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A comprehensive technique for optimal allocation of distributed energy resources in radial distribution systems

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HIGHLIGHTS

- Presents a parameter independent intelligent optimization technique.
- Proposed technique is suitable for both continuous and discrete variables.
- Optimization technique is validated through mathematical benchmark functions.
- Proposed technique used to optimally place energy resources in distribution systems.
- Performance improvement of distribution systems with distributed energy resources.

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ABSTRACT

Distributed generation (DG) is a better alternative to meet power demand near the load centers than centralized power generation. Optimal placement and sizing of DGs plays a crucial role in improving the performance of distribution systems in terms of network loss reduction, voltage profile improvement, reliability of power supply and stability issues. This paper presents a comprehensive teaching learning-based optimization (CTLBO) technique for the optimal allocation of DGs in radial distribution systems to improve network loss reduction, voltage profile and annual energy savings. The proposed technique can handle mixed integer variables, is parameter independent and possesses immunity to local extrema trappings. The effectiveness of the proposed method is first validated on standard mathematical benchmark functions. It is observed to have better convergence characteristics than teaching learning-based optimization (TLBO) and quasi-oppositional teaching learning-based optimization (QOTLBO). Subsequently, it is applied to optimal DG allocation in IEEE 33-bus, 69-bus and 118-bus radial distribution test systems. Both single and multi-objective formulations are considered. In addition, the selection of the optimal number of DGs in the distribution networks is also investigated and case studies are carried out. Results demonstrate that optimal allocation of DGs using the proposed technique results in marked improvement in the performance of distribution systems over TLBO and QOTLBO. The applicability of the proposed technique for DG allocation in distribution systems with practical load profiles results in further improvement in annual energy loss reduction and cost savings.

1. Introduction

Currently, centralized power generation is unable to meet the continuously rising global energy demand. Around 16% of the global populations still live without electricity [1]. In this perspective, Distributed Generation (DG) has proved to be a viable option where electricity is generated near the load centers. Although DGs have several environmental and economical benefits, they impose several operational issues in distribution systems. These may include but are not limited to relay co-ordination problems caused by reverse power flow, voltage rise issues, power quality and voltage stability issues, etc. [2,3]. Proper DG allocation have severe impact on power loss, voltage profile, line loadability, operational cost, reliability of power supply, pollution and stability issues of distribution systems. Therefore optimal DG allocation has been a global challenge for both the academia and the industry.

Several research works have been reported on the optimal siting and sizing of DGs in distribution systems. In this context, some of the comprehensive research works for the placement of DGs using analytical methods to reduce network power loss and improvement of voltage profile considering several loading conditions, have been reported in [4–11]. However, complexities in the formulation of objective

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functions caused by multiple DGs, different type of resources and multi-objective analysis affect the computational time with analytical methods.

Advancements in soft computing techniques have led to the development of several evolutionary optimization algorithms for the optimal allocation of DGs in distribution systems. Some notable ones among these are genetic algorithms (GA), particle swarm optimization (PSO), artificial bee colony (ABC), ant colony optimization (ACO), bacterial foraging optimization (BFO) etc. Some comprehensive research works on the use of GA for optimal allocation of DGs in distribution networks reported in [12–19]. However, GA requires increased computational time while suffering from premature convergence than analytical approach [4].

Particle swarm optimization (PSO) is another intelligent technique which has been widely used for DG placement in distribution networks. Some comprehensive research works on the use of PSO for optimal DG allocation in distribution systems presented in [20–22]. In addition, several variants of PSO based optimization technique have also been used. Some notable ones include multi-objective evolutionary PSO (MEPSO) [23] and discrete PSO [24]. Although PSO possesses better search capability than GA, it may converge to strong local minima if optimization parameters are not properly tuned.

Artificial Bee Colony (ABC) has been used [25] for optimal placement of DGs to minimize overall investment cost. Apart from GA, PSO and ABC, several other nature-inspired algorithms have also been proposed by researchers for optimal allocation of DGs. These include the modified honey bee mating algorithm [26], cuckoo search algorithm [27], bacterial foraging optimization (BFO) [28], modified bacterial foraging optimization algorithm [29], Firefly algorithm [30], Hereford Ranch algorithm [31], Modified shuffled leaping algorithm [32], chaotic symbiotic organisms search (CSOS) algorithm [33], Kalman Filter Algorithm [34], harmony search algorithm [35] and Gravitational Search algorithm [36]. Even if evolutionary methods are spontaneous, easy to realize and simple to implement as compared to analytical ones, the nature of the optimization variable (continuous, discrete or mixed) and inappropriate selection of algorithm parameters can lead to premature convergence in the event of strong local extrema. To avoid a non-optimal solution, these algorithms require proper parameter tuning.

In this perspective, teaching learning-based optimization (TLBO), reported in [37], is a parameter independent intelligent algorithm which was developed and subsequently used for the optimal placement of energy resources in distribution systems. Although TLBO is parameter independent and has a very fast convergence rates, it is prone to local maxima/minima trappings. It is observed that TLBO often converges to local minima when the numbers of DGs and/or operating constraints in the distribution system increase. In this context, a modified-TLBO algorithm [38] for DG placement has been suggested. However, it requires an additional mutation phase to find the global solution. QOTLBO [39], which utilizes opposition–based learning to enhance the exploration of the search space, has been implemented for DG placement in radial distribution systems. An improved TLBO, in which a cross over rate and a cross over parameter have to be specified, has been reported in [40]. However, this additional phase adds complexity to the TLBO and increases the computational time. Moreover, they need to be proper parameter tunning to achieve a satisfactory convergence while placing DGs in the distribution network.

In addition, optimal DG allocation of DGs deals with mixed integer variables. While sizing of solar-based energy resources deals with continuous variables, those of wind-based generators involve discrete ones. It is observed that many of the soft computing techniques are not equally proficient at handling mixed integer variables.

This paper presents a comprehensive TLBO (CTLBO) technique for the optimal siting and sizing of DGs, which possesses more exploration and exploitation capabilities over TLBO and QOTLBO. While TLBO gives the better result with unconstrained problems, CTLBO can deal with constrained optimization problems. The proposed technique is capable of handling mixed integer variables, is parameter independent and possesses immunity to strong local extrema trappings. In order to avoid local extrema trappings, a modified teaching phase has been proposed which results in better exploration and exploitation of the solution search space to ensure a global solution. The algorithm is first validated on eight standard mathematical benchmark functions. Comparative results in the form of mean value and standard deviation validate the superiority of the proposed optimization technique over several existing PSO, ABC, and TLBO. Subsequently, to demonstrate the applicability of the proposed algorithm to a specific application, a deterministic problem of optimal DG sizing and placement in radial distribution systems is considered. Both single and multi-objective criterions are utilized for optimal allocation of distributed energy resources. For the multi-objective analysis, power loss, voltage deviation and voltage stability index were considered as reported in [33,37,39]. Unlike a manual weight factor estimation approach as presented in [20,27,41,42] for multi-objective formulations, the proposed technique presents a mathematical formulation based on the ε-constraint method [43], which is independent of penalty factors. Several case studies were carried out with multiple DGs on the IEEE 33-bus, 69-bus, and 118-bus radial distribution test systems. The results demonstrate that optimal allocation of DGs using the proposed technique results in improvement in the performance of the radial distribution systems as compared to TLBO and QOTLBO [39]. A comparison of the reduction in annual energy losses and costs without and with DGs in the 33 and 69-bus radial distribution systems show improvement, which has used analytical methods [44] for DG allocation. These reiterate the superiority of the proposed method in the perspective of computational speed, accuracy, parameter independence and immunity to local extrema trappings, over existing TLBOs and QOTLBO.

The contribution of the paper can be summarized as follows:

- Development of a CTLBO algorithm which is capable of handling mix integer variables and constrained optimization problems
- Modification in the teaching phase improves the exploitation and exploration capability of the proposed algorithm over several modification of TLBO [39,40,45–47], which improves immunity to local extrema trappings and ensures a global solution.
- Multi-objective optimization is based on the ε-constraint method which is independent of penalty factors unlike [20,27,41,42].
- Direct power flow method based on the BIBC/BCBV matrix is used for the power flow which does not require either the network admittance matrix or the forward/backward substitution of the Jacobian matrix. This reduces the computational time substantially less than Exact loss formulation [21,36,37,39].
- Multiple case studies were conducted with standard mathematical benchmark functions and optimal allocation of DGs in IEEE 33-bus, 69-bus and 118-bus radial distribution test systems.
- CTLBO algorithm is further validated by DG allocation with real load profile of distribution systems, which further enhance the annual energy loss reduction and cost savings over analytical method [44].
- Results demonstrate a marked improvement in the performance indices (network active power loss, voltage profile improvement, voltage stability, etc.) of the distribution test systems over TLBO and QOTLBO[39].

The rest of the paper is organized as follows: Section 2 deals with the problem formulation. Section 3 presents the introduction and the proposed modifications carried out in TLBO. Section 4 illustrates the flowchart of the proposed technique. Section 5 deals with the mathematical validation of the proposed algorithm and its implementation in several radial distribution systems. Section 6 presents the practical application of DG allocation for energy loss reduction and cost savings. Section 7 presents the conclusions.

2. Mathematical problem formulation

The proposed technique is implemented on a deterministic problem of optimal DG sizing and placement in radial distribution systems addressing some core issues like active power losses, voltage deviation and voltage stability index [33,37,39]. Both single and multi-objective formulations have been carried out.

The analysis is based on the following assumptions:

a. The radial distribution networks under consideration are balanced.
b. The power factor of the DGs is unity.
c. Constant power load is considered. Nominal load level is considered.
d. The uncertainty of DER is not considered.
e. Variable load is considered for annual energy loss calculation

2.1. Single objective function

The objective of DG placement in the radial distribution system is to minimize power losses, improve voltage profile, and maximize voltage stability while satisfying all operating constraints. These objective functions are described below:

2.1.1. Power loss minimization

The optimal DG placement problem is mainly concerned with the minimization of real power loss. Several methods [46–48] are available in the literature for load flow calculation in the distribution network. The real power loss (F_1) formula may be defined as

$$F_1 = (P_{loss})_{minimum} \tag{1}$$

where P_{loss} is the real power loss of the distribution network and is given as [48]

$$P_{loss} = \sum_{j=1}^{nb} R_j\left[\left(\sum_{k=2}^{n} \mathrm{BIBC}(j,k-1)\frac{P_k\cos(\theta_k) + Q_k\sin(\theta_k)}{|V_k|}\right)^2 + \left(\sum_{k=2}^{n} \mathrm{BIBC}(j,k-1)\frac{P_k\sin(\theta_k) - Q_k\cos(\theta_k)}{|V_k|}\right)^2\right] \tag{2}$$

where $P_k = P_D - P_{DG}$ and $Q_k = Q_D - Q_{DG}$

In Eq. (2), ($P_k + jQ_k$) is the complex power at the k^{th} bus, ($P_D + jQ_D$) is the complex load at the k^{th} bus, ($P_{DG} + jQ_{DG}$) is the complex DG power at the k^{th} bus '$\mathbf{V_k}$' is the voltage phasor at the k^{th} bus, 'θ_k' is the phase angle of $\mathbf{V_k}$, 'R_j' is the resistance of the j^{th} branch, BIBC is the bus injection branch current matrix, 'n' is the number of buses and 'n_b' is the number of branches of the network.

2.1.2. Voltage profile improvement

DGs are connected near the load to improve the voltage profile of the network. Voltage profile improvement function (F_2) [39] is defined as:

$$F_2 = \sum_{k=1}^{n} (V_k - V_{rated})^2 \tag{3}$$

where 'V_k' is the voltage magnitude of bus 'k', expressed in p.u. V_{rated} is considered 1 p.u.

2.1.3. Maximize voltage stability index

The voltage profile of a distribution network is characterized [39] by its voltage stability index (VSI) [49] which should always be greater than zero. VSI must be maximized to improve the voltage profile of the distribution network. Voltage stability index of a radial distribution system is given by Fig. 1a as below,

$$VSI_{k+1} = |V_k|^4 - 4\{P_{k+1}X(j) - Q_{k+1}R(j)\}^2 - 4\{P_{k+1}R(j) + Q_{k+1}X(j)\}|V_k|^2 \tag{4}$$

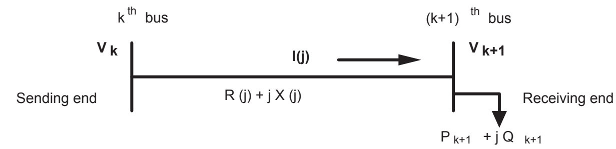

Fig. 1a. Equivalent circuit of the j^{th} branch of the network between buses 'k' and '(k + 1)'.

$$F_3 = \frac{1}{VSI_{min}} \tag{5}$$

where VSI_k is the voltage stability index of the k^{th} bus while R(j), X(j) are the resistance and reactance of the j^{th} network branch connected between the k^{th} and the $(k + 1)^{th}$ bus. Pk + 1 & Qk + 1 are the total real and reactive power demands at the $(k + 1)^{th}$ bus respectively.

2.2. Multi-objective function

A multi-objective function optimizes all the objective functions simultaneously, subject to the equality and inequality constraints. In this paper, a multi-objective function (MOF) [39] is used which simultaneously minimizes the power loss (F_1), improves voltage profile (F_2) and maximizes the voltage stability index (F_3) formulated by ε-constraints method [43] as detailed below.

$$\begin{aligned} &\text{MOF=Minimize } f_\mu(x),\\ &\text{Subject to } f_m(x) \leqslant \varepsilon_m \quad m= 1,2,3\ldots M \text{ and } m \neq \mu;\\ &g_j(X) \geqslant 0, \quad j= 1,2,3\ldots J;\\ &h_k(X) = 0, \quad k= 1,2,3\ldots K;\\ &x_i^{(L)} \leqslant x_i \leqslant x_i^{(U)}, \quad i= 1,2,3\ldots n; \end{aligned} \tag{6}$$

In this method, the multi-objective optimization problem is solved by targeting one of the objective functions and restricting the rest of the objective functions as constraints. The parameter ε_m represents the upper bound of the value of f_m. μ (F_1) and m (F_2 and F_3) are the objective function targeted and those considered as constraints, respectively. g_j and h_k are the inequality and equality constraints, respectively. $x_i^{(L)}$ & $x_i^{(U)}$ are lower and upper limit of variables, respectively.

2.2.1. Equality constraints

The above objective functions are subject to following constraints while placing DGs in the radial distribution network.

2.2.2. Active and reactive power balance constraints

$$P_G = P_{loss} + P_D \quad \& \quad Q_G = Q_{loss} + Q_D \tag{7}$$

$$\text{where } Q_{loss} = \sum_{j=1}^{nb} X_j\left[\left(\sum_{k=2}^{n} \mathrm{BIBC}(j,k-1)\frac{P_k\cos(\theta_k) + Q_k\sin(\theta_k)}{|V_k|}\right)^2 + \left(\sum_{k=2}^{n} \mathrm{BIBC}(j,k-1)\frac{P_k\sin(\theta_k) - Q_k\cos(\theta_k)}{|V_k|}\right)^2\right] \tag{8}$$

where P_G and Q_G are the active and reactive powers injected by the DG while P_D and Q_D are the active and reactive power load demands at the k^{th} node.

2.2.3. Voltage constraint

The voltage must be maintained between V_{max}(1.05 p.u.) and V_{min}(0.95 p.u.) at all system buses.

$$V_{min} \leqslant V_i \leqslant V_{max} \quad i = 1,2,3,4\ldots n \tag{9}$$

2.2.4. Thermal limit [50]

$$I_j \leqslant I_j^{max} \tag{10}$$

where I_j^{max} is the maximum loading of the distribution line 'j'.

2.2.5. Real power limit and reactive power limit [27]

$$P_k^{min} \leqslant P_k \leqslant P_k^{max} \tag{11}$$

where P_k^{min} and P_k^{max} are the lower and upper limits, respectively, of the active power of the k^{th} DG.

$$Q_k^{min} \leqslant Q_k \leqslant Q_k^{max} \tag{12}$$

where Q_k^{min} and Q_k^{max} are the lower and upper limits, respectively, of the reactive power of the k^{th} DG.

3. Teaching–Learning-Based Optimization (TLBO) algorithm

Teaching–Learning Based Optimization (TLBO) algorithm was first introduced by [45]. It is a nature-inspired algorithm where the best learner i.e. Teacher improves the performance of the remaining learners. This is known as the '*Teaching phase'* and each learner improves his knowledge by interacting with other fellow learners in the '*Learning Phase*'. In this manner, with proper interaction, the TLBO proceeds towards the global solution. In TLBO, the variables correspond to the different courses offered to a student and the marks obtained by the student in a course corresponding to the 'fitness', similar to other population-based optimization techniques. The best solution on the basis of knowledge (fitness) is considered as the teacher in that iteration. A teacher tries to improve the knowledge of his students and helps them to score better marks, as per his knowledge. Students also learn from their own effort by discussing among themselves. The complete process of TLBO is carried out in two phases as detailed below.

Teacher Phase: The teacher tries to improve the mean marks (knowledge) of a particular course (variable) to the best of his capacity. So, a random process takes place in order to get better knowledge (fitness). For each individual '$X_{old,i}$', a '$X_{new,i}$' is generated by:

$$X_{new,i} = X_{old,i} + r(X_{Teacher,i} - T_F M_i) \tag{13}$$

where $X_{old,i}$ and $X_{new,i}$ are the old and new variables, respectively, 'r' is a random number in the range $[0,1]$, $X_{Teacher,i}$ is the best learner (teacher) of the class in the current iteration, 'T_F' is a teaching factor and M_i is mean of the class outcome for the subject or course (variable). The value of 'T_F' corresponds to the knowledge transferred to the learner decided randomly with equal probability. It can be either 1 or 2 [45]. The new generated $X_{new,i}$ is accepted if its fitness (marks) is better than the old.

Learner Phase: This is an alternative way to improve the knowledge by one's own efforts without the teacher. Students randomly interact with other students in the class and improve their understanding of a particular subject. The learner phase is mathematically explained as below,

$$X_{new,i} = X_{old,i} + r(X_j - X_k) \quad \text{if } F(X_j) < F(X_k) \tag{14}$$

$$X_{new,i} = X_{old,i} + r(X_k - X_j) \quad \text{if } F(X_j) > F(X_k) \tag{15}$$

where 'i', 'j', 'k' are learners in the class in such a way that $i \neq j \neq k$ and $F(X)$ represents the fitness (marks) of a particular learner in a subject. If the fitness corresponding to '$X_{new,i}$' is found to be better than '$X_{old,i}$', '$X_{new,i}$' is accepted otherwise it is rejected.

The two stages i.e. teaching and learning phases comprise iteration. After several iterations, the global solution is reached by the TLBO algorithm. Although this algorithm has the minimum number of parameters to be tuned as compared to other population-based optimization techniques, it suffers from premature convergence due to strong local minima trappings of the objective function.

The following modifications are proposed to improve the performance of the TLBO and avoid premature convergence:

Modification in Teaching Phase:

3.1. Modification in the mean

In conventional TLBO, the new population vector is generated based on the class mean of the particular subject. In the proposed technique, instead of the mean, the worst vector of the class (i.e. having the worst fitness within the population) is selected. As shown in Eq. (13), for any given 'T_F', the value of the bracketed term on the right-hand side will be more if the class mean is replaced by the worst vector. This results in a wider search space for the new vector '$X_{new,i}$ ' and a higher probability of reaching the global solution.

This modification is shown below:

$$X_{new,i} = X_{old,i} + r(X_{Teacher,i} - T_F X_{worst,i}) \tag{16}$$

where $X_{worst,i}$ is the vector having the worst fitness function within the population.

3.2. Modification in the teaching factor (T_F)

TLBO method considers 'T_F' either 1 or 2 [45] which corresponds to a transfer of 0% or 100% knowledge from the teacher to the learner, respectively. But practically this assumption is incorrect as it should be between 0 and 100%. So this TF is modified as given below.

$$T_F = (1/rand)^a \tag{17}$$

where 'a' is defined as the teaching factor rate. If the value of 'a' is high, it increases the search space and hence the probability of reaching the global solution. It is observed that keeping the value of 'a' between 0 and 5 yields better results with several objective functions, as highlighted in the case studies and results (Section 5). So this modification results in a better transfer of knowledge than conventional TLBO.

3.3. Update of the population vector

The following steps are followed to update the population vector. The new vector generated by either the Teaching Phase or the Learner Phase is first compared with the old vector.

(a) if the fitness function corresponding to the new vector (X_{new}) is better than that of the old vector (X_{old}) and the fitness function corresponding to the old vector (X_{old}) is better than that of the worst vector (X_{worst}), 'X_{worst}' is replaced by 'X_{old}' and 'X_{old}' by 'X_{new}'.
(b) if the fitness function corresponding to the new vector (X_{new}) is better than that of the old vector (X_{old}) and the fitness function corresponding to the old vector (X_{old}) is worse than that of the worst vector (X_{worst}), 'X_{worst}' is retained and 'X_{old}' by 'X_{new}'.

This updating process occurs in each iteration that greatly improves the convergence time of the algorithm.

4. Algorithm of Comprehensive TLBO (CTLBO) applied to optimal DG allocation

The flowchart for the proposed CTLBO algorithm for both single and multi-objective optimal siting and sizing of DGs is shown in Fig. 1b.

5. Case studies and results

The proposed CTLBO was first implemented on eight standard mathematical benchmark functions for validation. The details of these functions and the results are shown in Tables 1 and 2, respectively. Comparative results in the form of mean value and standard deviation of eight mathematical benchmark functions, when subjected to 30,000 maximum function evaluations for 30 independent runs, validate that the proposed optimization technique is superior or equivalent to [45].

Subsequently, the proposed CTLBO was used for the siting and sizing of Type-1 DGs in the IEEE 33-bus, 69-bus and 118-bus radial

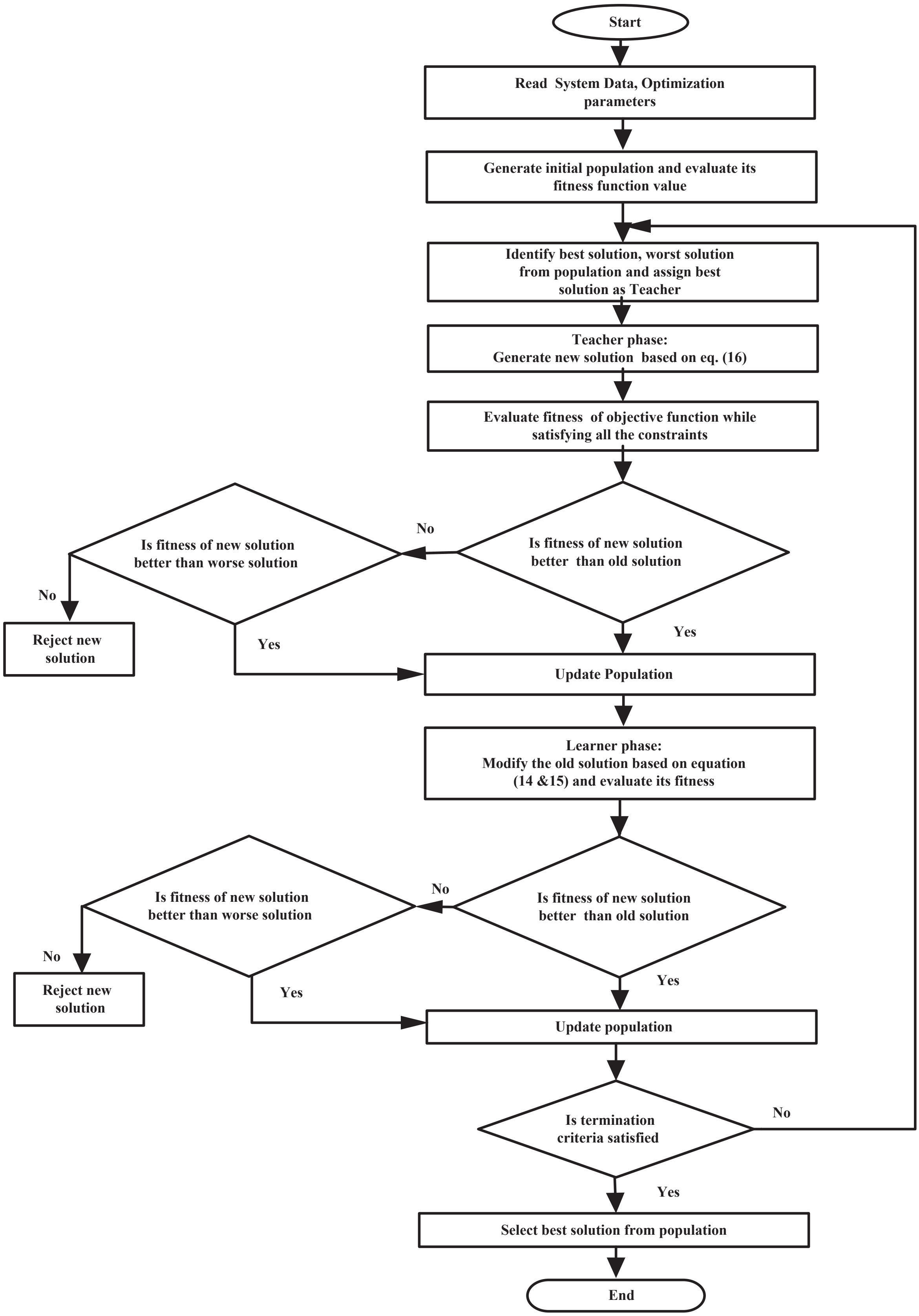

Fig. 1b. Flowchart of the proposed CTLBO algorithm.

Table 1
Mathematical benchmark functions [45].

No.	Function	Formulation	D	Search range
1.	Sphere	$F(x)_{min} = \sum_{i=1}^{D} x_i^2$	10	[−100,100]
2.	Rosenbrock	$F(x)_{min} = \sum_{i=1}^{D} [100(x_i^2 - x_{i+1})^2 + (1-x_i)^2]$	10	[−2.048,2.048]
3.	Ackley	$F(x)_{min} = -20e^{\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right)} - e^{\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right)} + 20 + e^1$	10	[-32.768,32.768]
4.	Griewank	$F(x)_{min} = \frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	10	[−600,600]
5.	Weierstrass	$F(x)_{min} = \sum_{i=1}^{D} (\sum_{k=0}^{k_{max}} [a^k \cos(2\pi b^k (x_i + 0.5))]) - D\sum_{k=0}^{k_{max}} [a^k \cos(2\pi b^k (0.5))]$ $a = 0.5, \quad b = 3 \quad k_{max} = 20$	10	[−0.5,0.5]
6.	Rastrigin	$F(x)_{min} = \sum_{i=1}^{d} [x_i^2 - 10\cos(2\pi x_i) + 10]$	10	[−5.12,5.12]
7.	NCRastrigin	$F(x)_{min} = \sum_{i=1}^{d} [y_i^2 - 10\cos(2\pi y_i) + 10] y_i = \begin{Bmatrix} x_i & \lvert x_i\rvert < 0.5 \\ \frac{round(2x_i)}{2} & \lvert x_i\rvert > 0.5 \end{Bmatrix}$	10	[−5.12,5.12]
8.	Schwefel	$F(x)_{min} = 418.9829{*}D - \sum_{i=1}^{D} (-x_i \sin(\sqrt{\lvert x_i\rvert}))$	10	[−500,500]

distribution systems. At first, the results are compared with TLBO and QOTLBO for the single objective function corresponding to (1) minimization of real power loss (2) minimization of voltage deviation (3) maximization of voltage stability index. Subsequently, the results are compared with TLBO and QOTLBO for a multi-objective function where all the three objective functions are implemented simultaneously. The proposed CTLBO algorithm was implemented in MATLAB R2015a on an Intel i5-4570, 3.2 GHz processor, 4 GB RAM, desktop PC.

5.1. Effect of number of DG placement on 33-bus, 69-bus and 118-bus distribution network

The effect of DGs penetration on distribution system active power loss and bus voltage deviation is investigated by increasing the number of DGs. From Figs. 2a and 2b, it can be observed that for both IEEE 33 and 69-bus distribution systems, although the system active power losses and the bus voltage deviation reduce when the number of DGs is increased from 3 to 4, the impact of the fourth DG is marginal. Hence, only 3 DGs placement have been considered for both 33 and 69-bus systems [51]. Figs. 2c and 2d shows that both power loss of system and voltage deviation at buses are reducing, by increasing number and the total size of DG on the 118-bus distribution system. But it is observed that rate of power loss reduction is decreasing. So more than 7 DG placement on 118-bus distribution system will be uneconomical.

5.2. Test case 2: IEEE 33-bus radial distribution system

The proposed CTLBO is first implemented on the IEEE 33-bus radial distribution system. The data for this network is taken from [52]. The 33-bus system consists of 33 buses, 3 laterals, 37 branches with 5 loops or tie switches being kept generally open. The rated voltage is 12.66 kV with a total active and reactive power loadings of 3.72 MW and 2.3 MVAr, respectively. The total active and reactive power losses are 210.998 kW and 143 kVAr, respectively. The voltage stability index of this network is 0.667168 without any DG [53]. The system base is chosen as 1000 KVA [52]. Subsequently, due to economical basis [51], only 3 DGs (Type–I) are considered for optimal sizing and placement. Results obtained with the CTLBO algorithm applied to optimal siting and sizing of DGs pertaining to the single objective function of minimization of real power loss are shown in Table 3. The achieved objective function value is shown in bold. From Table 3, it is observed that as compared to TLBO and QOTLBO [39], results with proposed CTLBO

Table 2
Comparative results of CTLBO algorithm with other algorithms [45] over 30 independent runs.

	Sphere	Rosenbrock	Ackley	Griewank
	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD
PSO–w	7.96E−051 ± 3.56E−050	3.08E+000 ± 7.69E−001	1.58E−014 ± 1.60E−014	9.69E−002 ± 5.01E−002
PSO–cf	9.84E−105 ± 4.21E−104	6.98E−001 ± 1.46E+000	9.18E−001 ± 1.01E+000	1.19E−001 ± 7.11E−002
UPSO	9.84E−118 ± 3.56E−117	1.40E+000 ± 1.88E+000	1.33E+000 ± 1.48E+000	1.04E−001 ± 7.10E−002
ABC	7.09E−017 ± 4.11E−017	2.08E+000 ± 2.44E+000	4.58E−016 ± 1.76E−016	1.57E−002 ± 9.06E−003
Modified ABC	7.04E−017 ± 4.55E−017	4.42E−001 ± 8.67E−001	3.32E−016 ± 1.84E−016	1.52E−002 ± 1.28E−002
TLBO	0.00 ± 0.00	1.72E+00 ± 6.62E−01	3.55E−15 ± 8.32E−31	0.00 ± 0.00
I-TLBO (NT = 4)	**0.00 ± 0.00**	2.00E−01 ± 1.42E−01	1.42E−15 ± 1.83E−15	0.00 ± 0.00
CTLBO	2.322E−209 ± 1.752E−209	**2.7847E−03 ± 2.523E−03**	**2.4409E−16 ± 1.567E−16**	**0.00 ± 0.00**

	Weierstrass	Rastrigin	NCRastrigin	Schwefel
	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD
PSO–w	2.28E−003 ± 7.04E−003	5.82E+000 ± 2.96E+000	4.05E+000 ± 2.58E+000	3.20E+002 ± 1.85E+002
PSO–cf	6.69E−001 ± 7.17E−001	1.25E+001 ± 5.17E+000	1.20E+001 ± 4.99E+000	9.87E+002 ± 2.76E+002
UPSO	1.14E+000 ± 1.17E+00	1.17E+001 ± 6.11E+000	5.85E+000 ± 3.15E+000	1.08E+003 ± 2.68E+002
ABC	9.01E−006 ± 4.61E−005	1.61E−016 ± 5.20E−016	6.64E−017 ± 3.96E−017	7.91E+000 ± 2.95E+001
Modified ABC	0.00E+000 ± 0.00E+000	1.14E−007 ± 6.16E−007	1.58E−011 ± 7.62E−011	3.96E+000 ± 2.13E+001
TLBO	2.42E−05 ± 1.38E−20	6.77E−08 ± 3.68E−07	2.65E−08 ± 1.23E−07	2.94E+02 ± 2.68E+02
I-TLBO (NT = 4)	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	1.10E+02 ± 1.06E+02
CTLBO	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	**0.92779E+02 ± 0.41E+02**

The achieved objective function value is shown bold.

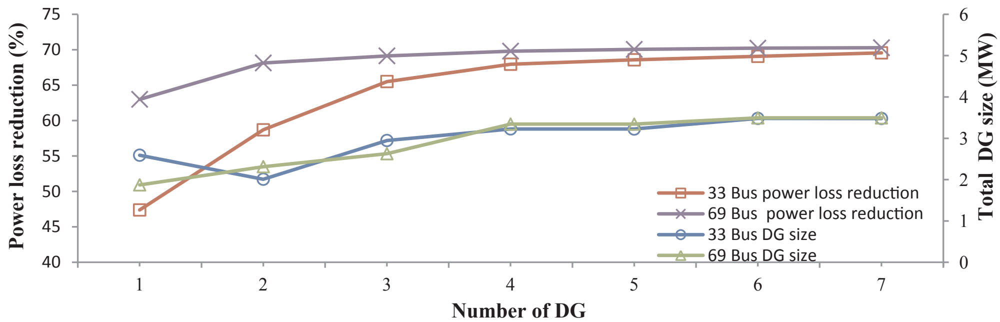

Fig. 2a. Impact of number of DGs on power loss and Total DG size for 33-bus and 69-Bus RDS.

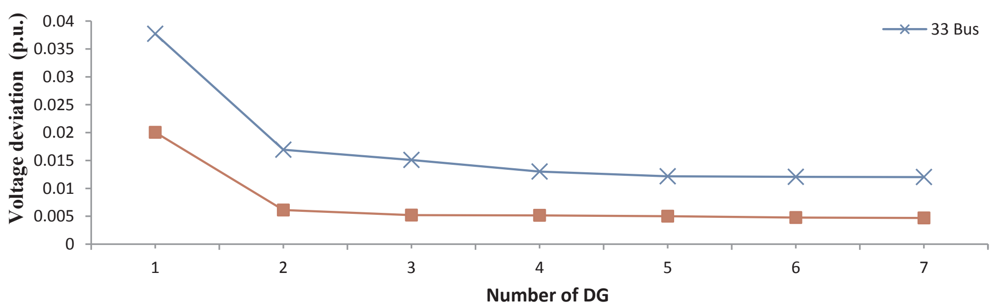

Fig. 2b. Impact of number of DGs on voltage deviation of 33-bus and 69-Bus RDS.

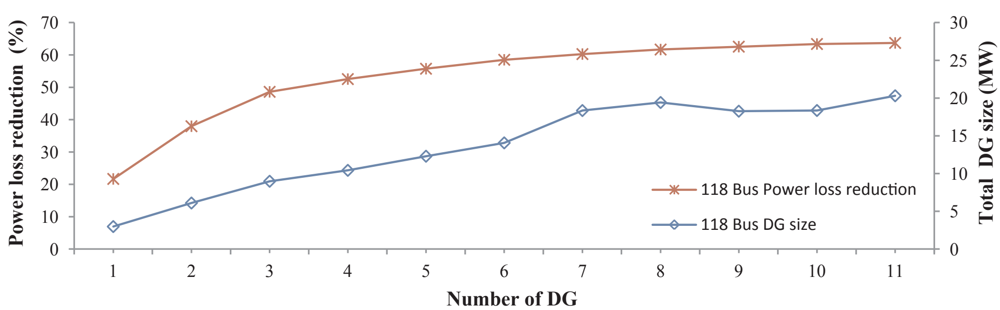

Fig. 2c. Impact of number of DGs on power loss and Total DG size for 118-Bus RDS.

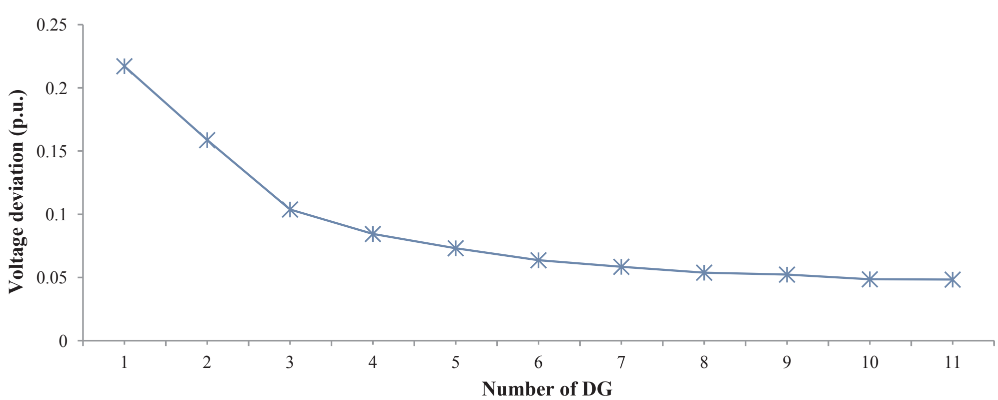

Fig. 2d. Impact of number of DGs on voltage deviation for 118-Bus RDS.

gives improved real power losses, voltage deviation and voltage stability index i.e 72.787 kW, 0.0151 p.u. and 0.8805 p.u. respectively. Table 4 shows the results with the proposed CTLBO applied to the optimal siting and sizing of DGs pertaining to the single objective function of minimization of voltage deviation. The achieved objective function value is shown in bold. From Table 4, it is observed that the proposed CTLBO results in values of real power losses, voltage deviation, and voltage stability index i.e 110.410 kW, 0.0004 p.u. and 0.9480 p.u. respectively, which are superior to both TLBO and QOTLBO [39]. Table 5 shows the results with the proposed CTLBO applied to the single objective function of minimization of voltage stability index. The achieved objective function value is shown bold. From Table 5, it is observed that the proposed CTLBO results in improved real power losses, voltage deviation and voltage stability index i.e. 110.008 kW, 0.0007 p.u. and 0.9756 p.u. respectively, as compared to TLBO [39]. Subsequently, the proposed CTLBO is applied to the multi-objective function for improvement in all the three quantities i.e. minimization of both real power losses and voltage deviation along with maximization of voltage stability index. The values of the individual objective function weights (‘a_1’, ‘a_2’ and ‘a_3’) are given in Table 6 [39]. The formulation of multi-objective formulation using weight factors (penalty coefficients) are detailed in the Appendix (A.1). The achieved values are

Table 3
Simulation results using TLBO, QOTLBO and CTLBO of 33 BUS system for power loss minimization.

	TLBO [39] Optimal DG		QOTLBO [39] Optimal DG		CTLBO Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	10	0.8246	12	0.8808	13	0.8017
	24	1.0311	24	1.0592	24	1.0913
	31	0.8862	29	1.0714	30	1.0536
Power loss (kW)	75.540		74.101		**72.787**	
Voltage deviation (p.u.)	0.0222		0.016		0.0151	
Voltage stability index^{-1}	1.1954		1.1552		1.1357	
Voltage stability index (p.u.)	0.8365		0.8656		0.8805	

Table 4
Simulation results using TLBO, QOTLBO and CTLBO of 33-BUS system for voltage deviation minimization.

	TLBO [39] Optimal DG		QOTLBO [39] Optimal DG		CTLBO Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	14	1.1320	14	1.0744	13	1.1894
	29	1.1980	27	1.200	25	0.7139
	30	1.0081	33	1.200	30	1.9221
Power loss (kW)	126.496		115.425		110.410	
Voltage deviation (p.u.)	0.0010		0.0009		**0.0004**	
Voltage stability index^{-1}	1.0750		1.0725		1.0269	
Voltage stability index (p.u.)	0.9302		0.9324		0.9480	

Table 5
Simulation results using TLBO, QOTLBO, and CTLBO of 33 BUS system for voltage stability index maximization.

	TLBO [39] Optimal DG		QOTLBO [39] Optimal DG		CTLBO Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	8	1.1993	6	1.1998	11	1.6046
	12	1.1996	11	1.200	25	0.7685
	31	1.1992	29	1.1983	31	1.4520
Power loss (kW)	132.691		104.878		110.008	
Voltage deviation (p.u.)	0.0023		0.0016		0.0007	
Voltage stability index^{-1}	1.0412		1.0397		1.0250	
Voltage stability index (p.u.)	0.9604		0.9618		**0.9756**	

Table 6
Simulation results using TLBO, QOTLBO and CTLBO of 33 BUS system for simultaneous optimization of power loss, voltage deviation and voltage stability index.

	TLBO [39]		QOTLBO [39] Penalty factors ($a_1 = 1.0$ $a_2 = 0.6$ $a_3 = 0.35$)		CTLBO		CTLBO (ε-constraints Method)	
	Optimal DG		Optimal DG		Optimal DG		Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	12	1.1826	13	1.0834	13	1.0364	13	1.1926
	28	1.1913	26	1.1876	24	1.1630	25	0.8706
	30	1.1863	30	1.1992	30	1.5217	30	1.6296
Power loss (kW)	124.695		103.403		85.9595		**96.1732**	
Voltage deviation (p.u.)	0.0011		0.0011		0.0026		**0.0009**	
Voltage stability index^{-1}	1.0523		1.0493		1.0548		**1.0375**	
Voltage stability index (p.u.)	0.9503		0.9530		0.9481		**0.9638**	

shown in bold. From Table 6, it is observed that with $a_1 = 1$, $a_2 = 0.65$ and $a_3 = 0.35$, the proposed method (CTLBO) results only in improved real power losses. However, using the ε-constraints method, CTLBO shows remarkable improvement in all the target objectives i.e. real power losses, voltage deviation and voltage stability index i.e 96.1732 kW, 0.0009 p.u. and 0.9638 p.u. respectively as compared to either TLBO or QOTLBO [39]. The bus voltage profile of the IEEE 33-bus radial distribution system without and with DGs is shown in Fig. 3a. From Fig. 3a, it is observed that in the presence of DGs, the bus voltage profile shows a marked improvement than that without DG. The convergence characteristic for single objective and multi-objective function of the proposed CTLBO algorithm vis-à-vis TLBO and QTLBO is shown

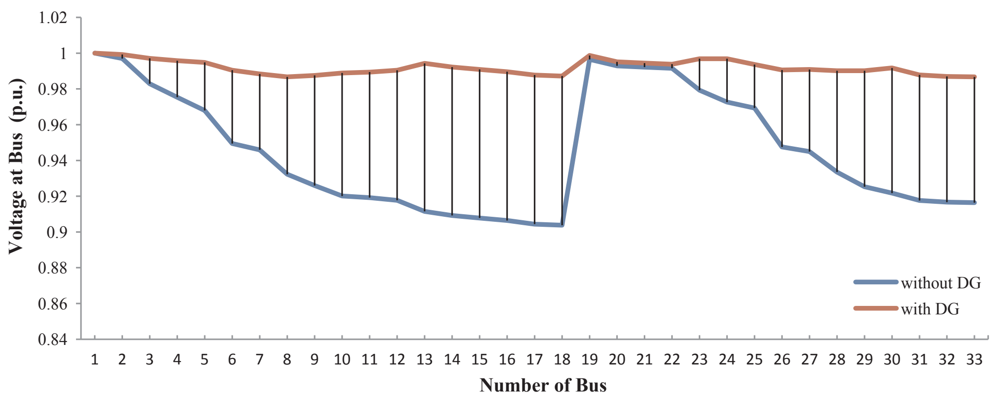

Fig. 3a. Bus voltage profile of the 33-bus radial distribution system without and with DG.

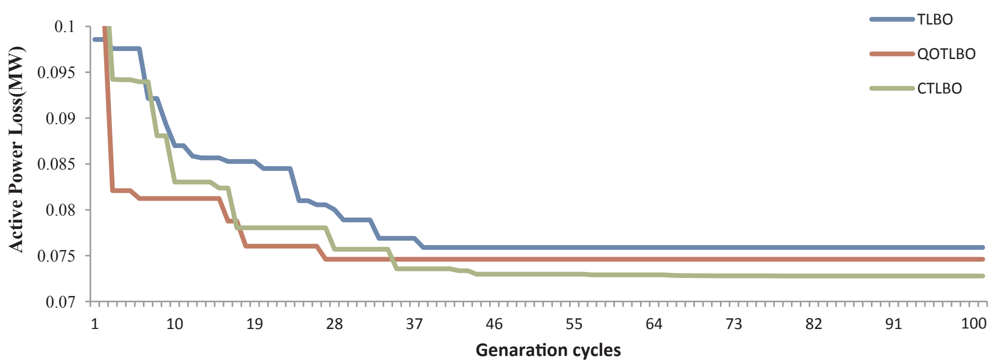

Fig. 3b. Comparison of power loss convergence characteristics of CTLBO, QOTLBO and TLBO for 33-bus RDS.

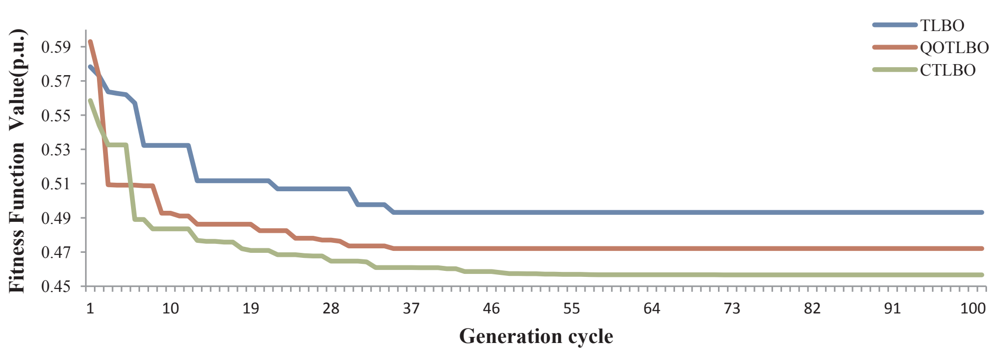

Fig. 3c. Comparison of fitness function convergence characteristics of CTLBO, QOTLBO and TLBO for 33-bus RDS.

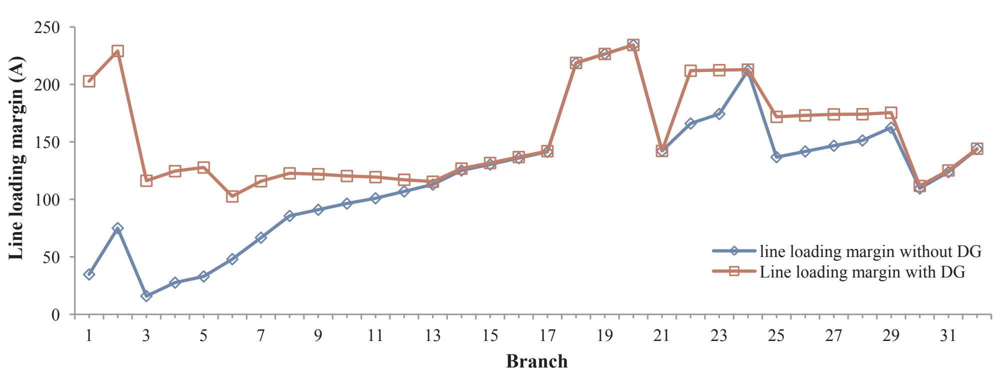

Fig. 3d. Available loading margins with 3 DGs placed in the 33-bus RDS.

in Fig. 3b and Fig. 3c for power loss minimization and multi-objective fitness function value respectively.

Fig. 3d shows the line loading margins (specified line current limit – actual line current magnitude) without and with DGs incorporated in the IEEE 33-bus radial distribution system. From the above Fig. 3d, it can be observed that DGs are very effective in relieving network congestion in the system in lines 1–13 and 21–29 in the 33-bus system.

5.3. Test case 2: 69-bus radial distribution system

The proposed algorithm is tested on the IEEE 69-bus radial distribution system. The data for this network is taken from [54]. The system consists of 69 buses, 7 laterals and 73 branches with 5 loops or tie switches being kept generally open. The rated voltage is 12.66 kV with a total active and reactive power loadings of 3.8 MW and

Table 7
Simulation results using TLBO, QOTLBO and CTLBO of 69 BUS system for power loss minimization.

	TLBO [39] Optimal DG		QOTLBO [39] Optimal DG		CTLBO Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	15	0.5919	18	0.5334	11	0.5268
	61	0.8188	61	1.1986	18	0.3796
	63	0.9003	63	0.5672	61	1.7190
Power loss (kW)	72.406		71.625		**69.388**	
Voltage deviation (p.u.)	0.0063		0.0062		0.0052	
Voltage stability index^{-1}	1.0908		1.0874		1.0887	
Voltage stability index (p.u.)	0.9167		0.9196		0.9185	

Table 8
Simulation results using TLBO, QOTLBO and CTLBO of 69 BUS system for voltage deviation minimization.

	TLBO [39] Optimal DG		QOTLBO [39] Optimal DG		CTLBO Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	14	0.9762	13	1.1764	10	1.0054
	59	1.1388	60	1.1177	20	0.4185
	64	1.1635	62	1.1962	61	2.2051
Power loss (kW)	90.102		90.670		83.154	
Voltage deviation (p.u.)	0.0003		0.00022		**0.00011**	
Voltage stability index^{-1}	1.0735		1.0873		1.0235	
Voltage stability index (p.u.)	0.9770		0.9197		0.9771	

Table 9
Simulation results using TLBO, QOTLBO and CTLBO of 69 BUS system for voltage stability index maximization.

	TLBO [39] Optimal DG		QOTLBO [39] Optimal DG		CTLBO Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	27	0.7026	22	1.1931	14	0.8878
	60	1.1716	61	1.1967	50	0.7067
	61	1.1630	62	1.1914	61	2.2908
Power loss (kW)	88.891		110.507		83.919	
Voltage deviation (p.u.)	0.0009		0.0072		0.0003	
Voltage stability index^{-1}	1.0244		1.0235		1.0151	
Voltage stability index (p.u.)	0.9762		0.9770		**0.9852**	

The achieved objective function value is shown bold.

Table 10
Simulation results using TLBO, QOTLBO and CTLBO of 69 BUS system for simultaneous optimization of power loss, voltage deviation and voltage stability index.

	TLBO [39]		QOTLBO [39] Penalty factors ($a_1 = 1.0$ $a_2 = 0.6$ $a_3 = 0.35$)		CTLBO		CTLBO (ε-constraints Method)	
	Optimal DG		Optimal DG		Optimal DG		Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	13	1.0134	15	0.8114	11	0.5603	12	0.9658
	61	0.9901	61	1.1470	18	0.4274	25	0.2307
	62	1.1601	63	1.0022	61	2.1534	61	2.1336
Power loss (kW)	82.172		80.585		76.372		**79.660**	
Voltage deviation (p.u.)	0.0008		0.0007		0.0008		**0.0003**	
Voltage stability index^{-1}	1.0262		1.0236		1.0235		**1.0235**	
Voltage stability index (p.u.)	0.9745		0.9769		0.9770		**0.9770**	

The achieved objective function value is shown bold.

2.69 MVAr, respectively. The total active and reactive power losses are 224.9 kW and 102.13 kVAr, respectively. The voltage stability index of this network is 0.6833 without any DG [53]. The system base is chosen as 1000 KVA [39].

Subsequently, 3 DGs (Type –I) are considered for optimal sizing and placement. Results obtained with the CTLBO algorithm applied to the optimal siting and sizing of DGs pertaining to the single objective function of minimization of real power loss i shown in Table 7. The

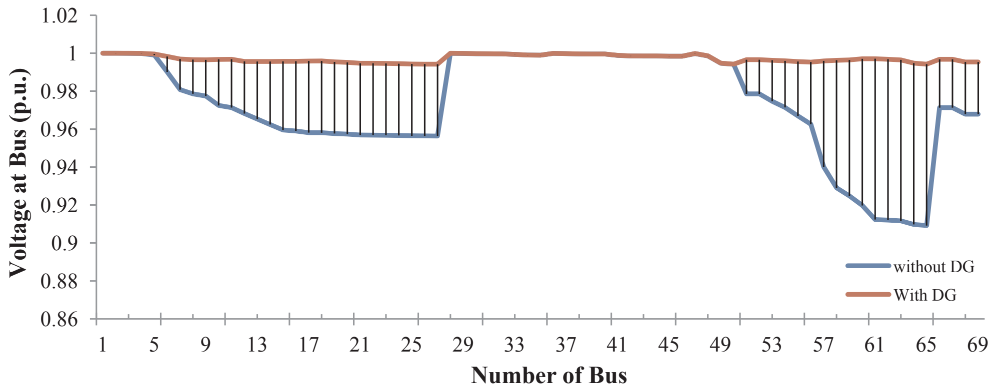

Fig. 4a. Voltage distribution of 69-bus radial distribution system without and with DGs.

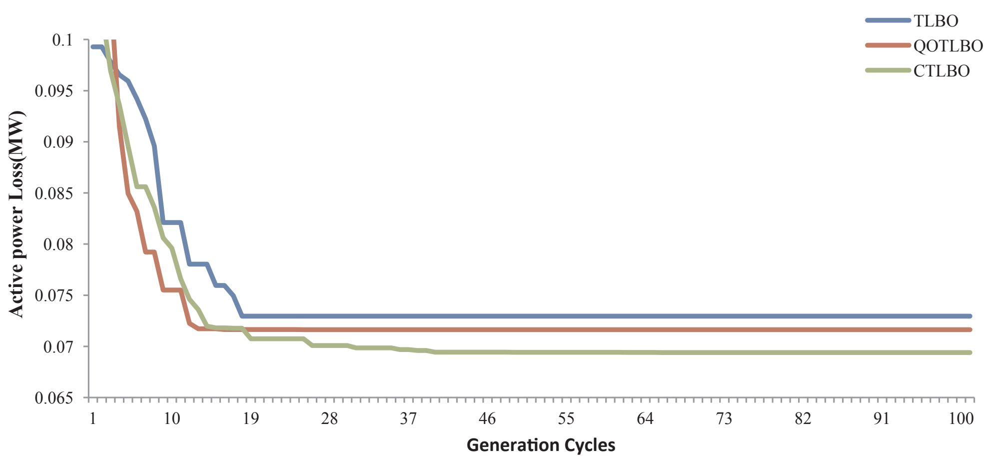

Fig. 4b. Comparison of power loss convergence characteristics of CTLBO, QOTLBO and TLBO for 69-bus RDS.

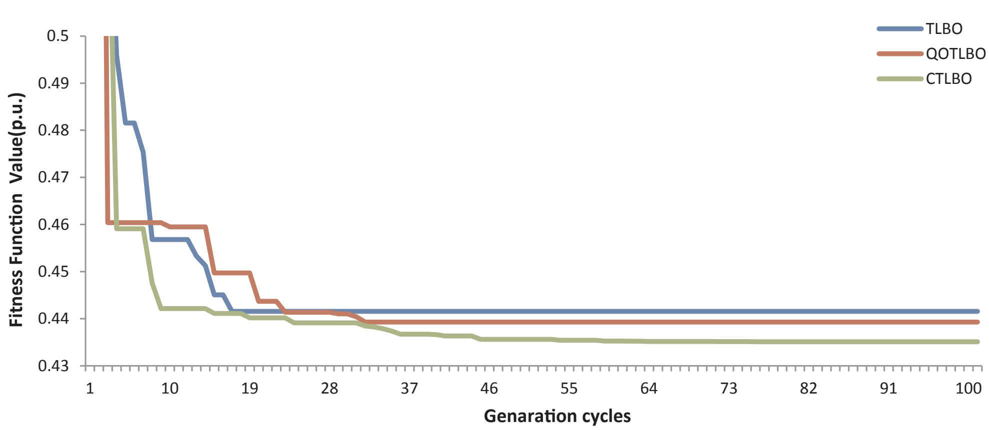

Fig. 4c. Comparison of fitness function convergence characteristics of CTLBO, QOTLBO and TLBO for 69-bus RDS.

achieved objective function value is shown in bold. From Table 7, it is observed that as compared to TLBO and QOTLBO [39], results with proposed CTLBO gives improved real power losses and voltage deviation i.e. 69.388 kW and 0.0052p.u. respectively. The values of the voltage stability index are superior to that with TLBO but slightly inferior to that with QOTLBO. Table 8 shows the results with the proposed CTLBO applied to the optimal siting and sizing of DGs for minimization of voltage deviation. The achieved objective function value is shown in bold. From Table 8, it is observed that the proposed CTLBO results in values of real power losses, voltage deviation and voltage stability index i.e. 83.154 kW, 0.00011 p.u. and 0.9771 p.u. respectively, which are superior to both TLBO and QOTLBO [39]. Table 9 shows the results with the proposed CTLBO applied to the single objective function of maximization of voltage stability index. From Table 9, it is observed that the proposed CTLBO results in improvement in all the three quantities i.e. real power losses, voltage deviation and voltage stability index i.e. 83.919 kW, 0.0003 p.u. and 0.9852 p.u. respectively, as compared to either TLBO or QOTLBO [39]. Subsequently, the proposed CTLBO has applied to the multi-objective function for improvement in all the three quantities i.e. minimization of both real power losses and voltage deviation along with the maximization of voltage stability index. The values of the individual objective function weights (‘a_1’, ‘a_2’ and ‘a_3’) are given in Table 10 to demonstrate the superiority of the proposed method over [39]. From Table 10, it is observed that $a_1 = 1$, $a_2 = 0.65$ and $a_3 = 0.35$, the proposed CTLBO results in the improvement of both real power losses and the voltage stability index. The per-unit voltage deviation is observed to be inferior to QOTLBO. However using the ε-constraints method, the proposed method shows remarkable improvement in all the three quantities i.e. real power losses, voltage deviation and voltage stability index i.e.

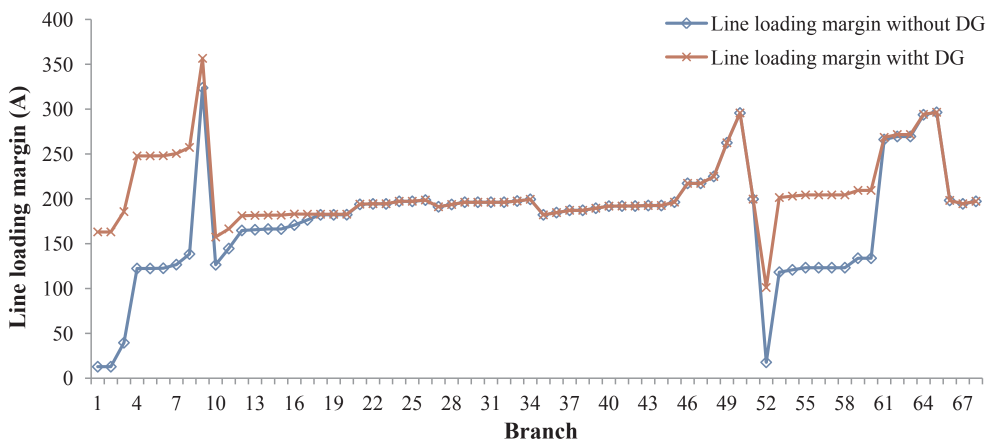

Fig. 4d. Available loading margins after placement of 3 DGs in 69-bus RDS.

Table 11
Simulation results using TLBO, QOTLBO and CTLBO of 118 BUS system for power loss minimization.

	TLBO [39] Optimal DG		QOTLBO [39] Optimal DG		CTLBO Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	8	1.7553	24	1.2463	20	1.8176
	10	0.5910	42	0.7322	44	1.2764
	36	1.5368	47	3.5392	52	2.7671
	49	2.6865	74	2.6792	75	2.5333
	71	2.5014	78	1.2483	83	2.0949
	79	2.4941	94	1.0865	100	1.6631
	110	2.6628	108	3.2432	114	3.1199
Power loss (kW)	590.697		576.182		**516.256**	
Voltage deviation (p.u.)	0.0939		0.0629		0.0572	
Voltage stability index^{-1}	1.2519		1.2093		1.2061	
Voltage stability index (p.u.)	0.7988		0.8269		0.8291	

Table 12
Simulation results using TLBO, QOTLBO, and CTLBO of 118 BUS system for voltage deviation minimization.

	TLBO [39] Optimal DG		QOTLBO [39] Optimal DG		CTLBO Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	33	3.0918	33	3.5158	23	1.4808
	45	1.5553	45	1.8064	44	1.8910
	49	4.4919	49	4.4480	51	6.4081
	71	4.1287	72	3.6721	76	3.5791
	86	3.5000	87	3.9364	85	3.0644
	96	2.9346	89	3.7719	100	2.5052
	110	3.9804	110	3.9690	114	4.6081
Power loss (kW)	820.6794		890.3024		826.844	
Voltage deviation (p.u.)	0.0143		0.0134		**0.0070**	
Voltage stability index^{-1}	1.1334		1.1326		1.1019	
Voltage stability index (p.u.)	0.8823		0.8829		0.9075	

The achieved objective function value is shown bold.

79.660 kW, 0.0003 p.u. and 0.9770 p.u., as compared to either TLBO or QOTLBO [39]. The bus voltage profile of the IEEE 69-bus radial distribution system without and with DGs is shown in Fig. 4a. From Fig. 4a, it is observed that in the presence of DGs, the bus voltage profile shows a marked improvement than that without DG. The convergence characteristic for single objective and multi-objective function of the proposed CTLBO algorithm vis-à-vis TLBO and QTLBO is shown in Fig. 4b and Fig. 4c. Subsequently, 3 DGs (Type–I) are considered for optimal sizing and placement. Results obtained for power loss minimization and multi-objective fitness function value respectively. It is observed from Figs. 4b and 4c that CTLBO have better convergence speed than TLBO and QTLBO. Fig. 4d shows the line loading margins without and with DGs incorporated in the IEEE 69-bus radial distribution system. From the above Fig. 4d, it can again be observed that DGs are very effective in relieving network congestion in the system in lines 1–17 and 51–61 in the 69-bus system.

5.4. Test case 2: 118-bus radial distribution system

The effectiveness of the proposed CTLBO algorithm is reiterated by implementing it on the IEEE 118-bus test system. The branch and load data are taken from [55]. The 118-bus system consists of 132 branches,

Table 13
Simulation results using TLBO, QOTLBO, and CTLBO of 118 BUS system for voltage stability index maximization.

	TLBO [39] Optimal DG		QOTLBO [39] Optimal DG		CTLBO Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	35	3.2536	21	3.2536	26	0.4541
	54	4.2454	43	1.4154	45	0.8362
	58	3.5129	54	4.2454	52	4.9067
	74	3.8290	74	4.9614	65	0.2214
	75	4.4863	80	3.5129	71	9.1134
	81	0.8286	94	3.2396	81	4.9382
	111	3.3889	111	3.9253	115	3.3851
Power loss (kW)	1840.075		1031.8933		1145.143	
Voltage deviation (p.u.)	0.1398		0.0301		0.0269	
Voltage stability index^{-1}	1.1501		1.1099		1.0864	
Voltage stability index (p.u.)	0.8695		0.9009		**0.9205**	

The achieved objective function value is shown bold.

Table 14
Simulation results using TLBO, QOTLBO and CTLBO of 118 BUS system for simultaneous optimization of power loss, voltage deviation, voltage stability index.

	TLBO [39]		QOTLBO [39] Penalty factors ($a_1 = 1.0$ $a_2 = 0.6$ $a_3 = 0.35$)		CTLBO		CTLBO (ε-constraints Method)	
	Optimal DG		Optimal DG		Optimal DG		Optimal DG	
	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)	Location	Size (MW)
	35	3.2462	43	1.5880	43	3.2693	22	2.0515
	48	2.8864	49	3.8459	51	5.9000	44	1.1333
	65	2.4307	54	0.9852	61	1.3302	51	4.4872
	72	3.3055	74	3.1904	76	3.4981	77	2.6457
	86	1.9917	80	3.1632	84	3.0069	81	4.6408
	99	1.6040	94	1.9524	100	2.4184	93	3.7585
	111	3.5984	111	3.6013	115	4.0687	115	3.2820
Power loss (kW)	705.8980		677.5881		781.789		**655.767**	
Voltage deviation (p.u.)	0.0327		0.0233		0.0110		**0.0228**	
Voltage stability index^{-1}	1.1699		1.1372		1.1315		**1.1175**	
Voltage stability index (p.u.)	0.8548		0.8794		0.8838		**0.8948**	

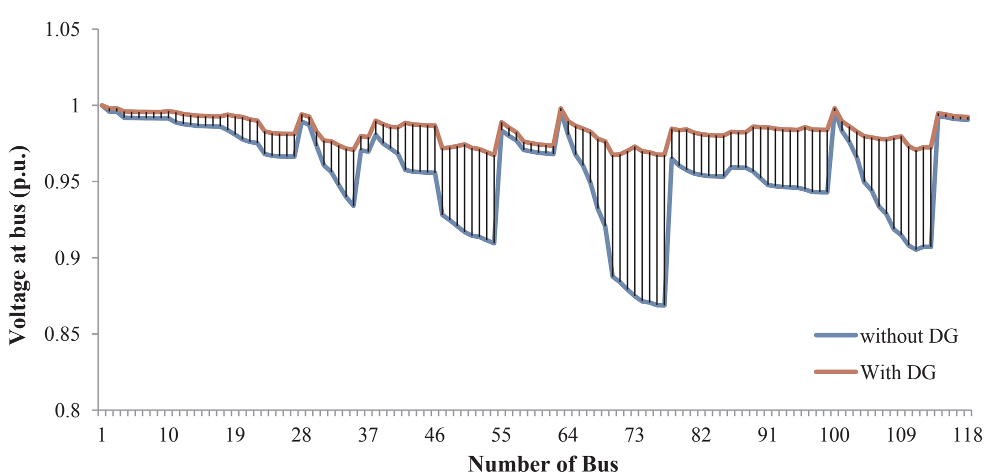

Fig. 5a. Voltage distribution of 118-bus radial distribution system with and without DG.

16 laterals, with 15 loops or tie switches being kept generally open. The rated voltage is 11 kV with a total active and reactive power loadings of 22.709 MW and 17.041 MVAr, respectively. The total active and reactive power losses are 1298.0916 kW and 978.736 kVAr, respectively. The voltage stability index of this network is 0.569734 without any DG [53]. The system base is chosen as 100 MVA [50]. Subsequently, 7 DGs of Type–I are considered for optimal sizing and placement. Results obtained with the CTLBO algorithm applied to the optimal siting and sizing of DGs pertaining to the single objective function of minimization of real power loss are shown in Table 11. The achieved objective function value is shown in bold. From Table 11, it is observed that as compared to TLBO and QOTLBO [39], results with the proposed CTLBO gives improved values of all three quantities i.e. real power losses, voltage deviation and voltage stability index (516.256 kW, 0.0572 p.u. and 0.8291 p.u. respectively). Table 12 shows the results with the proposed CTLBO applied to the optimal siting and sizing of DGs for minimization of voltage deviation. From Table 12, it is observed that the proposed CTLBO yields improved values of both voltage deviation

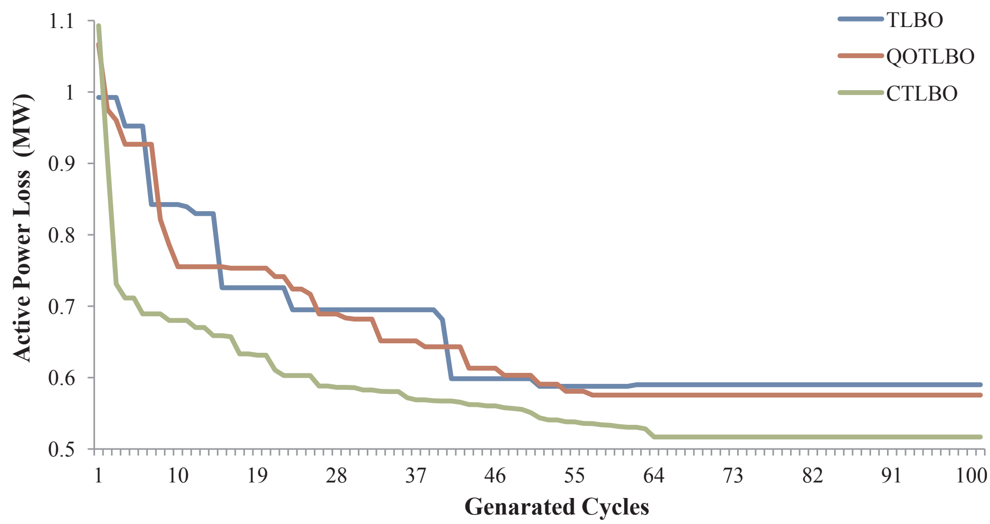

Fig. 5b. Comparison of power loss convergence characteristics of CTLBO, QOTLBO and TLBO for 118-bus RDS.

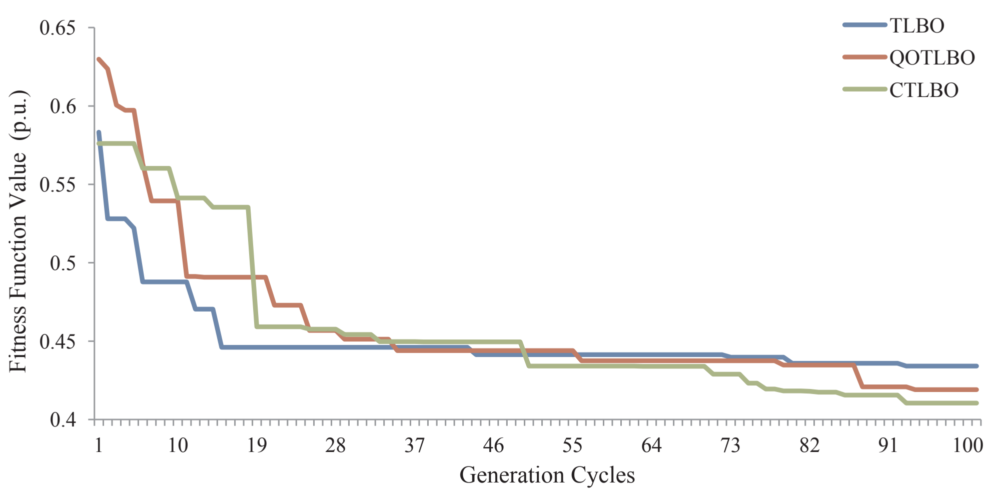

Fig. 5c. Comparison of fitness function convergence characteristics of CTLBO, QOTLBO and TLBO for 118-bus RDS.

Table 15
Results of DG placement.

Distribution system	33-Bus		69-Bus	
Optimization method used	Analytical [44]	CTLBO	Analytical [44]	CTLBO
Location (Bus)	6	6	61	61
Size (MVA)	3.025	3.106	2.222	2.244
Optimal power factor	0.82	0.825	0.82	0.823
DG penetration (%)	69.31	71.09	47.73	48.16
Annual energy loss before DG (MWh)	1299.59	1299.59	1381.53	1381.53
Annual energy loss after DG (MWh)	423.13	422.658	144.35	144.165
Annual energy loss reduction (%)	67.44	67.453	89.55	89.57
Saving ($) (tariff@$ 0.12/kWh)	105175.2	105231.84	148461.6	148483.8

and voltage stability index i.e 0.007 p.u. and 0.9075 p.u. respectively, which are superior to both TLBO and QOTLBO [39]. However, the real power loss value is slightly inferior to that obtained with TLBO. Table 13 shows the results with the proposed CTLBO applied to the single objective function of maximization of voltage stability index. From Table 13, it is observed that the proposed CTLBO results in improvement in both voltage deviation and voltage stability index i.e. 0.0269 p.u. and 0.9205 p.u respectively, as compared to either TLBO or QOTLBO [39]. However, the real power loss value is slightly inferior to that obtained with QOTLBO. Subsequently, the proposed CTLBO is applied to the Multi-objective function for improvement in all the three quantities i.e. minimization of both real power losses and voltage deviation along with the maximization of voltage stability index. The values of the individual objective function weights ('a_1', 'a_2' and 'a_3') are given in Table 14 [39]. The achieved values are shown in bold. From Table 14, it is observed that $a_1 = 1$, $a_2 = 0.65$ and $a_3 = 0.35$, the proposed CTLBO results in the improvement of real power losses as compared to either TLBO or QOTLBO. It is also observed that while the per-unit voltage deviation is observed to be inferior to both TLBO and QOTLBO, the voltage stability index is superior to TLBO and slightly inferior to QOTLBO. However, with the ε-constraints method, the proposed method shows remarkable improvement in all the three quantities i.e. real power losses, voltage deviation and voltage stability index i.e 655.767 kW, 0.0228 p.u. and 0.8948 p.u. respectively, as compared to either TLBO or QOTLBO [39].The bus voltage profile of the IEEE 118-bus radial distribution system without and with DGs is shown in Fig. 5a. From Fig. 5a, it is observed that in the presence of DGs, the bus voltage profile again shows a marked improvement than that without DG. The convergence characteristic for single objective and multi-objective function of the proposed CTLBO algorithm vis-à-vis

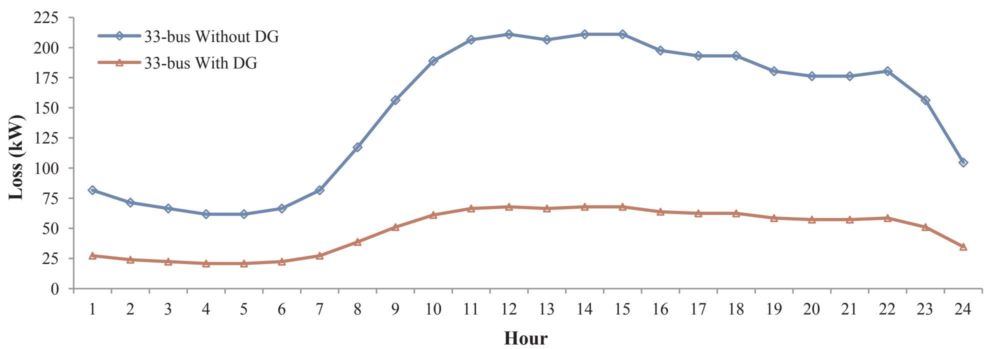

Fig. 6a. Hourly power loss of 33-bus radial distribution system without and with DG.

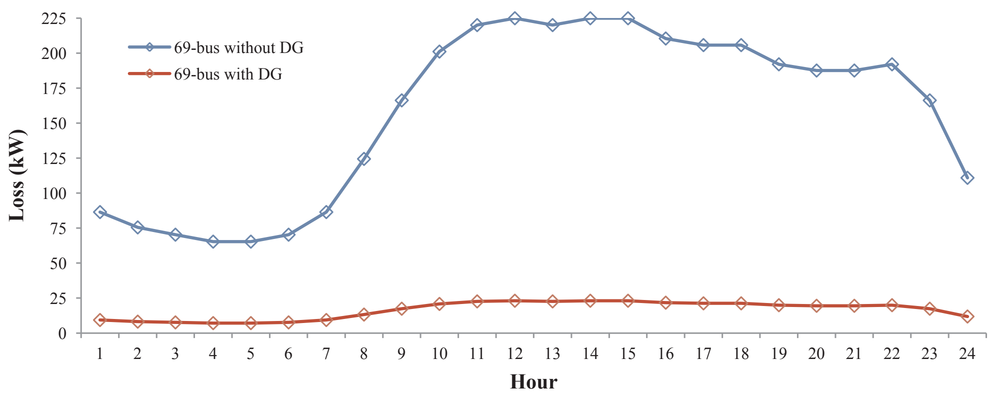

Fig. 6b. Hourly power loss of 69-bus radial distribution system without and with DG.

TLBO and QTLBO is shown in Fig. 5b and Fig. 5c for power loss minimization and multi-objective fitness function value respectively. It is observed that CLBO exhibit fast convergence characteristics in comparison to TLBO and QOTLBO.

6. Impact of optimal DG allocation on annual energy losses

The effects of allocation of DGs in the IEEE 33-bus and 69-bus radial distribution systems are shown in Table 15. It is to be noted that only one DG is considered in order to compare and demonstrate the superiority of the proposed technique over the analytical method reported in [59]. The hourly power losses in the 33 and 69-bus systems without and with DG are shown in Figs. 6a and 6b, respectively, corresponding to practical daily load profile data reported in [44]. The annual energy losses for both the systems, without and with DGs, are calculated (as per Appendix B) using Figs. 6a and 6b respectively. From Table 15, it is observed that using the proposed technique (CTLBO), proper sizing (3.106 MW for 33-bus and 2.224 MW for the 69-bus system) considering single DG installation results in 772 kWh and 185 kWh more annual energy savings, respectively, than the analytical approach reported in [44]. This results in an annual cost savings of \$ 56.64 and \$ 22.20 more as compared to [44].

7. Conclusions

A comprehensive teaching learning-based optimization (CTLBO) technique is presented in this paper for the optimal allocation of distributed energy resources in radial distribution systems. At first, CTLBO is applied to standard mathematical benchmark functions. Results show that the proposed technique can handle mixed integer variables, is parameter independent and is immune to local extreme trappings. Subsequently, the proposed method is implemented for optimal DG allocation in various radial distribution systems, using both single and multi-objective formulations. The multi-objective formulation is based on the ε-constraints method, which is independent of penalty factors, results in lower power losses, better voltage profiles and improves voltage stability index, over TLBO and QOTLBO. It is also observed that optimal placement of DGs results in marked reduction of system losses and voltage deviation up to a certain level of DG penetration, along with better network congestion management. The proposed CTLBO is further validated by DGs placement in distribution system while considering practical load profile, which results in additional annual energy loss reduction and cost savings.

Appendix A. Appendix A

A multi-objective function optimizes all the objective functions simultaneously, subject to the equality and inequality constraints. In this paper, a multi-objective function [39] is used which simultaneously minimizes the power loss (F_1), improves voltage profile (F_2) and maximizes the voltage stability index (F_3).

$$MOF = \text{Minimize}(a_1*F_1 + a_2*F_2 + a_3*F_3) \tag{A.1}$$

where a_1, a_2 and a_3 are penalty coefficients. If DGs are implemented with the objective of mitigating a specific problem, the corresponding penalty coefficient is increased. Any value of penalty coefficient can be chosen depending upon the importance of the objective function. However, for a normalized objective function, the sum of the penalty coefficients should be unity as shown below.

$a_i([0,1])$ *and* $\sum_{i=1}^{m} a_i = 1$ where a_i and m are weight factor and the total number of objective functions.

Appendix B. Appendix B

B.1. Energy loss calculation

The total annual energy loss E_{loss} (MWh) in a distribution system with time duration (Δt) of 1 h can be expressed as:

$$E_{loss} = 365\cdot\sum_{t=1}^{24} P_{loss}^{t}\cdot\Delta t \tag{A.2}$$

where P_{loss}^{t} is the power loss of the network at time t of the day.

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