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Heuristic optimization techniques for voltage stability enhancement of radial distribution network with simultaneous consideration of network reconfiguration and DG sizing and allocations

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Abstract: In this paper, heuristic optimization techniques, such as integrated particle swarm optimization (IPSO), teaching–learning-based optimization (TLBO), and Jaya optimization, were applied effectively for the first time to optimize the radial distribution network (RDN) by simultaneously considering reconfiguration of the network and allocation and sizing of the distributed generations (DG). The objectives were to maximize the voltage stability and to minimize the power loss of the network without violating the system constraints. In standard PSO technique, the movement of current particle depends upon global best position and its own best position up to current step. However, if the particle lies too close to any of these positions, the guiding role highly decreases and even vanishes. To resolve this problem and to find the global best solution, IPSO was utilized to optimize the network reconfiguration and DG allocation and sizing problem in the RDN. Also, the optimization techniques, such as TLBO and Jaya optimization, which do not require any tuning of parameters, unlike other heuristic optimization techniques, were implemented successfully in this paper. Seven test cases were generated from different combinations of network reconfiguration and DG allocation and sizing. Moreover, for comparison, the optimization techniques, such as particle swarm optimization (PSO), adaptive cuckoo search algorithm (ACSA), harmony search algorithm (HSA), and fireworks algorithm (FWA), were also applied to IEEE 33- and 69-bus distribution test networks. The comparison results prove overall superiority of Jaya optimization when applied on the two IEEE bus systems with seven test cases undertaken.

Key words: IPSO, TLBO, Jaya optimization, reconfiguration, distribution network, voltage stability, distributed generation

1. Introduction

Network reconfiguration is considered as nonlinear, mixed integer, nondifferentiable, multiobjective constraint optimization problem. The concept of distribution network reconfiguration (DNR) with the objective to minimize power losses was first proposed by Marlin and Back in 1975 [1]. Earlier; DNR problem, distributed generation (DG) placement, and/or DG sizing problems were considered separately. In recent years, various population-based metaheuristic optimization algorithms and their hybridization have been applied in the network reconfiguration problem to achieve objectives such as minimum power loss, voltage profile enhancement, and voltage stability improvement in the networks. Metaheuristic optimization techniques, such as particle swarm optimization (PSO) and its variants, are used to solve the reconfiguration problem with the objective

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to minimize node voltage deviation, number of switching operations, and total cost of active power generations by DGs and to enhance voltage stability and improve the load factor and reliability of the distribution network [2–6]. In [7], the reconfiguration problem was solved using a hybrid algorithm based on PSO and honey bee mating optimization (HBMO) with an objective to minimize power loss, fluctuation in node voltage, number of switching operation and to balance loads among the feeders. In [8,9], the feeder reconfiguration problem was solved using HBMO and modified HBMO. In [10–12], ant colony optimization (ACO) is proposed to solve feeder reconfiguration problem with the objective to minimize power loss in the network. In [13,14], hybrid algorithm based on PSO and ACO was used to solve feeder reconfiguration. Recently, other population-based metaheuristic optimizations, such as simulated annealing (SA) [15], hybrid algorithm based on SA and Tabu search [16], enhanced gravitational search algorithm (EGSA) [17], runner root algorithm [18], genetic algorithm (GA) [19–21], discrete firefly algorithm [22], modified plant growth simulation algorithm [23], and fuzzy firefly algorithm [24], have been applied to the network reconfiguration problem. Some researchers have integrated both DG allocation and DNR problem to optimize the efficiency of distribution network. Metaheuristic optimization techniques, such as harmony search algorithm (HSA) [25], fireworks algorithm (FWA) [26], integrated gravitational search algorithm (IGSA)[27], PSO [28], and ACO [29], have been applied to optimize the network reconfiguration and DG sizing with the objective to minimize power loss and enhance voltage stability.

In the literature, few works reported to simultaneously optimize the reconfiguration of network and DG allocation and sizing in distribution networks. In [30], cuckoo search algorithm (CSA) was utilized for optimization of simultaneous reconfiguration of network and location and sizing of DGs in the distribution network. In [31], hybrid optimization based on shuffled frog leaping algorithm (SFLA) and PSO was used to optimize the reconfiguration problem with multiple objectives, i.e. power loss minimization, voltage stability improvement, and number of switching optimization. In the available literature, the objectives found for the network reconfiguration problem are minimization of real power loss, voltage profile improvement, optimization of the number of switches etc., which are supposed to be important considerations for the operation of a traditional distribution network. Due to large penetration of DGs and high load demand, voltage stability has emerged as an important issue in the modern distribution network. Recently developed methods, such as Jaya algorithm, were utilized to optimize DGs location and sizing [32] and modified TLBO algorithm for optimization of reconfiguration and DG allocations in IEEE 33-bus radial distribution network [33]. In [34], IPSO was utilized to optimize the size, shape, and topologies of truss structure.

To date, to the best of our knowledge, IPSO technique has been an uncharted optimization technique in the radial distribution network. Also, for the first time, new heuristic optimization techniques such as IPSO, TLBO, and Jaya algorithm have been utilized for voltage stability enhancement and power loss minimization in the radial distribution network by simultaneous reconfiguration of the network and DG allocation and sizing. The test results on IEEE 33- and 69-bus distribution test system shows the superiority of the Jaya algorithm followed by ACSA over other optimization techniques, i.e. PSO, IPSO, TLBO, HSA and FWA.

2. Problem formulation

In a typical distribution network, total active power loss of the feeders ($P_{T_{loss}}$) can be calculated by adding the losses of all the feeders in distribution network and formulated as follows:

$$P_{T_{loss}} = \sum_{i=1}^{N} R_i \frac{P_i^2 + Q_i^2}{V_i^2}. \tag{1}$$

The power loss reduction in the distribution system can be calculated by Eq. (2).

$$\Delta P_{loss}^{R} = \frac{P_{loss}^{Rec}}{P_{loss}^{0}}, \tag{2}$$

where P_{loss}^{Rec} and P_{loss}^{0} are active power loss with and without reconfiguration. In this paper, voltage stability index (VSI) [35] was applied to monitor the network voltage stability. Critical values of this index lie between 0 and 1. The VSI value near zero at any node represents most vulnerable node in terms of stability. Higher values of VSI indicate higher stability in the network. The formulation of the considered VSI is given by Eq. (3).

$$VSI_{m+1} = |V_m|^2 - 4(P_{m+1}X_m - Q_{m+1}R_m)^2 - 4(P_{m+1}R_m - Q_{m+1}X_m)|V_m|^2, \tag{3}$$

where P_{m+1} and Q_{m+1} are the total real and reactive power fed from node 'm+1'. $|V_m|$ and $|V_{m+1}|$ are voltage magnitudes at node 'm' and 'm+1', respectively. R_m and X_m are feeder resistance and reactance, respectively. The deviation in VSI is given by Eq. (4).

$$\Delta VSI = (1 - VSI_m) \qquad m = 1, 2, 3, ..., N_{br}, \tag{4}$$

where N_{br} is the total number of branches in the radial distribution network. The combined objective to reduce power loss and enhance voltage stability can be formulated as follows:

$$F_{obj} = min(\Delta P_{loss}^{R} + \Delta VSI). \tag{5}$$

Subjected to constraints

$$\begin{aligned} & V^{min} \leq V_m \leq V^{max} && m = 1, 2, 3, ..., N_{br}, \\ & 0 \leq I_j \leq I_{max} && j = 1, 2, ..., N_{br}, \\ & |A| = 1, && \\ & 0 \leq P_{DG_i} \leq P_{DG_{max}} && i = 1, 2, ..., N_{DG}, \end{aligned} \tag{6}$$

where $|A|$ represents the determinant of the network incidence matrix having value 1 when the network is a radial distribution network. V^{min} and V^{max} represents the minimum and maximum node voltage limits. I_{max} denotes the maximum current in feeder j. $P_{DG_{max}}$ represents the maximum DG size.

3. Mathematical modelling of optimization techniques

The mathematical formulation of optimization techniques TLBO, Jaya, and IPSO algorithm are given as follows:

3.1. Teaching learning based optimization (TLBO)

The TLBO is a heuristic optimization technique which simulates the process of teaching and learning in a class. The teaching–learning process is partitioned in two phases, i.e. teacher phase and learners phase.

Teacher phase: A teacher can improve the mean (e.g., average marks of all students) of the class to a certain extent depending upon the quality of the students in class and the knowledge delivered to the students. Let T_k be the teacher and M_k the mean at any iteration k. By delivering knowledge to students, teacher (T_k)

will try to improve the class mean from M_k to a new mean (M_{new}). The difference between the existing and new mean can be mathematically formulated by Eq. (7):

$$\Delta M = r_k \times (M_{new} - T_F M_i), \tag{7}$$

where r_k represents a random number between 0 and 1; T_F represents teaching factor whose value can be either 1 or 2 and calculated as $T_F = round[1 + r_k \times (2-1)]$. The solution vector can be updated by solving Eq. (8):

$$X_{k+1} = X_k + \Delta M. \tag{8}$$

Learners phase: Students can enhance their knowledge by two means, either by learning from teacher or through their fellow students in the class. Mathematical formulation of the student's learning can be expressed as follows:

For i=1:npop
Randomly select two learners X_i and X_j, where $i \neq j$
If $f(X_i) < f(X_j)$
$X_{new,i} = X_{old,i} + r_i(X_i - X_j)$
Else
$X_{new,i} = X_{old,i} + r_i(X_j - X_i)$
End If
End For
Accept X_{i+1} if it gives better function value.

Here, npop is the size of solution vector or population.

3.2. Jaya optimization

Like TLBO, Jaya optimization is a population-based optimization technique which does not require any tuning of parameters. TLBO requires two phases (i.e. teaching phase and learner phase) whereas Jaya optimization requires only one phase to solve the constrained optimization problem. Let the function $f(x)$ be optimized. Assume that initially there are 'P' numbers of the solution vector (also called population) and each solution vector contains m number of design variables. Let at any iteration k, $X_{i,m,k}$ be the i^{th} design variable for the m^{th} solution vector during the k^{th} iteration. The updated value of $X_{i,m,k}$ is given as follows:

$$X'_{i,m,k} = X_{i,m,k} + rand_k \times (X_{i,best,k} - |X_{i,m,k}|) - rand_k \times (X_{i,worst,k} - |X_{i,m,k}|), \tag{9}$$

where $X'_{i,m,k}$ is the updated value of $X_{i,m,k}$, $X_{i,best,k}$ is the value of design variable i for the best solution vector, $X_{i,best,k}$ is the value of design variable i for the worst solution vector, and $rand_k$ is a random variable that varies in the range [0,1] during k^{th} iteration. The optimization technique always tries to get closer to the best solution and tries to avoid the worst solution in each iteration. $X'_{i,m,k}$ is accepted if it gives better function value, otherwise $X_{i,m,k}$ will be retained.

3.3. Integrated particle swarm optimization

In standard PSO, the main drawback of the algorithm appears when the particle flies near to global or local positions and the guiding path of particles decreases [36]. Under this condition, there is risk of being trapped in local minima. To counter this problem, a third particle called weighted particle (X_w) is introduced into the velocity updating formulation [34]:

$$X^{w}=\sum_{i=1}^{M}\bar{C}_{i}^{w}X_{i}^{P}, \tag{10}$$

where $\bar{C}_i^w = \left(\hat{C}_i^w / \sum_{i=1}^{M} \hat{C}_i^w\right)$ and $\hat{C}_i^w = \frac{\max_{1\le k\le M}\left(f\left(X_k^p\right)\right)-f\left(X_i^p\right)+\epsilon}{\max_{1\le k\le M}\left(f\left(X_k^p\right)\right)-\min_{1\le k\le M}\left(f\left(X_k^p\right)\right)+\epsilon}$; N_{pop} represents the population of particles; X^w is the position vector of weighted particles; $\hat{C}_i^w$ is the weighted constant of each particle. The function $f(.)$ represents the fitness of the particle, while $\max_{1\le k\le M}\left(f\left(X_k^p\right)\right)$ and $\min_{1\le k\le M}\left(f\left(X_k^p\right)\right)$ represent the maximum and minimum fitness values in Pbest. Finally, ϵ specifies a small positive number (0.0001) to prevent division by zero condition. In IPSO, particle position vectors with weighted particle are updated as follows:

IF $\quad rand_{0i} \le \alpha$,

$$\begin{aligned} {}^{t+1}V_i &= 0,\\ {}^{t+1}X_i &= {}^{t}X_i + \phi_{4i}\left({}^{t}X^{w} - {}^{t}X_i\right),\\ \phi_{4i} &= C_4 \times rand_{4i}. \end{aligned} \tag{11}$$

IF $\quad rand_{0i} > \alpha$,

$$\begin{aligned} {}^{t+1}V_i &= w_i \times {}^{t}V_i + (\phi_{1i}+\phi_{2i}+\phi_{3i})({}^{t}X_j^{P} - {}^{t}X_i) + \phi_{2i}({}^{t}X^{G} - {}^{t}X_j^{P}) + \phi_{3i}({}^{t}X^{w} - {}^{t}X_j^{P}),\\ {}^{t+1}X_i &= {}^{t}X_i + {}^{t+1}v_i, \end{aligned} \tag{12}$$

where $\phi_{1i} = C_1 \times rand_{1i}$, $\phi_{2i} = C_2 \times rand_{2i}$, $\phi_{3i} = C_3 \times rand_{3i}$; superscripts 't' and 't+1' denotes present and next iteration respectively; ${}^{t}V_i$ and ${}^{t+1}V_i$ are the present and updated velocity of particles; w_i represents an inertia factor for the present velocity, which is a random number chosen from [0.5,0.55] in each iteration.

4. Implementation of TLBO, Jaya, and IPSO for network reconfiguration considering DGs

4.1. Implementation of TLBO algorithm for RDN with DGs

Step 1: Determine the primary loops in the radial distribution network [30]. Obtain the minimum and maximum limits of tie line in each primary loop, minimum and maximum limits of location, and output power (kW) of DGs.

Step 2: Initialize the size of population equal to N_{pop} and generate the solution vectors given as follows:

$$X_k = [SW_1, \ldots, SW_{NO}, Lo\_DG_1, \ldots, Lo\_DG_m, Size\_DG_1, \ldots, Size\_DG_3],$$

where $SW_1, SW_2, \ldots, SW_{NO}$ are tie switches in primary loops PL_1 to PL_{N_Tie}; $Lo\_DG_1, \ldots, Lo\_DG_m$, and $Size\_DG_1, \ldots, Size\_DG_3$ are the locations and sizes of 'm' DG units, respectively. The number of tie switches are N_Tie. The random generation of variables in each solution vector X is deduced from Eq. (13):

$$\begin{aligned} SW_k &= round\left[SW_{LB,m_1}^{k} + rand \times (SW_{UB,m_1}^{k} - SW_{LB,m_1}^{k})\right],\\ Lo\_DG_k &= round[Lo_{LB,m_2}^{k} + rand \times (Lo_{UB,m_2}^{k} - Lo_{LB,m_2}^{k})],\\ Size\_DG_k &= round[Size_{LB,m_3}^{k} + rand \times (Size_{UB,m_3}^{k} - Size_{LB,m_3}^{k})], \end{aligned} \tag{13}$$

where $m_1 = 1, 2, ..., N\_Tie$; $m_2 = 1, 2, ..., m$; $m_3 = 1, 2, ..., m$; SW_{LB} and SW_{UB} are minimum and maximum tie switch positions in any fundamental loop m_1; Lo_{LB} and Lo_{UB} are lower and upper limits of DG locations, which vary between node 2 and the maximum number of nodes in the network. Similarly, $Size_{LB}$ and $Size_{UB}$ represent the lower and upper limits of DG power output (kW).

Step 3: Check radial condition of each host nest by checking the system radial algorithm [30].

Step 4: Initialize the iteration number.

Step 5: Calculate the mean of each element in the solution vector columnwise, which represents the average mark obtained in a particular subject and is represented as follows:

$$M_{pop} = [M_{SW1}, \ldots\ldots, M_{SW2}, M_{Lo,1}, \ldots.., M_{Lo,m}, M_{size,1}, \ldots\ldots M_{size,m}].$$

Step 6: Find the fitness function for all the generated solution vectors. The solution vector whose fitness function value is minimum shall be considered as a teacher.

Step 7: In the teacher phase, the teacher will try to enhance the mean of class from Mpop to Xteacher, which is the updated value of mean for the current iteration. The difference between two means can be formulated as follows:

$$dM = rand \times (X_{teacher} - T_F * M_{pop}), \tag{14}$$

where TF represents a teaching factor which is randomly selected between 1 or 2. The updated solution is represented by Eqs. (15) and (16).

$$X^{t+1} = X^t + dM; \tag{15}$$

$$X^{t+1} = [round(X_{m1}^{t+1}), round(X_{m2}^{t+1}), X_{m3}^{t+1}]. \tag{16}$$

The limits of each tie switch and DG location and sizing are checked by Eq. (17):

$$\begin{aligned} SW_{m1}^{lim} &= \begin{cases} SW_{LB,m1} & \text{if} \quad SW_{m1} < SW_{LB,m1} \\ SW_{UB,m1} & \text{if} \quad SW_{m1} > SW_{UB,m1} \\ SW_{m1} & \text{otherwise} \end{cases} \\ Lo\_DG_{m2}^{lim} &= \begin{cases} 2 & \text{if} \quad Lo_{m2} < 2 \\ Lo_{UB,m2} & \text{if} \quad Lo_{m2} > Lo_{UB,m2} \\ Lo_{m2} & \text{otherwise} \end{cases} \\ Size\_DG_{m3}^{lim} &= \begin{cases} 2 & \text{if} \quad Size_{LB,m3} < Size_{LB,m3} \\ Size_{UB,m3} & \text{if} \quad Size_{m3} > Size_{UB,m3} \\ Size_{m3} & \text{otherwise} \end{cases} \end{aligned} \tag{17}$$

The radiality checking algorithm is run to check the radiality of the updated solution. Accept the new solution if it gives the better fitness function.

Step 8: In the learners phase, the mathematical formulation is explained in Section 3.1.

Step 9: Increase the iteration number. Stop the process if termination criteria (maximum number of iterations) are reached, otherwise repeat from Step 5.

4.2. Implementation of Jaya optimization for RDN with DGs

Steps 1 to 4 are similar to those of TLBO algorithm defined in Section 4.1.

Step 5: Find the best and worst solution vectors in N_{pop} solution vectors. In this paper, the best solution vector represents the minimum value of fitness function and the worst solution vector represents the maximum value of the fitness function.

Step 6: Set maximum no. of iterations (Maxiter) and start the iteration counter (Iter = 1).

Step 7: Update the solution vector using Eq. (9).

Step 8: Find the best and worst solution vectors. If best function value is better than the previous best solution, accept the updated solution vector $X'_{i,m,k}$.

Step 9: Increase the iteration number (Iter = Iter + 1). Stop the process when termination criteria (maximum number of iterations) are reached.

4.3. Implementation of IPSO algorithm for RDN with DGs.

Steps 1 to 4 are similar to those of TLBO algorithm defined in Section 4.1.

Step 5: Calculate the fitness function value for each particle and obtain the global best (G_{best}) and the personal best (P_{best}) positions of particles.

Step 6: Set maximum no. of iterations and start the counter (Iter = 1).

Step 7: Calculate weighted particle X_w using Eq. (10).

Step 8: If $rand_{0i} \leq 0.4$, update velocity $({}^{t+1}V_i)$ vector and X_i using Eq. (11). Else $rand_{0i} > 0.4$, update the velocity vector $({}^{t+1}V_i)$ and X_i using Eq. (12), where $rand_{0i}$ is a random number generated between 0 and 1.

Step 9: Evaluate fitness function for current particle $f(X_i)$ and also for weighted particle $f(X^w)$.

If $(min(f(X_i), f(X^w)) < f(X_{P_{best}})$

Update P_{best}

If $(min(f(X_i), f(X^w)) < f(X_{G_{best}})$

Set $G_{best} = X_i$ or X_w

End If where X_{Pbest} is the previous best position of the current particle. Replace X_{Pbest} and X_{Gbest} with X_i or X^w, whichever has better fitness value.

Step 10: Increase iteration number (Iter = Iter + 1). Stop the process when termination criteria (maximum number of iterations) are reached.

5. Results and analysis

The mathematical formulation of applied optimization techniques was validated through IEEE 33- and 69-bus distribution test networks. The installed locations of DGs were restricted to three only for the considered test systems. Each DG size lies between 0 and 2 kW. The seven different test cases were examined with PSO, IPSO, TLBO, and Jaya algorithm and compared with HSA, FWA, and ACSA. The simulation was performed on MATLAB software on Intel i7 processor, 2.4 GHz, 8 GB RAM computer. All the cases considered for optimization are as follows: **Case 1:** Base case; **Case 2:** Reconfiguration only; **Case 3:** DG allocation only; **Case 4:** DG allocation after reconfiguration; **Case 5:** Reconfiguration after DG allocation; **Case 6:** Simultaneous reconfiguration and DG sizing; **Case 7:** Simultaneous reconfiguration and DG allocation and sizing. For the load flow solutions for each considered case, the forward–backward sweep algorithm was utilized in this paper.

5.1. IEEE 33-bus distribution test system

The IEEE 33-bus test system includes 37 branches, 32 sectionalizing switches, and 5 tie switches. The parameters of test systems were taken from [37]. Total active and reactive loads of the test system are 3.72 MW and 2.3 MVAr, respectively. The branches 33, 34, 35, 36, 37 are tie branches which builds the primary loops. The results obtained from all the cases considered are summarized in Table 1. For Cases from 2 to 7, the optimization methods, i.e. IPSO, TLBO, PSO, and Jaya algorithm, are applied and compared with ACSA, FWA, and HSA. It is observed from Table 1 that the power loss in the base case is 202.67 kW, which gets reduced to 139.98, 72.95, 60.86, 60.85, 65.87, and 58.49 for cases from 2 to 7, respectively when Jaya optimization is applied. The percentage power loss reduction for cases from 2 to 7 are 30.93, 64.01, 69.97, 69.97, 67.49, and 71.14, respectively. The magnitude of minimum voltage in p.u. for the network gets improved from 0.9131 (base case) to 0.9813 (case 7). Moreover, a significant improvement in minimum VSI value in various cases have been observed; it is improved from 0.6951 (base case) to 0.9272 (case 7). The optimal reconfiguration in case 2 is obtained with tie switches 7, 14, 9, 32, 28 using IPSO, TLBO, PSO, Jaya, ACSA, and FWA. The nodes 14, 24, and 30 are identified as optimal locations when only DG allocation is considered (i.e. case 3), whereas the optimal DG allocation gets shifted to nodes 30, 12, and 16 when the Jaya optimization technique is applied after network reconfiguration (i.e. case 4). A similar pattern to that of Jaya algorithm is observed for TLBO, IPSO, PSO, ACSA, FWA, and HSA optimization techniques whereby the percentage loss reduction and minimum VSI are improved for the rest of the cases in comparison to the base case.

It can also be observed from Table 1 that the minimum power loss occurs in the test system in case 7 when simultaneous consideration of network reconfiguration and DG allocations and sizing are considered irrespective of the optimization techniques applied. However, it is also observed that when both reconfiguration and DG installation are considered for the distribution network (i.e. case 4 and case 5), the voltage profile and VSI values have higher increment compared to when only reconfiguration or DG installation (i.e. case 2 and

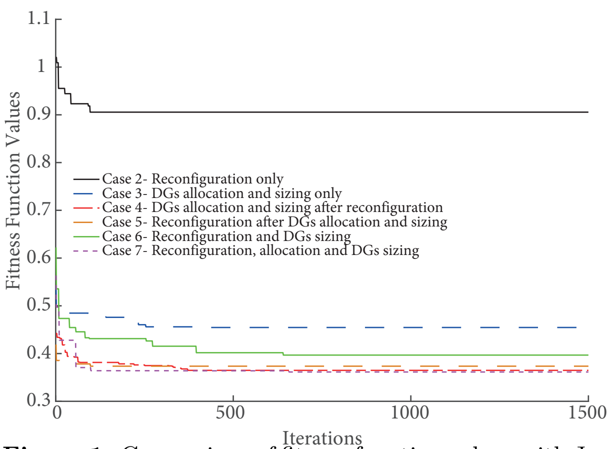

Figure 1. Comparison of fitness function values with Jaya algorithm.

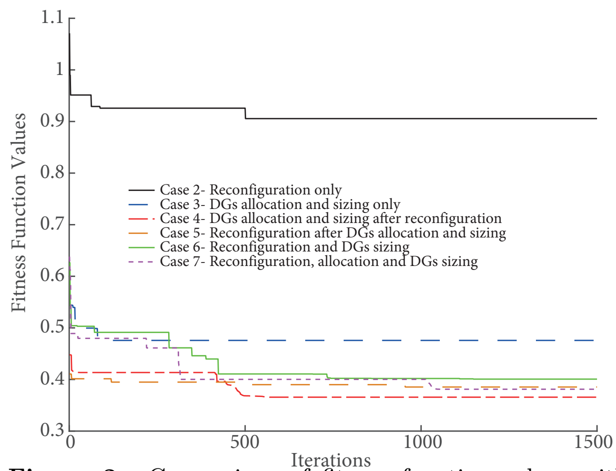

Figure 2. Comparison of fitness function values with TLBO.

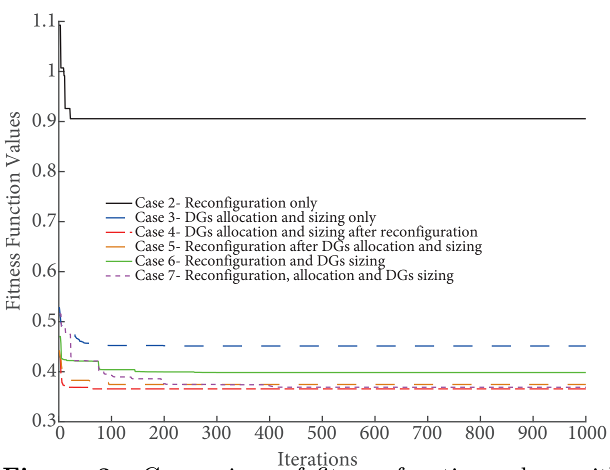

Figure 3. Comparison of fitness function values with PSO.

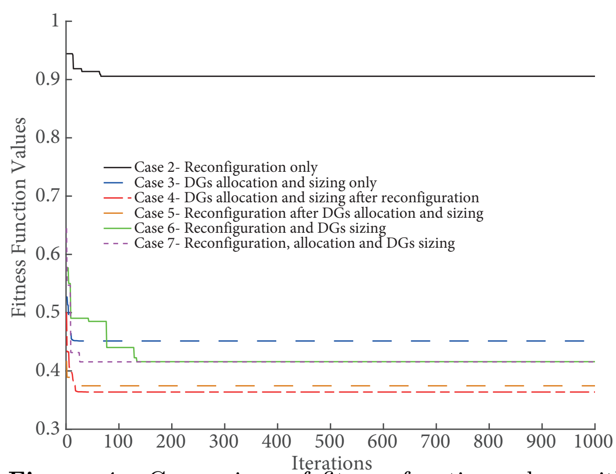

Figure 4. Comparison of fitness function values with IPSO.

case 3) is performed. It can be seen from Figures 1–4 that the fitness function value is minimum for case 4 for the optimization methods ACSA, TLBO, PSO, and IPSO whereas for Jaya method, the fitness function value is minimum for case 7. Hence, with the help of Table 2, it can be concluded that Jaya algorithm, which is one of the simplest algorithms, is also the most efficient one for all the considered cases.

5.2. IEEE 69 bus distribution test system

To examine the performance of various optimization techniques on the medium scale distribution network, a 69-bus distribution test system was considered in this study. Test system includes 73 branches, 68 sectionalizing switches, and 5 tie switches. The test system has 3.802 MW and 2.695 MVAr of active and reactive loads, respectively. Primary loops for 69 bus test system are obtained by the algorithm given in [30]. Similar to 33-bus test system, the optimization problem for cases 2 to 7, are solved using optimization techniques, i.e. PSO, TLBO, IPSO, and Jaya algorithm, and compared with ACSA, FWA, and HSA. Tuning of parameters for optimization techniques (i.e. PSO, IPSO) is set similar to the IEEE 33-bus system. Like 33-bus test system, in order to reduce network power losses and voltage stability improvement, seven different cases were considered in this study. The results obtained from the seven cases are summarized in Table 3. It is observed from Table 3 that the power loss in the base case is 224.99 kW, which gets reduced to 99.59, 72.44, 37.53, 41.57, 43.35, and 44.04 for cases 2 to 7 respectively when Jaya optimization is applied. The percentage power loss reduction for cases 2 to 7 are 55.74, 67.80, 83.32, 81.52, 80.73, and 80.42 respectively. The magnitude of minimum voltage in p.u. for the network gets improved from 0.9092 (base case) to 0.9807 (case 7). Moreover, a significant improvement in minimum VSI value in various cases was observed, which gets improved from 0.6833 (base case) to 0.9239 (case 7). The optimal reconfiguration in Case 2 was obtained with tie switches 69, 70, 14, 61, 56 using Jaya and FWA. The nodes 11, 19, and 61 are identified as optimal locations when only DG allocation is considered (i.e. case 3), whereas the optimal DG allocation gets shifted to nodes 11, 64, and 61 when the Jaya optimization technique is applied after network reconfiguration (i.e. case 4). A pattern similar to that of Jaya algorithm was observed for TLBO, IPSO, PSO, ACSA, FWA, and HSA optimization techniques whereby the percentage loss reduction and minimum VSI are improved for the rest of the cases in comparison to the base case.

The power loss is significantly reduced in Case 7 while using ACSA optimization while the minimum voltage magnitude and VSI are improved in Case 3. The performance of optimization techniques is summarized in Table 4. Hence, with the help of Table 4. it can be concluded that Jaya algorithm, which is one of the simplest algorithms, is also the most efficient one for all the considered cases. Figures 5–8 reflect that the fitness function value is minimum for case 4. This implies that in order to obtain minimum power loss and maximum voltage stability, DG should be installed after reconfiguration only.

It is observed from Figures 5–8 that the fitness function value is minimum for Case 4. This implies that in order to obtain minimum power loss and maximum voltage stability, DG should be installed after reconfiguration.

6. Conclusions

In this paper, optimization techniques such as PSO, IPSO, TLBO, and Jaya were used for simultaneously optimizing the network reconfiguration and DG location and size. The objectives were to minimize the power loss and maximize the voltage stability of the distribution network. Seven different cases, i.e. base case (without reconfiguration and DG allocation and sizing), reconfiguration only, DG allocation only, DG allocation

Table 1. Results analysis for IEEE 33-bus test system.

Sr. No.	Item	Integrated PSO	TLBO	PSO	Jaya	ACSA	FWA	HSA
Case 1	Tie switch (Open)	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37
	Power loss (kW)	202.67	202.67	202.67	202.67	202.67	202.67	202.67
	Minimum voltage (p.u.)	0.9131	0.9131	0.9131	0.9131	0.9131	0.9131	0.9131
	Minimum VSI	0.6951	0.6951	0.6951	0.6951	0.6951	0.6951	0.6951
Case 2	Tie switch (Open)	7,9,14,28,32	7,9,14,28,32	7,14,9,32,28	7,14,9,32,28	7,14,9,32,28	7,14,9,32,28	7,14,9,32,37
	Power loss (kW)	139.98	139.98	139.98	139.98	139.98	139.98	139.55
	% Loss reduction	30.93	30.93	30.93	30.93	30.93	30.93	31.14
	Minimum voltage (p.u.)	0.9413	0.9413	0.9413	0.9413	0.9413	0.9413	0.9378
	Minimum VSI	0.7850	0.7850	0.7850	0.7850	0.7850	0.7850	0.7735
Case 3	Tie switch (Open)	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37	33,34,35,36,37
	DG (MW) (Bus No.)	0.8044(14)	0.9142(12)	0.8049(14)	0.7628(14)	0.7798(14)	0.5897(14)	0.1070(18)
		1.1063(24)	1.2001(30)	1.1059(24)	1.1072(24)	1.1251(24)	0.1895(18)	0.5724(17)
		1.3917(30)	1.2405(24)	1.3929(30)	1.2809(30)	1.3496(30)	1.0146(32)	1.0462(33)
	Power loss (kW)	75.35	73.89	75.38	72.95	74.26	88.68	96.76
	% Loss reduction	62.82	63.54	62.80	64.01	63.35	56.24	52.25
	Minimum voltage (p.u.)	0.9795	0.9710	0.9795	0.9754	0.9778	0.9680	0.9673
	Minimum VSI	0.9205	0.8889	0.9205	0.9054	0.9141	0.8778	0.8755
Case 4	Tie switch (Open)	7,14,9,32,28	7,14,9,32,28	7,14,9,32,28	7,14,9,32,28	7,14,9,32,28	7,14,9,32,28	7,14,9,32,37
	DG (MW)(Bus No.)	29(1.74707)	1.8555(29)	1.8505(29)	1.6590(30)	1.7536(29)	0.5996(32)	0.2686(32)
		17(0.3834)	0.5008(16)	0.5383(12)	0.5879(12)	0.5397(12)	0.3141(33)	0.1611(31)
		21(0.9836)	0.5518(32)	0.5038(16)	0.5133(16)	0.5045(16)	0.1591(18)	0.6612(30)
	Power loss (kW)	60.00	60.22	60.13	60.86	58.78	83.91	97.13
	% Loss reduction	70.39	70.28	70.33	69.97	70.99	58.59	52.07
	Minimum voltage (p.u.)	0.9803	0.9824	0.9823	0.9835	0.9803	0.9612	0.9479
	Minimum VSI	0.9236	0.9314	0.9310	0.9355	0.9234	0.8536	0.8028
Case 5	Tie switch (Open)	8,36,9,33,26	7,17,9,34,28	33,9,8,36,26	33,9,8,36,26	33,9,8,36,27	7,34,9,32,28	–
	DG (MW) (Bus No.)	14(0.8044)	0.9142(12)	0.8049(14)	0.7628(14)	0.7798(14)	0.5897(14)	–
		24(1.1063)	1.2001(30)	1.1059(24)	1.1072(24)	1.1251(24)	0.1895(18)	–
		30(1.3917)	1.2405(24)	1.3929(30)	1.2809(30)	1.3496(30)	1.0146(32)	–
	Power loss (kW)	62.99	62.13	63.01	60.85	62.97	68.28	–
	% Loss reduction	68.92	69.34	68.91	69.97	68.92	66.31	–
	Minimum voltage (p.u.)	0.9837	0.9717	0.9837	0.9811	0.9826	0.9714	–
	Minimum VSI	0.9363	0.9212	0.9364	0.9266	0.9322	0.8896	–

Table 1. Condituen.

Case 6	Tie switch (Open)	7,12,9,31,26	7,9,32,34,26	7,10,12,32,26	33,9,8,32,26	7,10,13,32,27	7,14,11,32,28	7,14,10,32,28
	DG (MW) (Bus No.)	0.5647(18)	0.3999(32)	0.4561(32)	0.462(32)	0.4263(32)	0.5367(32)	0.5258(32)
		1.4618(29)	1.2450(29)	1.2327(29)	1.287(29)	1.2024(29)	0.6158(29)	0.5586(31)
		0.4173(32)	0.7602(18)	0.8463(18)	0.765(18)	0.7127(18)	0.5315(18)	0.5840(33)
	Power loss (kW)	64.56	65.26	65.84	65.87	63.69	67.11	73.41
	% Loss reduction	68.14	67.79	67.51	67.49	68.57	66.88	63.77
	Minimum voltage (p.u.)	0.9748	0.9794	0.9811	0.9815	0.9786	0.9711	0.9704
	Minimum VSI	0.9030	0.9201	0.9265	0.9282	0.9172	0.8892	0.8866
Case 7	Tie switch (Open)	33,34,9,32,28	6,14,10,32,37	7,13,11,32,27	33,13,9,28,30	33,34,11,31,28	–	–
	DG (MW)(Bus No.)	0.5575(18)	1.3289(8)	1.7321(29)	0.801(18)	0.8968(18)	–	–
		0.9223(7)	1.1724(24)	0.8089(16)	1.215(25)	1.4381(25)	–	–
		0.9313(30)	0.7259(31)	0.5498(7)	0.7450(9)	0.9646(7)	–	–
	Power loss (kW)	59.63	58.08	59.37	58.49	53.21	–	–
	% Loss reduction	70.58	71.34	70.70	71.14	73.75	–	–
	Minimum voltage (p.u.)	0.9683	0.9752	0.9804	0.9813	0.9807	–	–
	Minimum VSI	0.8789	0.9043	0.9240	0.9272	0.9249	–	–

Table 2. Performance analysis of optimization techniques for IEEE 33-bus test system.

Case No.	Description	Objective Functions	
		Voltage profile and VSI maximization	Power loss minimization
Case–1	Base case	HSA, FWA, ACSA, Jaya, PSO, TLBO, IPSO	HSA, FWA, ACSA, Jaya, PSO, TLBO, IPSO
Case–2	Reconfiguration only	HSA, FWA, ACSA, Jaya, PSO, TLBO, IPSO	HSA
Case–3	DG allocation only	PSO, IPSO	Jaya
Case–4	DG allocation after reconfiguration	Jaya	ACSA
Case–5	Reconfiguration after DG allocation	PSO, IPSO	Jaya
Case–6	Simultaneous reconfiguration and DG sizing	Jaya	ACSA
Case–7	Simultaneous reconfiguration, allocation and sizing of DG	Jaya	ACSA

Table 3. Results analysis for IEEE 69-bus test system.

Sr. No.	Item	Integrated PSO	TLBO	PSO	Jaya	ACSA	FWA	HSA
Case 1	Tie switch (Open)	69,70,71,72,73	69,70,71,72,73	69,70,71,72,73	69,70,71,72,73	69,70,71,72,73	69,70,71,72,73	69,70,71,72,73
	Power loss (kW)	224.99	224.99	224.99	224.99	224.99	224.99	224.99
	Minimum voltage (p.u.)	0.9092	0.9092	0.9092	0.9092	0.9092	0.9092	0.9092
	Minimum VSI	0.6833	0.6833	0.6833	0.6833	0.6833	0.6833	0.6833
Case 2	Tie switch (Open)	69,70,14,57,61	69,70,14,58,61	55,70,14,61,69	69,70,14,61,56	69,70,14,57,61	69,70,14,56,61	69,18,13,56,61
	Power loss (kW)	99.59	99.59	99.59	99.59	99.59	99.59	99.59
	% Loss reduction	55.74	55.74	55.74	55.74	55.74	55.74	55.74
	Minimum voltage (p.u.)	0.9428	0.9428	0.9428	0.9428	0.9428	0.9428	0.9428
	Minimum VSI	0.7898	0.7898	0.7898	0.7898	0.7898	0.7898	0.7898
Case 3	Tie switch (Open)	69,70,71,72,73	69,70,71,72,73	69,70,71,72,73	69,70,71,72,73	69,70,71,72,73	69,70,71,72,73	69,70,71,72,73
	DG (MW) (Bus No.)	0.6027 (11)	0.5302(17)	0.3803(18)	0.5958(11)	0.6022(11)	0.4085(65)	0.1018(65)
		0.3804(18)	1.8480(61)	0.6027(11)	0.3819(19)	0.3804(18)	1.1986(61)	0.3690(64)
		2.000(61)	0.2404(66)	2.000(61)	2.000(61)	2.000(61)	0.2258(27)	1.3024(63)
	Power loss (kW)	72.47	70.72	72.47	72.44	72.47	77.88	86.78
	% Loss reduction	67.79	68.56	67.78	67.80	67.78	65.38	61.42
	Minimum voltage (p.u.)	0.9890	0.9826	0.9890	0.9890	0.9890	0.9740	0.9677
	Minimum VSI	0.9569	0.9323	0.9569	0.9569	0.9569	0.8999	0.8769
Case 4	Tie switch (Open)	69,70,14,56,61	69,70,14,58,61	55,70,14,61,69	69,70,14,61,56	69,70,14,57,61	69,70,14,56,61	69,18,13,56,61
	DG (MW)(Bus No.)	0.5659(27)	0.2754(69)	0.4899(64)	0.5309(11)	1.7254(61)	1.0014(61)	1.0666(61)
		0.9189(50)	1.4912(61)	1.7433(61)	0.4897(64)	0.4666(64)	0.2145(62)	0.3525(60)
		1.6186(61)	0.2883(27)	0.5318(11)	1.7434(61)	0.3686(12)	0.1425(64)	0.4257(58)
	Power loss (kW)	39.96	39.54	37.54	37.53	37.58	44.23	59.95
	% Loss reduction	82.23	82.42	83.31	83.32	83.29	80.34	73.35
	Minimum voltage (p.u.)	0.9817	0.9735	0.9810	0.9810	0.9807	0.9657	0.9615
	Minimum VSI	0.9284	0.8979	0.9250	0.9251	0.9241	0.8696	0.8527
Case 5	Tie switch (Open)	12,69,13,58,64	10,70,12,54,64	69,14,70,55,64	69,70,13,56,64	69,70,14,58,64	69,70,12,58,61	–
	DG (MW) (Bus No.)	0.6027 (11)	1.8480(61)	0.3803(18)	0.5958(11)	0.6022(11)	0.4085(65)	–
		0.3804(18)	0.5302 (17)	0.6027(11)	0.3819(19)	0.3804(18)	1.1986(61)	–
		2.000(61)	0.2404 (66)	2.0000(61)	2.0000(61)	2.0000(61)	0.2258(27)	–
	Power loss (kW)	41.71	42.01	41.64	41.57	41.65	39.98	–
	% Loss reduction	81.46	81.33	81.49	81.52	81.49	82.23	–
	Minimum voltage (p.u.)	0.9753	0.9714	0.9753	0.9753	0.9753	0.9700	–
	Minimum VSI	0.9049	0.8903	0.9049	0.9049	0.9049	0.8853	–

Table 3. Condituen.

Case 6	Tie switch (Open)	10,20,13,55,61	69,13,12,55,63	69,14,12,55,62	69,16,12,57,61	69,70,12,58,61	69,70,13,55,63	69,17,13,58,61
	DG (MW) (Bus No.)	1.5527(61)	1.0246(61)	0.7722(61)	1.776(61)	1.7496(61)	1.1272(61)	1.0666(61)
		0.1995(62)	0.7440(62)	0.8716(62)	0.305(62)	0.1566(62)	0.2750(62)	0.3525(60)
		0.2099(65)	0.50511(65)	0.5832(65)	0.253(65)	0.4090(65)	0.4159(65)	0.4257(62)
	Power loss (kW)	42.91	41.45	40.59	43.35	40.83	39.56	44.67
	% Loss reduction	80.93	81.57	81.96	80.73	81.85	82.42	80.15
	Minimum voltage (p.u.)	0.9751	0.9804	0.9783	0.9814	0.9810	0.9732	0.9736
	Minimum VSI	0.9041	0.9230	0.9156	0.9272	0.9257	0.8969	0.8985
Case 7	Tie switch (Open)	9,17,13,57,63	38,13,19,52,61	9,70,12,58,62	10,18,14,58,63	69,70,14,58,61	–	–
	DG (MW)(Bus No.)	1.2012(63)	0.8898(21)	1.0227(38)	0.6226(68)	0.5413(11)	–	–
		1.7594(50)	1.5022(61)	0.8834(23)	0.4773(65)	0.5566(65)	–	–
		1.4167(12)	1.3862(3)	1.3403(61)	1.790(62)	1.7240(61)	–	–
	Power loss (kW)	48.37	47.87	41.85	44.04	37.36	–	–
	% Loss reduction	78.50	78.72	81.40	80.42	83.39	–	–
	Minimum voltage (p.u.)	0.9740	0.9741	0.9718	0.9807	0.9807	–	–
	Minimum VSI	0.8999	0.8992	0.8920	0.9239	0.9239	–	–

Table 4. Performance analysis of optimization techniques for IEEE 69-bus test system.

Case No.	Description	Objective Functions	
		Voltage profile and VSI maximization	Power loss minimization
Case–1	Base case	HSA, FWA, ACSA, Jaya, PSO, TLBO, IPSO	HSA, FWA, ACSA, Jaya, PSO, TLBO, IPSO
Case–2	Reconfiguration only	HSA, FWA, ACSA, Jaya, PSO, TLBO, IPSO	HSA, FWA, ACSA, Jaya, PSO, TLBO, IPSO
Case–3	DG allocation only	ACSA, Jaya, PSO, IPSO	TLBO
Case–4	DG allocation after reconfiguration	Jaya, PSO	Jaya
Case–5	Reconfiguration after DG allocation	Jaya, ACSA, PSO, IPSO	Jaya
Case–6	Simultaneous Reconfiguration and DG sizing	Jaya	FWA
Case–7	Simultaneous Reconfiguration, allocation and sizing of DG	ACSA, Jaya	ACSA

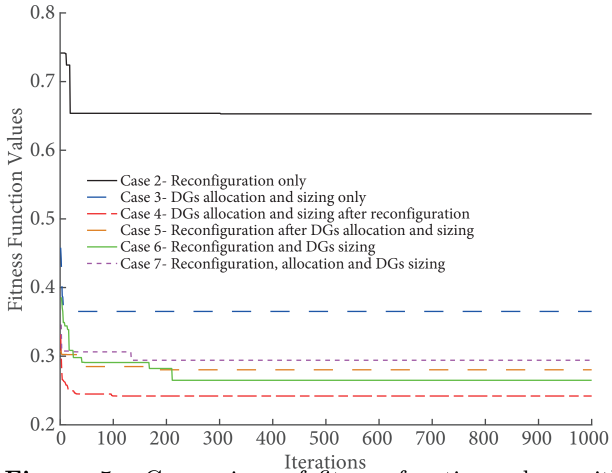

Figure 5. Comparison of fitness function values with PSO.

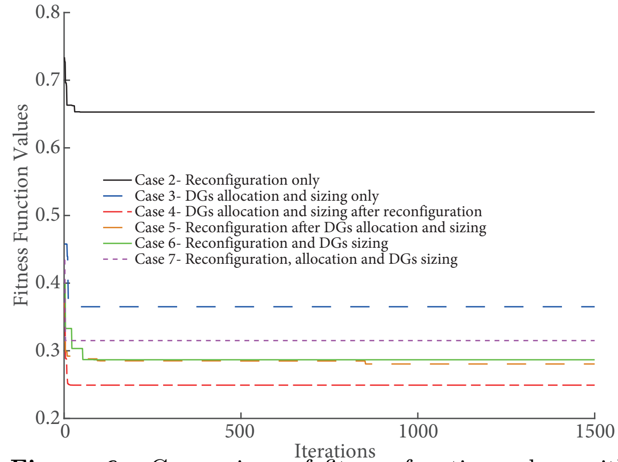

Figure 6. Comparison of fitness function values with IPSO.

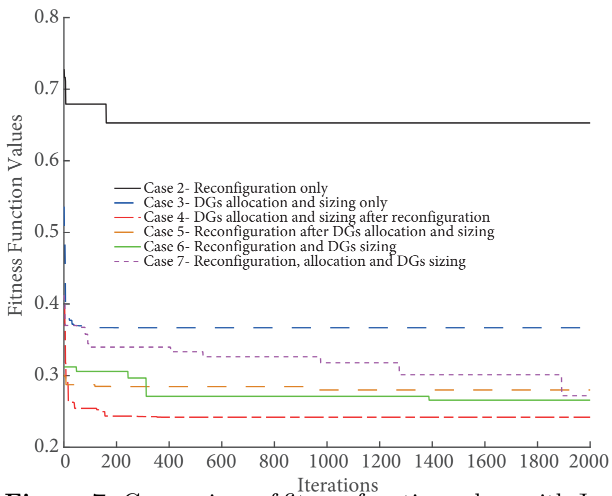

Figure 7. Comparison of fitness function values with Jaya algorithm

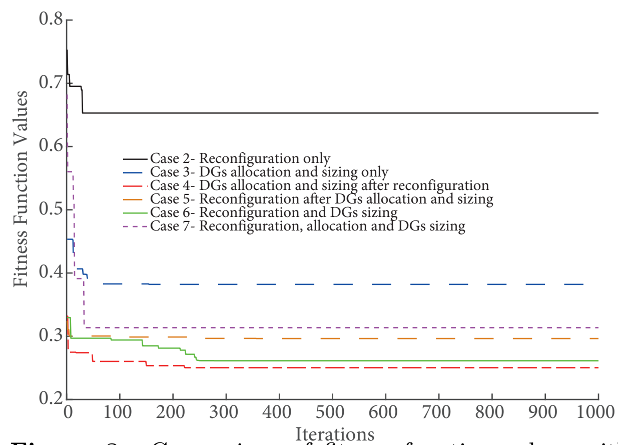

Figure 8. Comparison of fitness function values with TLBO

after reconfiguration, reconfiguration after DG allocation, simultaneous reconfiguration and DG sizing, and simultaneous reconfiguration and DG allocation and sizing were considered. The optimization problem was formulated with multiple objectives of minimization of power loss along with maximization of system VSI and was evaluated for IEEE 33- and 69-bus radial distribution networks. The optimization problem was solved using various techniques, i.e. PSO, IPSO, TLBO, and Jaya optimization and was also compared with ACSA, HSA, and FWA. The Jaya and TLBO optimization techniques do not require any tuning of parameters. Moreover, among all optimization techniques considered, Jaya optimization showed the best performance in all the seven cases framed for IEEE 33- and 69-bus distribution networks. The simulation results highlighted the fact that in simultaneously working on the application of network reconfiguration and DG installation, there is a significant reduction in power loss and enhancement in voltage stability of the network which is in contrast to when only reconfiguration or DG installation was done. The convergence results also revealed that the minimum fitness function was obtained for case 4. Therefore, in order to achieve the combined objective of power loss minimization and voltage stability maximization, a protocol is set to allocate the DGs only after reconfiguration.

This will help in the voltage stability enhancement of radial distribution network empowered by simple, easy, hassle-free Jaya algorithm.

References

[1] Merlin A, Back H. Search for a minimum-loss operating spanning tree configuration for an urban power distribution system. In: Proceedings of 5th PSCC 1975; pp. 1: 1-18.

[2] Olamaei J, Niknam T, Gharehpetian G. Application of particle swarm optimization for distribution feeder reconfiguration considering distributed generators. Appl Math Comput 2008; 201: 575-586.

[3] Esmin AA, Lambert-Torres G, De Souza AZ. A hybrid particle swarm optimization applied to loss power minimization. IEEE Trans Power Syst 2005; 20: 859-866.

[4] Sivanagaraju S, Rao JV, Raju PS. Discrete particle swarm optimization to network reconfiguration for loss reduction and load balancing. Elect Power Compon Syst 2008; 36: 513-524.

[5] Chang RF, Lu CN. Feeder reconfiguration for load factor improvement. In: IEEE Power Engineering Society Winter Meeting; 27–31 May 2002; New York, USA: IEEE. pp. 980-984.

[6] Yin SA, Lu CN. Distribution feeder scheduling considering variable load profile and outage costs. IEEE Trans Power Syst 2009; 24: 652-660.

[7] Niknam T. An efficient hybrid evolutionary algorithm based on PSO and HBMO algorithms for multi-objective distribution feeder reconfiguration. Energ Convers Manage 2009; 50: 2074-2082.

[8] Niknam T. An efficient multi-objective HBMO algorithm for distribution feeder reconfiguration. Expert Syst Appl 2011; 38: 2878-2887.

[9] Olamaei J, Niknam T, Arefi SB. Distribution feeder reconfiguration for loss minimization based on modified honey bee mating optimization algorithm. Energy Procedia 2012; 14: 304-311.

[10] Teng JH, Lui YH. A novel ACS-based optimum switch relocation method. IEEE Trans Power Syst 2003; 18: 113-120.

[11] Carpaneto E, Chicco G, Ant-colony search based minimum losses reconfiguration of distribution systems, In: 12th IEEE Mediterranean Electrotechnical Conference (MELECON); 12–15 May 2004, Dubrovinik, Croatia: IEEE. pp. 971-974.

[12] Khoa TQD, Phan BTT. Ant colony search based loss minimum for reconfiguration of distribution systems. In: IEEE Power India Conference; 10–12 April 2006; New Delhi, India: IEEE. pp. 1-6.

[13] Niknam, T. An efficient hybrid evolutionary algorithm based on PSO and ACO for distribution feeder reconfiguration. Int T Electr Energy 2010; 20: 575-590.

[14] Heidari MA. Optimal network reconfiguration in distribution system for loss reduction and voltage-profile improvement using hybrid algorithm of PSO and ACO. CIRED, Open Access Proc J 2017; 1: 2458-2461.

[15] Parada V, Ferland JA, Arias M, Daniels K. Optimization of electrical distribution feeders using simulated annealing. IEEE Trans Power Del 2004; 19: 1135-1141.

[16] Jeon YJ, Kim JC. Application of simulated annealing and tabu search for loss minimization in distribution systems. Int J Electr Power Energy Syst 2004; 26: 9-18.

[17] Narimani MR, Vahed AA. Azizipanah-Abarghooee R, Javidsharifi M. Enhanced gravitational search algorithm for multi-objective distribution feeder reconfiguration considering reliability, loss and operational cost. IET Gener Transm Distri 2014; 8: 55-69.

[18] Nguyen TT, Nguyen TT, Truong AV, Nguyen QT, Phung TA. Multi-objective electric distribution network reconfiguration solution using runner-root algorithm. Appl Soft Comput 2017; 52: 93-108.

[19] Nara K, Shiose A, Kitagawa M, Ishihara T. Implementation of genetic algorithm for distribution systems loss minimum reconfiguration. IEEE Trans Power Syst 1992; 7: 1044-1051.

[20] Enacheanu B, Raison B, Caire R, Devaux O, Bienia W, HadjSaid N. Radial network reconfiguration using genetic algorithm base on the matroid theory. IEEE Trans Power Syst 2008; 23:186-195.

[21] Abdelaziz M, Distribution network reconfiguration using a genetic algorithm with varying population size. Electr Power Syst Res 2017; 142: 9-11.

[22] Chen Y, Gao L, Zhang H, Xu R, Ding, W. Discrete firefly algorithm based distribution networks reconfiguration. In: 11th IEEE Conference on Industrial Electronics and Applications (ICIEA); 5–7 June 2016; Hefei, China: IEEE. pp. 1045-1048.

[23] Rajaram R, Kumar KS, Rajasekar N. Power system reconfiguration in a radial distribution network for reducing losses and to improve voltage profile using modified plant growth simulation algorithm with Distributed Generation (DG). Energy Reports 2015; 1: 116-122.

[24] Kaur M, Ghosh S. Network reconfiguration of unbalanced distribution networks using fuzzy-firefly algorithm. App Soft Comp 2016; 49:868-886.

[25] Rao RS, Ravindra K, Satish K, Narasimham SV. Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation. IEEE Trans Power Syst 2013; 28: 317-325.

[26] Imran AM, Kowsalya M, Kothari DP. A novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution networks. Int J Electri Power Energy Syst 2014; 63: 461-472.

[27] Chidanandappa R, Ananthapadmanabha T. An integrated gravitational search multi-objective algorithm for distribution network feeder reconfiguration with DGs. In: IEEE International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), 3–5 March 2016, Chennai, India: IEEE. pp. 1973-1979.

[28] Aman MM, Jasmon GB, Bakar AH, Mokhlis H. A new approach for optimum DG placement and sizing based on voltage stability maximization and minimization of power losses. Energy Convers Manage 2013; 70: 202-210.

[29] Wu YK, Lee CY, Liu LC, Tsai SH. Study of reconfiguration for the distribution system with distributed generators. IEEE Trans Power Del 2010; 25: 1678-85.

[30] Nguyen TT, Truong AV, Phung TA. A novel method based on adaptive cuckoo search for optimal network reconfiguration and distributed generation allocation in distribution network. Int J Electr Power Energy Syst 2016; 78: 801-815.

[31] Azizivahed A, Narimani H, Naderi E, Fathi M, Narimani MR. A hybrid evolutionary algorithm for secure multi-objective distribution feeder reconfiguration. Energy 2017; 138: 355-373.

[32] Venkaiah C, Jain, RV. Multiobjective Jaya algorithm based optimal location and sizing of distributed generation in a radial distribution system. In: IEEE Asia-Pacific Power and Energy Engineering Conference (APPEEC), 8–10 Nov. 2017, Banglore India. IEEE. pp. 1-6.

[33] Ghosh A, Kumar D, Samantaray SR. Simultaneous reconfiguration with DG placement using bit-shift operator based TLBO. In: IEEE National Power Systems Conference (NPSC), 19–21 Dec 2016, Bhubaneswar, India. IEEE. pp. 1-6.

[34] Mortazavi A, Toğan V. Simultaneous size, shape, and topology optimization of truss structures using integrated particle swarm optimizer. Struct Multidiscip O 2016; 54: 715-736.

[35] Chakravorty M, Das D. Voltage stability analysis of radial distribution networks. Int J Electr Power Energy Syst 2001; 23: 129-135.

[36] Kennedy J, Eberhart RC. Particle swarm optimization. In: EEE International Conference on Neural Networks. 1995. pp. 1942–1948.

[37] Dolatdar E, Soleymani S, Mozafari B. A new distribution network reconfiguration approach using a tree model. World Acad Sci Eng Technol 2009; 58: 1186-1193.