}} + V_{sub} - \tilde{V}_i^{c^{without\_DG}})/3)} \quad (4)$$

(iii) *Total neutral current reduction index:* The total neutral current reduction index is defined as below.

$$\tilde{TNCRI} = \frac{\tilde{TNC}^{with\_DG}}{\tilde{TNC}^{without\_DG}} \quad (5)$$

$$TNC = \sum_{p=a}^{c}\sum_{i=1}^{NBR} I_i^p \quad (6)$$

Where $I_i^p$ represent branch current of phase $p$ of the $i^{th}$ branch.

(iv) *Total cost reduction index:* The total cost reduction index is defined as below.

$$\tilde{TCRI} = \frac{\tilde{TC}^{with\_DG}}{\tilde{TC}^{without\_DG}} \quad (7)$$

$$TC = C_{sub} + \sum_{i=1}^{NDG} C_i \quad (8)$$

$$C_{sub} = P_{sub} \cdot k_{sub} \quad (9)$$

$$C_i = a_i + b_i \cdot P_i \quad (10)$$

$$a = \frac{\text{Captial cost (\$/kW)} \times Rated\ capacity \times Gr}{Life\ time(year) \times 365 \times 24 \times CF} \quad (11)$$

$$b = O\&M\ cost(\$/\text{kWh}) + fuelcost\ (\$/\text{kWh}) \quad (12)$$

Where, $TC$ [19], $C_{sub}$, $P_{sub}$, and $k_{sub}$ represents total system cost in \$/h , power supplied by substation in kW, and purchase price of electric energy from substation in \$/kWh respectively; the price of DG power generation of unit $i$ , is denoted as $C_i$ (\$/h) [19]; $Gr$ denotes the annual rate of benefit and $CR$ represents capacity factor of DG units.

The weighted sum of all objectives functions are defined as:

$$fit = k1\text{RM}(\tilde{TPLRI}) + k2\text{RM}(\tilde{MAVDI}) + k3\text{RM}(\tilde{TNCRI}) + k4\text{RM}(\tilde{TCRI}) \quad (13)$$

Where, $k_1+k_2+k_3+k_4=1.0$ (14)

In which, $k_w$ denotes the weighting factor and $k_1$, $k_2$, $k_3$, and $k_4$ are considered to be 0.25.

The fitness function (FT) for DE is assigned as follows:

Maximize $FT = 1/(1+fit)$ (15)

This fitness function is maximized under the following constraints:

*i. Voltage constraint*: Voltage at each bus must remain within the permissible range.

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

*ii. Thermal constraint*: The current flowing through each branch must be within the maximum current-carrying capacity of the conductor.

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

*ii. DG power generation constraint*:

$$PDG_{\min} < \text{RM}(\tilde{PDG_i}) < PDG_{\max} \quad (18)$$

## 4. Implementation of hybrid DE-CSA algorithm for DG allocation

The proposed DG allocation technique with DE-CSA utilizes a fuzzy three-phase load flow algorithm as a subroutine to obtain bus voltage magnitudes and power loss of a system. DE-CSA algorithm is used to update the chromosome representing decision variables such as DG location and rating. The load flow algorithm including DG is explained in Section 4.1 and application of Hybrid DE-CSA is described in Section 4.2.

*4.1 Modified three phase forward-backward sweep load flow algorithm incorporating DG*

The proposed algorithm [25] uses three matrices *A*, *B* and *C* to find power flow solutions. The downstream buses connected to a particular bus are determined using matrix *A*. The end buses are identified with the help of matrix *B* and matrix *C* is developed to obtain the branch currents. This load flow algorithm basically consists of two steps. In the first step, the backward sweep is executed to find out the branch currents. This is explained as follows:

The load currents in unbalanced radial distribution systems are calculated using the following equations:

$$\overline{IL}_j^a = \left(\frac{P_j^a - iQ_j^a}{\overline{V}_j^{a*}}\right) \tag{19}$$

$$\overline{IL}_j^b = \left(\frac{P_j^b - iQ_j^b}{\overline{V}_j^{b*}}\right) \tag{20}$$

$$\overline{IL}_j^c = \left(\frac{P_j^c - iQ_j^c}{\overline{V}_j^{c*}}\right) \tag{21}$$

Where, $\overline{IL}_j^a$, $\overline{V}_j^{a*}$, $P_j^a$, $Q_j^a$ are the load current and voltage conjugate (in phasor form), active and reactive power demand at bus *j* for phase a

Then the branch currents are computed as follows:

$$\overline{I}^a(jk) = \overline{I}^a(k) + \sum_{j \in T} \overline{IL}_j^a \tag{22}$$

$$\overline{I}^b(jk) = \overline{I}^b(k) + \sum_{j \in T} \overline{IL}_j^b \tag{23}$$

$$\overline{I}^c(jk) = \overline{I}^c(k) + \sum_{j \in T} \overline{IL}_j^c \tag{24}$$

Where $\overline{I}^a(jk)$ denotes the current flowing (in phasor form) in branch *jk* for phase- a and the set *T* consists of all buses connected to $jk^{th}$ branch.

Then, the forward sweep is executed to obtain the bus voltages. This step is performed to obtain the voltage at each bus of an unbalanced distribution system as follows:

$$\begin{bmatrix} \overline{V}_k^a \\ \overline{V}_k^b \\ \overline{V}_k^c \end{bmatrix} = \begin{bmatrix} \overline{V}_j^a \\ \overline{V}_j^b \\ \overline{V}_j^c \end{bmatrix} - \begin{bmatrix} Z_{jk}^{aa} & Z_{jk}^{ab} & Z_{jk}^{ac} \\ Z_{jk}^{ba} & Z_{ij}^{bb} & Z_{jk}^{bc} \\ Z_{jk}^{ca} & Z_{jk}^{cb} & Z_{jk}^{cc} \end{bmatrix} \begin{bmatrix} \overline{I}_{jk}^a \\ \overline{I}_{jk}^b \\ \overline{I}_{jk}^c \end{bmatrix} \tag{25}$$

Where, bus *j* and *k* denote the sending end bus and receiving end bus, respectively for branch *jk*.

*4.1.1 Incorporation of DG model in Fuzzy distribution load flow*

The load flow algorithm [25] is modified for considering fuzzy load and generation model by taking *β*-cuts [18] of load flow. To incorporate the DG model, the active and reactive power demand at the bus at which a DG unit is placed, say, at bus *i*, Eqs. (19)-(21) are modified by:

$$\begin{aligned} P_{D_{jp}}^{DG} &= P_{D_{jp}}^{base} - P_{jp}^{DG} \\ Q_{D_{jp}}^{DG} &= Q_{D_{jp}}^{base} \pm Q_{jp}^{DG} \end{aligned} \tag{26}$$

Where, $P_{D_{ip}}^{DG}$ and $Q_{D_{ip}}^{DG}$ are the active and reactive power demand for $p^{th}$ phase of $j^{th}$ bus with a DG unit and $P_{D_{jp}}^{base}$ and $Q_{D_{jp}}^{base}$ are the active and reactive power demand for $p^{th}$ phase of $j^{th}$ bus of the base-case network; $P_{jp}^{DG}$ is the active power generated by the DG unit placed at $p^{th}$ phase of $j^{th}$ bus.

*4.2 Proposed Planning Approach Using DE-CSA*

DE-CSA is used as the solution methodology for planning problem of unbalanced radial distribution systems. A brief overview on DE and CSA is provided in the following subsection. The pseudocode of the planning approach using DE-CSA is provided in Section 4.5.

*4.2.1 Differential Evolution (DE) Algorithm: An Overview*

DE is a population-based multi-point search algorithm [22]. There are several variants of DE algorithm [22]. The different variants of DE are classified using the notation: *DE/α/β/δ*; where α indicates the method for selecting the parent chromosome, *β* indicates the number of difference vectors used to perturb the base chromosome, and δ indicates the crossover mechanism used to create the offspring population. In this work, *DE/rand/1/bin* variant is used. The acronym *bin* indicates crossover operation is controlled by a series of binomial experiments. The search starts with a randomly chosen initial population of *n*-dimensional chromosomes which are iteratively evolved using three operations, i.e., mutation, crossover, and selection. The $i^{th}$ population member in iteration $t$ is given by:

$$x_i(t) = (x_{i1}(t), x_{i2}(t), ..., x_{in}(t)) \tag{27}$$

In each iteration, also called generation, a mutant vector is created, which is a vector difference of two randomly selected chromosomes. Then, crossover and selection operations are performed to generate trial vectors. The better chromosomes are selected by using selection operation. These processes are briefly discussed below.

*4.2.2 Mutation*: For each target individual $x_i(t)$, a mutant vector $h_i(t)$ is generated according to

$$h_i(t+1) = x_{r1}(t) + F(x_{r2}(t) - x_{r3}(t)) \quad r1 \neq r2 \neq r3 \neq i \tag{28}$$

Where, indices $r1$, $r2$, $r3$ $\in [1, \eta_{pop}]$ are generated randomly, $F \in [0, 2]$ is a scale factor which controls the mutation size, and $\eta_{pop}$ denotes population size.

*4.2.3 Crossover:* The trial vector is generated as follows

$$v_i(t) = (v_{i1}(t), v_{i2}(t), ..., v_{in}(t)) \tag{29}$$

$$v_{ij}(t+1) = \begin{cases} h_{ij}(t+1) & rand_{ij}[0,1] \leq CR \ or \ j = j_{rand} \\ x_{ij}(t) & rand_{ij}[0,1] > CR \ or \ j \neq j_{rand} \end{cases} \tag{30}$$

Where, CR is a crossover constant in the range [0, 1] specified by user, and $j_{rand}$ is a randomly chosen integer in the range $[1, \eta_{pop}]$ to ensure that the trial vector $v_i$ gets at least one element from the mutant vector, $rand_{ij}$ [0, 1] is a uniformly distributed random number for each $j^{th}$ component of the $i^{th}$ parameter vector.

*4.2.4 Selection:* The selection operation generates better offspring (vectors) from the target (parent) individual and the trial (child) vector and is done as follows:

$$x_i(t+1) = \begin{cases} v_i(t+1) & FT(v_i(t+1)) > FT(x_i(t)) \\ x_i(t) & FT(v_i(t+1)) < FT(x_i(t)) \end{cases} \tag{31}$$

Where $FT$ (.) is the fitness function to be maximized.

*4.2.5. Cuckoo Search Algorithm (CSA): An Overview*

Cuckoo search algorithm (CSA) was developed by Xin-She Yang and Suash Deb by observing the intelligent egg laying strategy of cuckoos. They lay their eggs in a randomly chosen host nest for their survival. If the host nest 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 solution or decision variable for the optimization problem. The CSA follows three rules [23] as:

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

CSA generates random host nest using levy flight for new solution $x_i^{t+1}$ as:

$$x_i^{t+1} = x_i^t + \alpha \times \text{Levy}(\lambda) \tag{32}$$

Where $\alpha$>0, denotes the step size,

$$Levy(\lambda) = \left| \frac{\Gamma(1+\lambda) \times \sin(\frac{\pi \times \lambda}{2})}{\Gamma(\frac{1+\lambda}{2}) \times \lambda \times 2^{\frac{\lambda - 1}{2}}} \right|^{\frac{1}{\lambda}} \tag{33}$$

*4.2.6 Encoding Strategy*

A chromosome for DE-CSA representing a candidate solution in this planning problem consists of three decision variables and is represented as a vector $L$ as follows:

$$L = [\text{NDG}, \beta, \text{PDG}] \tag{34}$$

$$\beta = [\beta_1, \beta_2, .., \beta_M] \tag{35}$$

$$\text{PDG} = [PDG_1, PDG_2, \ldots, PDG_N] \tag{36}$$

Where $\beta$ denotes the vector of DG locations; PDG vector represents the active power generated by DGs, and NDG represents the number of DGs.

*4.2.7 Pseudo Code of the Proposed Approach*

**Begin**

// $\eta_{pop}$ = Size of population

//*max_iter* = Maximum number of iterations

Generate initial population for DE randomly using proposed encoding scheme and initialize the DE and CSA parameters such as F, CR, and $\lambda$ respectively.

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

*Iteration*=1

While *Iteration* <= *max_iter*

**For** i=1,…, $\eta_{pop}$

Select $r_1, r_2, r_3$ from the population such that $r_1 \neq r_2 \neq r_3$

Obtain mutant vectors using equations (28)

Generate a random number $r$ between 0-1
**If** $r$ < CR
Keep the Trial vector V generated by DE using Eqs. (29)- (30)
**Else**
Generate Trial vector V by CSA using Eqs. (32)- (33)
**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 vectors and define as fit1
Calculate $FT$ for trial vectors and define as fit2
**For** i=1,…, $\eta_{pop}$
**If** fit2>fit1
Target vector=trial vector
**Else**
Target vector=target vector
**End If**
**End for**
Find out the fittest chromosome form the target vectors for each iteration
Iteration=iteration+1
**End while**
Obtain the best chromosome from the set of fittest chromosome
**End**

**Fig. 3**. *Pseudo code of the proposed approach using DE-CSA*

## 5. Simulation Results and discussions

The computer simulation study for the proposed planning approach is done in MATLAB R2012 environment using two test systems, i.e., 19-bus and 25-bus unbalanced radial distribution systems. The load and line data of the 25-bus system and 19-bus system are taken from [14]. The base voltage and base MVA for the 19-bus system are taken as 11 kV and 1 MVA, respectively. For the 25-bus system, these are 4.16 kV and 30 MVA, respectively. The total active and reactive power demand for the 19-bus system are 365.94 kW and 177.27 kVAR, respectively. For 25-bus system, these demands are 3240 kW and 2393 kVAR, respectively. The power loss, complex power unbalance, neutral current, ZSUF, and NSUF for the base case network of the 19- and 25-bus systems are given in appendix Table 1. The DE, CSA, and hybrid DE-CSA parameters are optimized by taking repetitive simulation runs, and the optimal parameters are shown in Table 2. 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. Two hybrid DG systems are considered. The cost parameters of DG such as $Gr$, $CF$, and other parameters are taken from [16]. Each hybrid system consists of two photovoltaic (PV) and one wind turbine (WT) based DG placed at phases a, b, and c of a bus in a three-phase unbalanced system. The maximum power generated by DGs are considered to be 30 kW and 400kW for 19-bus and 25-bus system. The DG units are assumed to be operated at unity power factor. Four different planning optimization cases are used. They are:

- *Case A*: Deterministic load and generation
- *Case B*: Fuzzy load and deterministic generation
- *Case C*: Deterministic load and fuzzy generation
- *Case D:* Fuzzy load and fuzzy generation

Peak load and maximum generation are used for deterministic cases. A triangular fuzzy number is utilized to model the uncertainty of load and generation. The scenario considered for load and generation is as follows.

Load demand $\tilde{L}$ = (0.5, 1, 1.3) p.u. of peak load demand and DG generation as (0.3, 1, 1.5)
All the objective functions are aggregated with equal weights so as to get simultaneous optimization of all of them.

Table 1: Base case values for the 19- and 25-bus systems without DG units

| Parameters | DE | CSA [21] | DE-CSA[22] |
|---|---|---|---|
| $\eta_{pop}$ | 100 | 100 | 100 |
| $IT_{max}$ | 150 | 150 | 150 |
| Individual parameters | CR=0.8 | $\lambda$ (constant)=1 | CR =0.8, $\lambda$=1 |
| | F=1.0 | --- | F=1.0 |

Table 2: Optimal parameters used in DE, CSA, and DE-CSA

| Objective | 19-bus system | 25-bus system |
|---|---|---|
| PL (kW) | 13.470 | 150.12 |
| $TS_u$ (MVA) | 0.0218 | 0.0927 |
| $AV_d$ (%) | 3.3083 | 4.7866 |
| ZSUF (%) | 0.0715 | 0.1835 |

A comparison of fitness value among hybrid DE-CSA, DE, and CSA for 19-bus system is shown in Fig. 4. It is observed that DE-CSA is converging at a faster rate than DE and CSA. From Fig. 8. , it can be viewed that DE-CSA converges at iteration number 37, DE reaches convergence at 95 iterations and CSA at 127 iterations. This validates that performance of

DE-CSA in comparison to other meta-heuristic techniques such as DE and CSA. Hybridization of DE with CSA provides faster convergence than DE and CSA.

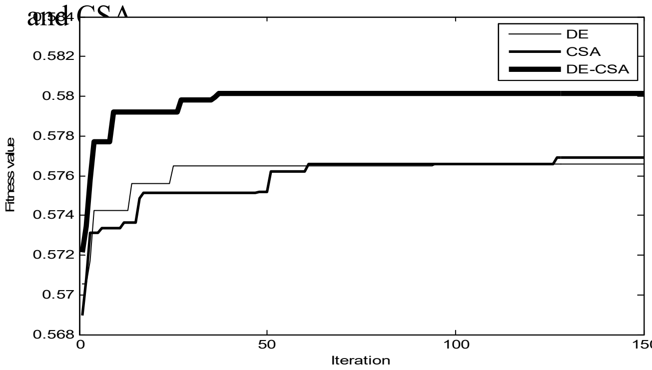
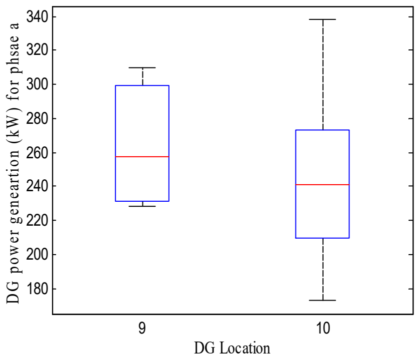
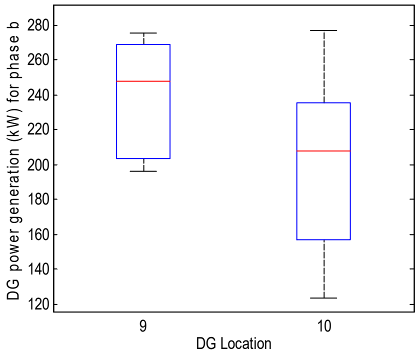



Fig. 4. Comparison of fitness value among DE-CSA, DE and CSA for a 19-bus system considering Case D for a sample run

*A. Simulation results multiple Runs*

The optimal locations and power generations for 19-bus and 25-bus systems using hybrid DE-CSA for scenario 1 for 25 runs shown in Fig. 5 and 6 respectively. It can be seen from Fig. 5 that locations 9 and 10 are found to be best locations for hybrid DG systems1 because the median value of DG power generation is found to be positive for 25-bus system. Similarly, locations 13 and 14 are found to be suitable location for hybrid DG system 2 as viewed from Fig. 6. for Case A planning. Same locations are obtained for Case B, C, and D planning for 25-bus system. From Fig. 7 and 8 for hybrid DG systems1, location 10 and 13 are found to be best location in 19-bus system and for hybrid DG systems 2 location 14 is the most effective location for DG integration for 19-bus system for case D planning. Same locations are obtained for Case A, B, and C planning for 19-bus system.



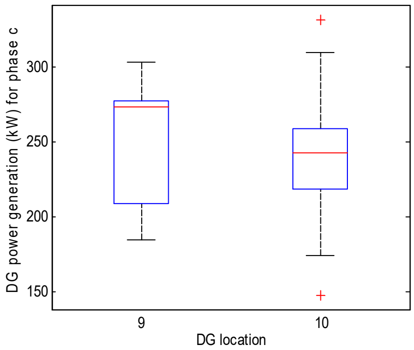
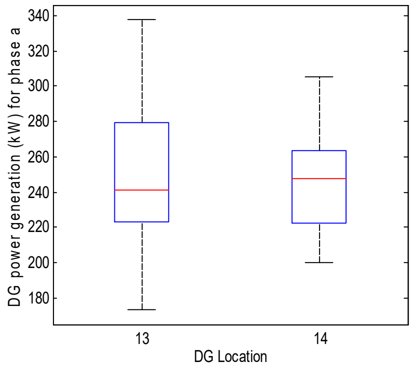
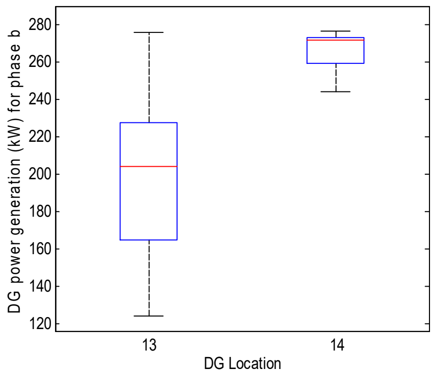




Fig. 5. Boxplot of the location and DG power generation for the 25-bus system with hybrid DE-CSA for scenario 1 for hybrid DG systems 1 for case A



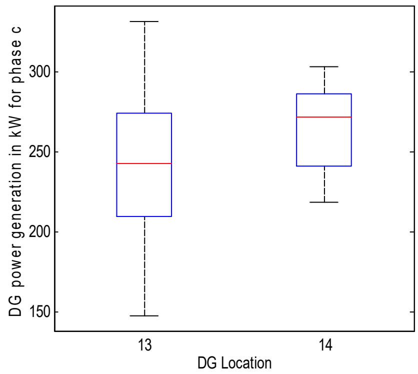



Fig. 6. Boxplot of the location and DG power generation for 25 runs with hybrid DE-CSA for scenario 1 for hybrid DG systems 2 for case A

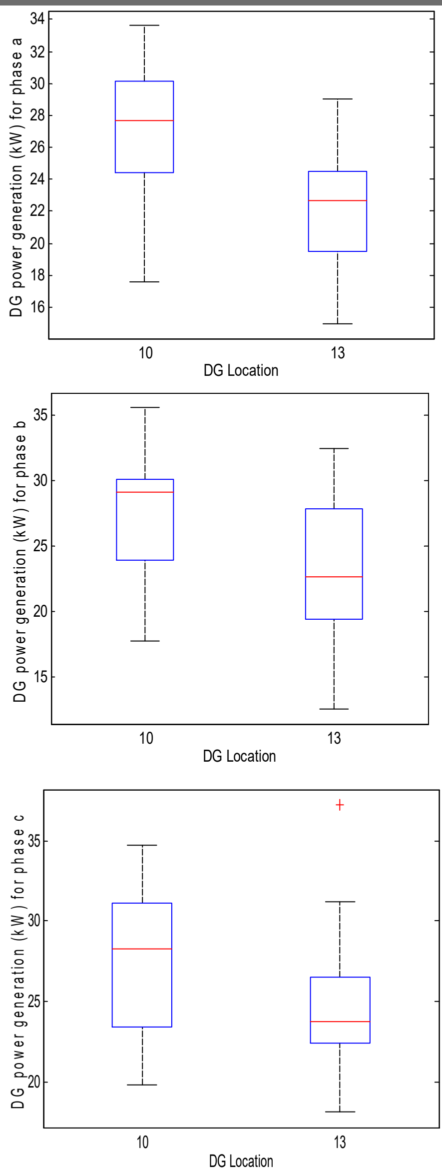



Fig. 7. Boxplot of the location and DG power generation for 19-bus system with hybrid DE-CSA for scenario 1 for hybrid DG systems 1 for case D

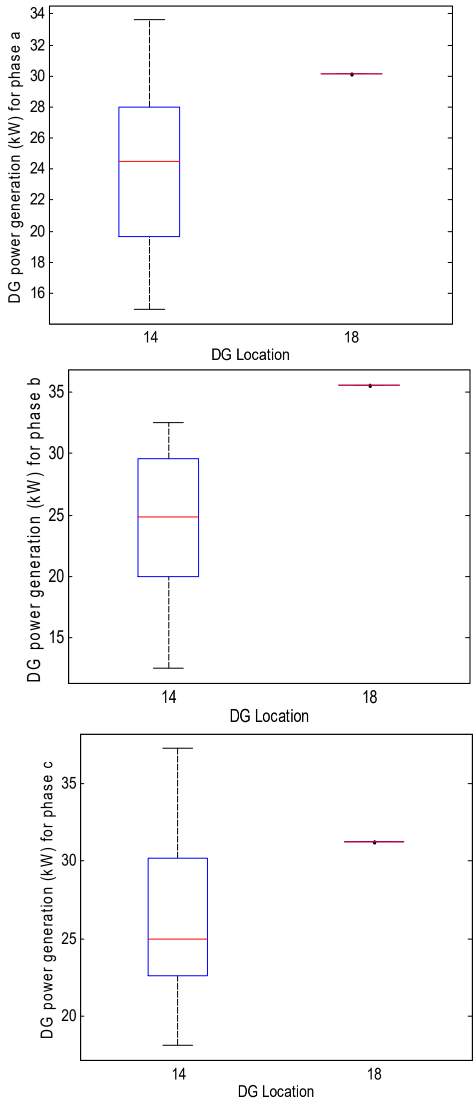



Fig. 8. Boxplot of the location and DG power generation for 19-bus system with hybrid DE-CSA for scenario 1 for hybrid DG systems 2 for case D

### *B. Comparison among different objective function solutions for planning cases (A-D) with using hybrid DE-CSA*

Table 3 and 4 shows the Comparison among different objective function solutions for planning cases (A-D) with using hybrid DE-CSA for 19-bus and 25-bus system respectively. The solutions with planning Case B and D are found to be lower in view of power loss, maximum average voltage deviation (p.u.), total neutral current, and total cost of system as compared to planning Case A and C for both 19-bus and 25-bus system. This may be due to the decrease in load demand at buses with Case B and Case D planning. As the load demand reduces, the line loading also decreases causing lower power loss, neutral current, cost, and voltage deviation.

Table 3: Comparisons among the different objective functions solutions for different planning cases for 19-bus (Scenario 1) using hybrid DE-CSA

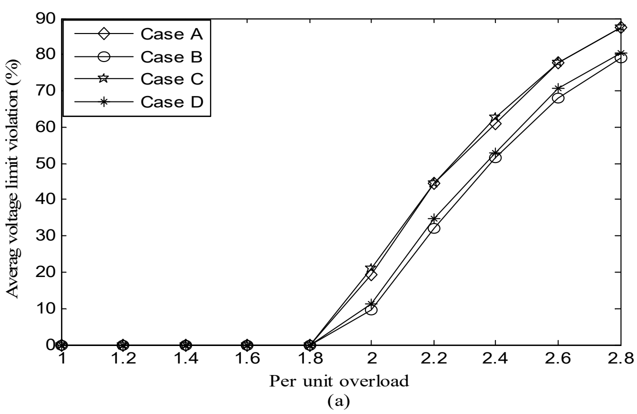
| Objective function | 19-bus system | | | | |
|---|---|---|---|---|---|
| | Without DG | With DG | | | |
| | | Case A | Case B | Case C | Case D |
| TPL(kW) | 13.470 | 4.7947 | 4.5965 | 4.7895 | 4.1316 |
| MAVDI(p.u.) | 0.494 | 0.0243 | 0.0230 | 0.0240 | 0.0220 |
| TNC (p.u.) | 2.384 | 1.4512 | 1.4420 | 1.4543 | 1.3542 |
| TC($/h) | 21.24 | 17.0903 | 17.0812 | 17.6418 | 16.4272 |

Table 4: Comparisons among the different objective functions solutions for different planning cases for 25-bus (Scenario 1) using hybrid DE-CSA

| Objective function | 25-bus system | | | | |
|---|---|---|---|---|---|
| | Without DG | With DG | | | |
| | | Case A | Case B | Case C | Case D |
| TPL(kW) | 150.12 | 70.6714 | 63.2339 | 71.5642 | 62.8120 |
| MAVDI(p.u.) | 0.0689 | 0.0370 | 0.0349 | 0.0365 | 0.0345 |
| TNC (p.u.) | 0.6375 | 0.4820 | 0.4635 | 0.4810 | 0.4585 |
| TC($/h) | 189.84 | 161.3886 | 153.9511 | 160.6431 | 150.8145 |

### *C. Impact of load growth*

In this section, the impact of load growth on 19-bus and 25-bus system considering equal per unit loading for planning cases (A-D) is studied. Figs. 9 and 10 depict the percentage of buses violating the voltage limit and percentage of currents violating current limits for 19-bus and 25-bus respectively. It is observed that Cases B-D are able to hold 120%-140% and 80% load growth without violating any constraints for 19-bus system and 25-bus system respectively. The higher percentage load growth rate of 19-bus system may be due to reason that individual load demand at the phases of the system is lower as compared to 25-bus system. It is found that fuzzy based planning approaches provide better solutions in sustaining future load growth while maintaining voltage and thermal constraint.




(a)

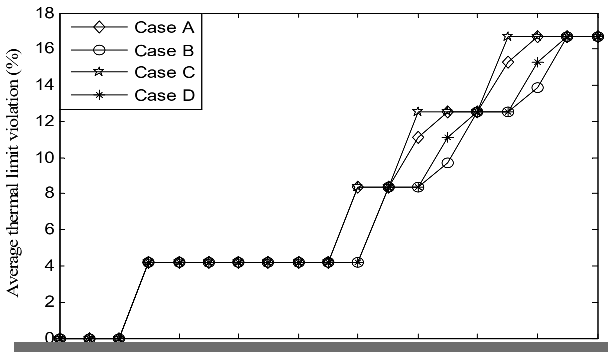
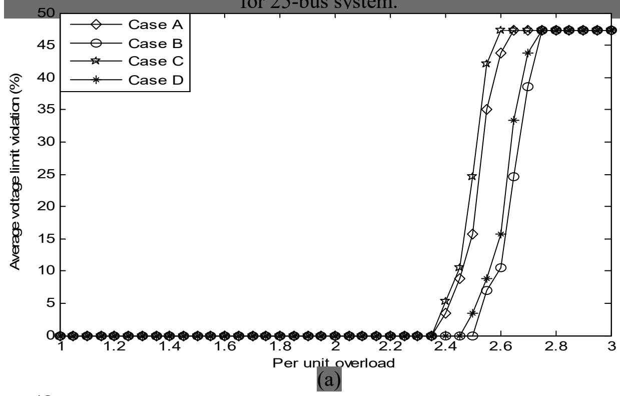
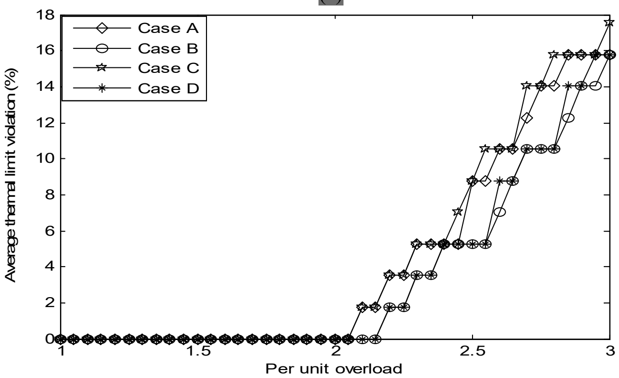



Fig. 9. Percentage of: (a) buses violating the voltage limit and (b) branches violating thermal limit constraint due to load growth for 25-bus system.




(a)




(b)

Fig. 10. Percentage of: (a) buses violating the voltage limit and (b) Branches violating thermal limit constraint due to load growth for 19-bus system.

### *D. Performance Comparison of DE-CSA with DE, and CSA*

The comparative results among the solutions obtained with the DE-CSA, DE, and CSA for the planning Case D are given in Table 4. In Table 4, the mean (MN) and standard deviation (SD) values of system power loss, maximum average voltage deviation, total neutral current, and total cost of the system is shown. The objective function values with the DE-CSA technique are better than the values obtained with DE and CSA. Similar pattern in results are also obtained for planning cases A, B, and C. This confirms the superiority of the proposed technique for the DG planning problem.

Table 4: Comparison of the results as obtained with DE-CSA, DE, and CSA for Case D planning

| System | Solution strategy | TPL(kW) | | MAVDI(p.u.) | | TNC (p.u.) | | TC($/h) | |
|---|---|---|---|---|---|---|---|---|---|
| | | MN | SD | MN | SD | MN | SD | MN | SD |
| 19-bus | DE-CSA | 4.1316 | 0.0386 | 0.0220 | 0.0005 | 1.3542 | 0.0386 | 16.4272 | 0.0005 |
| | DE | 4.3315 | 0.0386 | 0.0229 | 0.0006 | 1.3871 | 0.0388 | 16.6221 | 0.0006 |
| | CSA | 4.3353 | 0.0541 | 0.0230 | 0.0007 | 1.3886 | 0.0541 | 16.6309 | 0.0007 |
| 25-bus | DE-CSA | 62.8120 | 0.4005 | 0.0345 | 0.0006 | 0.4585 | 0.0034 | 150.8145 | 0.0006 |
| | DE | 68.1358 | 0.4621 | 0.0362 | 0.0007 | 0.4768 | 0.0035 | 158.8530 | 0.0007 |
| | CSA | 68.2691 | 0.5662 | 0.0363 | 0.0012 | 0.4775 | 0.0036 | 158.9863 | 0.0012 |

## 6. Conclusion

In this paper, a planning approach has been implemented to determine the optimal DG location (s) and power generation of unbalanced radial distribution systems by optimizing the power loss, the maximum average voltage deviation, the total neutral current, and the total cost of the system. A forward-backward load flow algorithm including the DG model has been developed and used in the planning approach. A hybrid DE-CSA based algorithm is used as the solution methodology. The salient outcomes of this work are:

- A hybrid DE-CSA optimization approach for the DG location (s) and the DG power allocation provides a network with reduced power loss, better voltage profile, and lower system cost.
- The performance of DE-CSA algorithm is found to be better and consistent as compared to DE and CSA algorithm.

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