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Optimal multi-objective reconfiguration and capacitor placement of distribution systems with the Hybrid Big Bang–Big Crunch algorithm in the fuzzy framework

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Abstract Network reconfiguration and capacitor placement are useful options applied to reduce power losses and to keep voltage profiles within permissible limits in distribution systems. This study presents an efficient algorithm for optimization of balanced and unbalanced radial distribution systems by a network reconfiguration and capacitor placement. An important property of the proposed approach is solving the multi-objective reconfiguration and capacitor placement in fuzzy framework and its high accuracy and fast convergence. The considered objectives are the minimization of total network real power losses, the minimization of buses voltage violation, and load balancing in the feeders. The proposed algorithm has been implemented in three IEEE test systems (two balanced and one unbalanced systems). Numerical results obtained by simulation show that the performance of the Hybrid Big Bang Big Crunch (HBB–BC) algorithm is slightly higher than or similar to other meta-heuristic algorithms.

1. Introduction

Capacitors have been applied to compensate for network reactive power losses, and are used to prevent the violation of voltage profile from permissible limits as well. The advantages of compensation depend on the location and size of capacitors. Two types of switches are used in distribution systems that can change network topology. These switches are normally closed switches (sectionalizing switches) and normally open switches (tie switches). Feeder reconfiguration is the process of changing the topology and configuration of distribution systems by altering the open or closed status of switches. Optimal network reconfiguration and capacitor placement have been separately investigated in many papers, and different approaches have been used to solve the problems associated with feeder reconfiguration and capacitor placement. These approaches which include different objective

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functions and optimizing methods for obtaining the optimal solution are different from one another.

In recent years, many algorithms have been developed for loss reduction and other utilization factors using network reconfiguration of distribution systems. Most of these algorithms are based on heuristic techniques and artificial intelligence methods. Many studies have focused on network reconfiguration. In [1], a new Meta-heuristics Fireworks Algorithm is proposed to optimize the radial distribution network while satisfying the operating constraints. Ref. [2] presents a step-by-step heuristic algorithm for the reconfiguration of radial electrical distribution systems, aiming at power loss minimization, based on a Dynamic Switches Set approach, which is updated due to topological changes in the electrical network and to avoid the premature convergence of the algorithm in suboptimal solutions. A method to improve the power quality and reliability of distribution systems by employing optimal network reconfiguration is presented in [3], which is applied independently to a system in a specified period to minimize the number of propagated voltage sags and other reliability indexes. The Quantum-Inspired Binary Firefly Algorithm is used to find the optimal network reconfiguration. In [4] a Modified Tabu Search (MTS) algorithm is used to reconfigure distribution systems so that active power losses are globally minimized with turning on/off sectionalizing switches. Tabu Search algorithm is introduced with some modifications such as using a Tabu list with variable size according to the system size. A salient feature of the MTS method is that it can quickly provide a global optimal or near-optimal solution to the network reconfiguration problem. A methodology for the reconfiguration of radial electrical distribution systems based on the bio-inspired meta-heuristic Artificial Immune System (AIS) to minimize energy losses is presented in [5], which radiality and connectivity constraints are considered as well as different load levels for planning the system operation. In [6] an efficient HBB–BC optimization algorithm to solve the multi-objective reconfiguration of balanced and unbalanced distribution systems in a fuzzy framework was presented. The objectives considered were the minimization of total real power losses, the minimization of buses voltage deviation, and load balancing in the feeders. In [7] allocation of power losses to consumers connected to radial distribution networks before and after network reconfiguration in a deregulated environment is presented. The network reconfiguration algorithm is based on the fuzzy multi-objective approach and the max–min principle is adopted for the multi-objective optimization in a fuzzy framework. Multiple objectives are considered for real-power loss reduction in which nodes voltage deviation is kept within a range, and an absolute value of branch currents is not allowed to exceed their rated capacities. An adapted Ant Colony Optimization (ACO) for the reconfiguration of radial distribution systems and minimization of real power loss was used in [8] that conventional ant colony optimization is adapted by the graph theory to always create feasible radial topologies during the whole evolutionary process which avoids tedious mesh check and hence reduces the computational burden.

Ref. [9] introduces an optimal distribution network reconfiguration based on a branch exchange strategy. The goals of optimization are minimization of the cost of power losses and the cost of damages due to power supply interruption. In [10] a Binary Particle Swarm Optimization (BPSO) is used for finding the optimal status of the switches for distribution system reconfiguration. Maximizing the reliability indices and minimizing the real power loss are the goals of optimization. In [11] a Pareto based optimization technique called Micro Genetic Algorithm is utilized for distribution system reconfiguration. This algorithm finds the optimal status switches for maximizing the reliability indices and minimizing the real power loss. Ref. [12] uses an efficient fuzzy decision-making based on Bellman–Zadeh method for optimal distribution network reconfiguration. The goal was to reduce power losses, enhance the voltage profile for customers, and increase the reliability levels. Zidan et al. [13] proposed an approach based on a trial and error algorithm and evaluation of switching indices for optimal reconfiguration in distribution networks. Two objectives were minimized: power losses and average system interruption frequency. Tomoiaga et al. [14] propose a Pareto based optimal reconfiguration of power distribution systems by a Genetic Algorithm Based on NSGA-II. The minimization of active power losses and system average interruption frequency index are the goals of optimization. Mazza et al. [15] introduce the optimal reconfiguration of distribution network using a Pareto based Genetic Algorithm. The goals are minimizing the total energy losses: the total Energy Not Supplied (ENS) and the Load Balancing Index (LBI).

The problem of capacitor placement for loss reduction in electric distribution systems has been extensively researched in many articles. For example, a Fuzzy based approach is proposed in [16]. In [17] a mixed integer Linear Programming (LP) model is proposed to determine the size, location and number of capacitor banks in distribution systems; in [18] a two stage method for loss reduction is considered in the formulation, and by using a genetic algorithm the optimal operation status of the devices is determined, which in turn determines the location and number of capacitors. In [19], to solve the capacitor placement problem, a single objective probabilistic optimal allocation is considered. In [20], the author uses a Honey Bee Foraging Approach (HBFA) to optimal capacitor placement for reduction of harmonic distortion. In [21] the optimal allocation and sizing of capacitors are found using BB–BC optimization algorithm.

There are many studies simultaneously dealing with both network reconfiguration and capacitor placement [22–24]. For example, in [25], the Simulated Annealing (SA) algorithm is employed for reconfiguration of the distribution network and a discrete optimization algorithm is used to find the optimal capacitor. In [26], three heuristic methods include Genetic, Simulated Annealing and Tabu Search algorithms which are used for optimal distribution network's reconfiguration and capacitor compensation. Ref. [27] deals with the problem of optimal voltage regulation and power losses minimization in distribution systems that are equipped with shunt capacitor banks. In [27] with the optimal control of tie-switches and capacitor banks on the feeders of a large radially operated meshed distribution system, the power losses and voltage deviations are minimized using adopted Evolutionary Algorithm for optimization and fuzzy set theory for scaling of objectives. The membership function for scaling is a bell-shaped normal distribution function and operator for combining the two objectives values which are their minimum (intersection), and their product [27]. In [28] Zhang et al. have used the Improved Adaptive Genetic Algorithm (IAGA) and a simplified branch exchange algorithm for capacitor placement and reconfiguration problems respectively. In [29] Farahani et al. have used the simple branch exchange method for the reconfiguration problem and have shown that loops selection sequence affects the optimal configuration and the network loss. They have also proposed a joint optimization algorithm for combining this improved method of reconfiguration and capacitor placement. In [29], the discrete Genetic Algorithm (GA) is used to optimize the location and size of capacitors and the sequence of loops selection. In [30] Chung-Fu Chang has developed new algorithms for solving the optimal feeder reconfiguration and capacitor placement problems. There, he uses the Ant Colony Search Algorithm (ACSA) for solving feeder reconfiguration optimization and capacitor placement problems simultaneously. In [31] Montoya et al. utilize a Minimum Spanning Tree (MST) algorithm to determine the configuration of minimum losses in reconfiguration problem and use GA to achieve the greatest savings through the optimal capacitor placement problem. In [32] Guimarąes et al. use a modified dedicated Genetic Algorithm-based approach that has been successfully developed and implemented. It presents low computational effort and is able to find good quality configurations and capacitor allocation. In [33] some planning issues for the priority of reconfiguration and capacitor placement problems in power distribution networks are investigated based on a new Improved Binary Particle Swarm Optimization (IBPSO) algorithm. The proposed method employs a different structure for the optimization problem.

Considering the above mentioned features, the contribution of this paper is to present the simultaneous optimal reconfiguration and capacitor placement problems in distribution systems using a fuzzy-based multi-objective programming method. The objective functions include the minimization of total real power losses and buses voltage violation and also load balancing in the feeders. We here also considered unbalanced power systems in the reconfiguration and capacitor allocation problem, a matter which has been rarely addressed in the literature. A fuzzy-based framework is used to transform objective functions into fuzzy memberships and then finally to combine them into a single objective function, which is optimized subject to a variety of power system operational constraints. The HBB–BC algorithm, as one of the latest evolutionary optimization tools to solve multi-objective problems, is modified here by adding a mutation operator to improve its exploration capability [34] and then it is used to solve the proposed problem. The proposed method is tested on balanced 33-bus and 94-bus distribution systems and a 25-bus unbalanced distribution system. Numerical results show the efficiency of the HBB–BC algorithm compared to the other algorithms.

2. Proposed method for reconfiguration and capacitor allocation

In this section, the proposed formulation for distribution system reconfiguration in the presence of capacitors is elaborated with its objective functions and constraints.

2.1. Objective functions

- *Minimization of power losses*

Minimizing active power losses has been one of decisive issues in distribution systems. It is calculated as sum of power loss of branches as

$$\min f_1 = P_{loss} = \sum_{k=1}^{N_{br}} R_k |I_k|^2 \tag{1}$$

where R_k and I_k represent the resistance and current of branch k, respectively; N_{br} is the total number of branches in the system.

- *Minimization of Bus Voltage Deviation Index (VDI)*

For the purpose of minimizing the bus voltage violation, the index of Voltage Deviation Index (VDI) is defined as follows:

$$\min f_2 = \mathrm{VDI}_i = \max(|1 - V_{\mathrm{mini}}| \text{ and } |1 - V_{\mathrm{maxi}}|) \tag{2}$$

where V_{mini} and V_{maxi} are the minimum and maximum values of bus voltage for each configuration respectively.

- *Minimization of Load Balancing Index (LBI)*

For the purpose of Load Balancing, first an appropriate parameter is defined, indicating what portion of the branches has been loaded. This portion is defined as the line usage index for the ith branch, calculated as follows [35]:

$$\text{Line Usage Index} = \frac{I_k}{I_k^{\max}} \tag{3}$$

where I_k represents the current of branch k; $I_k^{\max}$ is the permitted rating of branch k.

LBI is calculated and parameter of Y is expressed as follows:

$$Y = \left[\frac{I_1}{I_1^{\max}} \; \frac{I_2}{I_2^{\max}} \; \frac{I_3}{I_3^{\max}} \cdots \frac{I_{N_{br}}}{I_{N_{br}}^{\max}} \right] \tag{4}$$

So the LBI index is expressed as follows:

$$\min f_3 = \mathrm{LBI} = Var(Y) \tag{5}$$

where Var represents the variance operation. However, the smaller value of the LBI index indicates that the load balancing has been conducted more efficiently.

2.2. Fuzzy-based combination of objective functions

In order to find a solution in which all objective functions are optimized, we should use a multi-objective programming method. In view of the fact that the three considered objective functions have different scales, using the simple method of combining them into one objective function results in scaling problems. In order to transform objective functions into the same range, we here use the fuzzification method [36]. Using this method, all objective functions are fuzzified and transformed into the same range of $[0, 1]$. The fuzzy linear membership for objective function i, which is for minimization, is defined as follows:

$$\rho_i = \begin{cases} 1 & f_i \leqslant f_i^{\min} \\ \frac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}} & f_i^{\min} \leqslant f_i \leqslant f_i^{\max} \\ 0 & f_i \geqslant f_i^{\max} \end{cases} \tag{6}$$

where $f_i^{\min}$ and $f_i^{\max}$ represent the *ideal* and *nadir* values for objective function i, respectively; f_i is objective function value; ρ_i is its fuzzy membership value.

Ideal and nadir values represent the best and worst accessible value of each objective function, respectively, in the solution space of the problem. The ideal value for each objective function is obtained by individually optimizing the objective function regardless of other objective functions. Then, we should carry out three individual single objective optimization tasks to get the ideal value of three objective functions described in the previous subsection. By individually optimizing each objective function, the value of other objective functions is also obtained and they may not be optimal if objective functions are competing; that is, optimizing one objective function makes others be deteriorated. Among the obtained values from individual optimizations, the worst value of each objective function gives its nadir value. More details can be found in [36].

The fuzzy membership as a function of objective function is depicted in Fig. 1. In this figure, a smaller value of the objective function leads to a larger membership function, which is more preferred when the objective function is for minimization. In the proposed method, three memberships of ρ_{Loss}, ρ_{VDI} and ρ_{LBI} are calculated for objective functions of loss, VDI and LBI, respectively. There are several methods to combine these memberships and constitute an overall fuzzy satisfaction function representing the fitness of the solution of the multi-objective problem. If the combination of objective functions is done carefully without scaling problems, the Pareto optimality of the solution can be guaranteed [37] and at the same time, it has less computation burden than Pareto-based methods [37]. This type of combining objective functions has already been used in some papers such as [36] using some operators. In [38], Gupta et al. introduced a newer operator named "*max geometric mean*" that gives better performance than other techniques of combining objective functions. Using this technique, the degree of overall fuzzy satisfaction is computed as follows:

$$\mu_f = (\rho_{Loss} \cdot \rho_{VDI} \cdot \rho_{LBI})^{1/3} \quad (7)$$

where μ_f represents the overall fitness function of the solution. This overall fitness function is the objective function that is maximized in our multi-objective problem.

2.3. Constraints

The proposed multi-objective problem for simultaneous reconfiguration and capacitor allocation is optimized subject to following constraints:

- *Power flow equations*

Active and reactive power balance at each node of the network should be observed using following constraints:

$$PG_i - PD_i = \sum_{j=1}^{N_{bus}} |V_i||V_j||Y_{ij}|\cos(\delta_i - \delta_j - \varphi_{ij}) \quad i = 1, \ldots, N_{bus} \quad (8)$$

$$QG_i - QD_i = \sum_{j=1}^{N_{bus}} |V_i||V_j||Y_{ij}|\sin(\delta_i - \delta_j - \varphi_{ij}) \quad i = 1, \ldots, N_{bus} \quad (9)$$

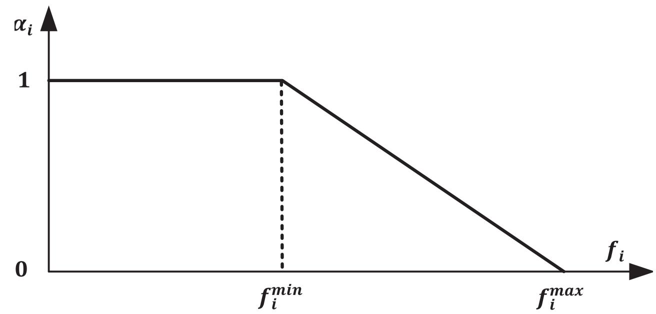

Figure 1 Trapezoidal fuzzy membership function for objective functions.

where PG_i and QG_i are active and reactive generations at bus i; PD_i and QD_i are active and reactive demands at bus i; V_i and δ_i represent the magnitude and angle of voltage phasor at bus i; $|Y_{ij}|$ and φ_{ij} are the magnitude and angle of ij entry from the bus admittance matrix; and N_{bus} is number of buses.

- *Network radiality and connectivity*

This can be achieved by using the Kirchhoff algebraic method based on the bus incidence matrix that proposed in [4,39]. This connection matrix obtained by graph theory has one row for each branch and one column for each node. Each member of this matrix is determined by the following rules:

- $a_{i,j} = 0$ if branch i is not connected to node j
- $a_{i,j} = 1$ if branch i is directed away from node j
- $a_{i,j} = -1$ if branch i is directed toward node j

The first column corresponding to the reference node is removed, and the resultant square branch-to-node matrix is denoted by A. The system radiality is specified by the value of the determinant of A. If the determinant of A is equal to 1 or −1, then the system configuration is radial, but if the determinant of A is equal to zero, the system configuration is not radial or some loads are not energized.

- *Branch current limits*

In order to protect cables and feeders against excessive currents, their rating should be taken into account:

$$|I_k| \leqslant I_k^{\max} \quad k = 1, \ldots, N_{br} \quad (10)$$

- *Bus voltage permissible range*

Bus voltages after reconfiguration and capacitor allocation should remain in their permissible range specified by the system operator:

$$V_{\min} \leqslant V_j \leqslant V_{\max} \quad j = 1, \ldots, N_{bus} \quad (11)$$

where $V_{\min}$ and $V_{\max}$ are minimum and maximum allowable voltages, respectively, which are considered as $V_{\min} = 0.95$ p.u. and $V_{\max} = 1.05$ p.u.

3. HBB–BC algorithm

In this section, after briefly reviewing the basic BB–BC method, the modified version of HBB–BC which is used to solve the proposed formulation, is introduced.

3.1. Basic BB–BC

In this section, first we introduce the BB–BC algorithm, and then will explain how this algorithm can be combined with the capabilities of the PSO algorithm to create the HBB–BC algorithm. The HBB–BC algorithm is a combination of the BB–BC algorithm [40,41] and the PSO algorithm. In fact, this algorithm utilizes the PSO's abilities to improve the search ability and also uses mutation operator to avoid trapping into the local optimum. The BB–BC optimization algorithm is a powerful method with several advantages. These include few control parameters and optimization capabilities such as quick convergence and easy implementation. This algorithm comprises two basic sages:

Stage 1: the random distribution of the initial candidate in the search space, called the Big Bang phase.

Stage 2: the continuation of the previous stage with Big Crunch phase that is a convergence operator with some input and only one output called center of mass. Each individual is generated in initial population and is considered as candidate solution. The center of mass is computed with respect to the positions of each individual in the population as follows:

$$A_i^{c(k)} = \frac{\sum_{j=1}^{N} \frac{1}{f_j} A_i^{c(k,j)}}{\sum_{j=1}^{N} \frac{1}{f_j}} \quad i = 1, 2, \ldots, D \tag{12}$$

where $A_i^{c(k)}$ is the ith component of the center of mass in the kth iteration and $A_i^{c(k,j)}$ represents the ith component of the jth candidate generated in the kth iteration; D represents the number of control variables; f_j represents the fitness function value of candidate j; N represents the population size in the stage 1 of BB–BC algorithm or Big Bang phase randomly generated within the search space.

After the Big Crunch phase, the algorithm generates new candidate solution as the Big Bang phase to be used for the next iteration using center of mass.

Using normal distribution function the new candidates for the next iteration of the Big Bang are normally distributed around the center of mass and the standard deviation of this normal distribution function reduces by increasing the number of iterations as follows:

$$A_i^{(k+1,j)} = A_i^{c(k)} + \frac{r_j \alpha_1 (A_{i\max} - A_{i\min})}{k+1}, \quad i = 1, 2, \ldots, D \tag{13}$$

where r_j represents a random number obtained from the standard normal distribution function and changes for each candidate; α_1 represents a parameter for limiting the size of the search space; k is number of iterations; $A_{i\max}$ and $A_{i\min}$ represent the upper and lower limits for the ith control variable respectively.

All of the above steps will be repeated until a stopping criterion has been satisfied.

3.2. Overview of PSO

PSO is a swarm intelligence class method which was invented in the mid-1990s [42]. The PSO is a population-based stochastic optimization algorithm and recently, it has acquired wide applications in optimizing design problems because of its simplicity and ability to optimize complex constrained objective functions in multimodal search spaces [43]. In the PSO each potential solution is referred as a particle and each set of particles composes a population. Each particle maintains the position associated with the best fitness ever experienced by it in a personal memory called pbest. Besides, the position associated with the best value obtained so far by any particle is called gbest. In any iteration, the pbest and gbest values are updated and each particle modifies its velocity to move toward them stochastically. This concept can be formulated as

$$V_j^{(k+1)} = w \times V_j^{(k)} + c_1 r_1 (pbest_j^{(k)} - x_j^{(k)}) + c_2 r_2 (gbest^{(k)} - x_j^{(k)}) \tag{14}$$

$$x_j^{(k+1)} = x_j^{(k)} + V_j^{(k+1)} \quad j = 1, \ldots, N \tag{15}$$

where V is particle velocity; x is particle position; w is inertia weight factor; c_1, c_2 are cognitive and social acceleration factors, respectively; r_1, r_2 are uniformly distributed random numbers in the range $(0, 1)$; $pbest_j^{(k)}$ and $gbest^{(k)}$ represents the best position of the jth particle and the best global position up to iteration k, respectively.

Appropriate selection of c_1, c_2 and w plays an important role in effective performance of the PSO. In some cases the convergence is premature, especially for small inertia weight factor. As the early found global best in the searching procedure may be a local minimum, an Improved PSO (IPSO) is used to avoid such a case. This variant of PSO has been proposed by [44] and called as IPSO. Initially, we define a growth indicator β for each particle, which will be increased if the current fitness value of particle is smaller than that of the previous iteration. When the personal bests of all particles are updated in each generation, we consider personal bests having smaller fitness values than the global best as the candidate global best. Finally, the global best will be replaced by the candidate personal best with the highest growth indicator β.

3.3. Hybrid BB–BC algorithm

As mentioned above, the HBB–BC algorithm uses the PSO capacities and also mutation operator to have better efficiency. This operator reduces the problem of trapping into the local optimum. As we know the PSO algorithm uses a swarm of particles as candidate solutions for the optimization problem in which each particle tunes its trajectory toward the best local and global positions found. Eq. (13) for the HBB–BC algorithm is expressed as follows, so that in addition to the center of mass the best local and global positions are also used to generate the new candidates.

$$\begin{aligned} A_i^{(k+1,j)} &= \alpha_2 A_i^{c(k)} + (1-\alpha_2)(\alpha_3 A_i^{gbest(k)} + (1-\alpha_3) A_i^{lbest(k,j)}) \\ &\quad + \frac{r_j \alpha_1 (A_{i\max} - A_{i\min})}{k+1} \begin{cases} i = 1, 2, \ldots, D \\ j = 1, 2, \ldots, N \end{cases} \end{aligned} \tag{16}$$

In (16), parameters of α_2 and α_3 are used for controlling the effect of the best global and local positions on the new position of the candidates respectively, and $A_i^{lbest(k,j)}$ and $A_i^{gbest(k)}$ represent the best position of the jth particle and the best global position for variable control ith up to iteration k, respectively.

To obtain the discrete solution, the function of round(X) is used, which rounds the elements of X to the nearest integers.

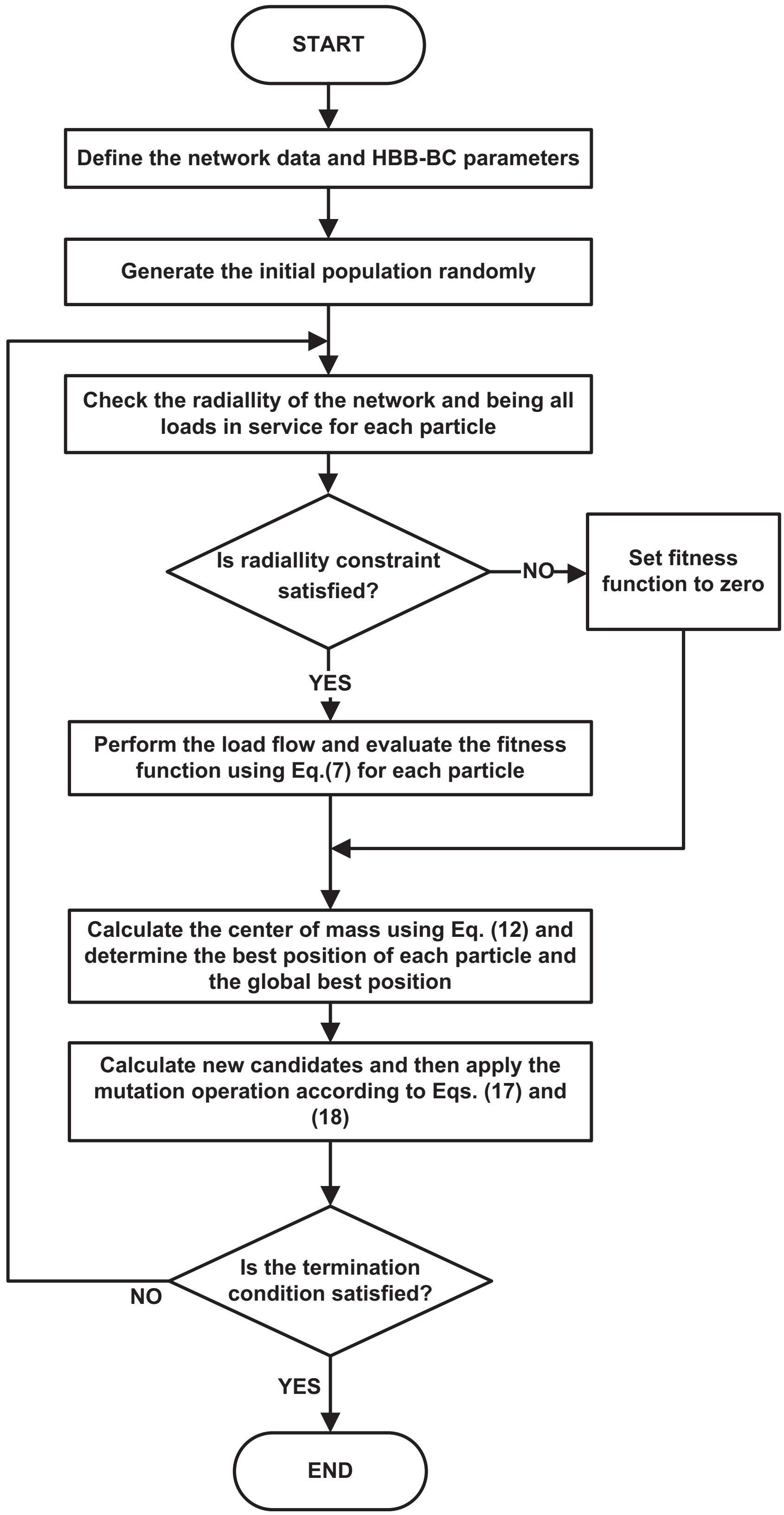

Figure 2 Flowchart of proposed HBB–BC algorithm.

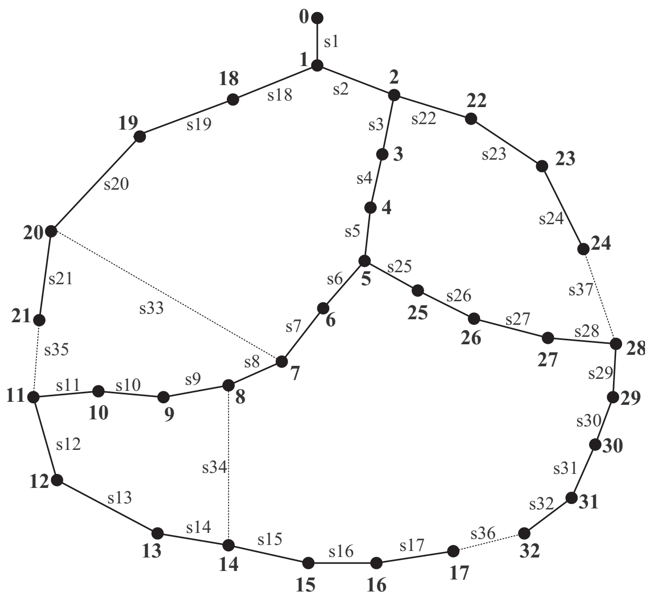

Figure 3 Baran and Wu distribution test system (33-bus).

$$A_i^{(k+1,j)} = round\Big(\alpha_2 A_i^{c(k)} + (1-\alpha_2)\Big(\alpha_3 A_i^{gbest(k)} + (1-\alpha_3) A_i^{lbest(k,j)}\Big) + \frac{r_j \alpha_1 (A_{i\max} - A_{i\min})}{k+1}\Big) \quad (17)$$

Furthermore, as mentioned before, the mutation operator is used to avoid trapping into the local optimum. In (18) rand() is a number generated between zero and 1, and if this number is smaller than the mutation probability, the new candidate for the next iteration ($A_i^{(k+1,j)}$) is expressed as follows:

$$A_i^{(k+1,j)} = \text{round}(A_{i\min} + \text{rand}() \times (A_{i\max} - A_{i\min})) \text{ if rand}() < Pm \quad (18)$$

Note that Pm is a mutation probability.

4. Implementation of the HBB–BC Algorithm

In the proposed algorithm, the number of switchs to be opened to maintain a feasible radial configuration and the capacitors that should be placed in candidate buses are considered as control variables. So control variables are integer numbers, and the number of those is the sum of the number of tie switches and the number of buses that is candidate for capacitor placement, which is expressed as follows:

$$N_{cv} = N_L + N_{busc} \quad (19)$$

where N_{cv} is the number of control variables, N_L is the number of tie switches and N_{busc} is the number of network buses that are candidates for capacitor placement. Due to practical and economical considerations, some researchers of distribution systems have not considered all of network buses as candidates for capacitor installation [45]. However, in many research, all network buses except the slack bus are candidate places for capacitor installation [16,18–21,30,33,48]. The latter case is considered in this paper. The number of tie switches is obtained as follows [6]:

$$N_L = N_{br} - N_{bus} + 1 \quad (20)$$

where N_L is the number of tie switches, N_{br} is the total number of network branches and N_{bus} is the number of network buses.

For example in 33-bus system shown in next section, the number of tie switches is 5 and the number of buses for capacitor placement is 32 (the bus zero is slack bus and is ignored for capacitor placement). So the total number of control variables is 37. Each candidate solution or individual has 37 sections.

In the first step, loop and capacitor vectors should be defined. In the proposed algorithm each loop vector consists of switches that form a loop in network. In other words, the number of loop vectors is equal to the number of fundamental loops or tie switches. In 33-bus system the number of fundamental loop is five, and so the number of loop vectors is five too.

$$\text{loop vectors } 1 = [s_2, s_3, s_4, s_5, s_6, s_7, s_{33}, s_{20}, s_{18}, s_{19}]$$
$$\text{loop vectors } 2 = [s_8, s_9, s_{10}, s_{11}, s_{35}, s_{21}, s_{33}]$$
$$\text{loop vectors } 3 = [s_9, s_{10}, s_{11}, s_{12}, s_{13}, s_{14}, s_{34}]$$
$$\text{loop vectors } 4 = [s_{22}, s_{23}, s_{24}, s_{37}, s_{28}, s_{27}, s_{26}, s_{25}, s_5, s_4, s_3]$$
$$\text{loop vectors } 5 = [s_{25}, s_{26}, s_{27}, s_{28}, s_{29}, s_{30}, s_{31}, s_{32}, s_{36}, s_{17}, s_{16}, s_{15}, s_{34}, s_8, s_7, s_6]$$

To define the capacitor vectors for one bus, six sizes of capacitors 300, 600, 900, 1200, 1500 and 1800 kvar are used [33]. In this paper it is assumed that for each bus of system a capacitor is selected and placed from capacitor vectors as follows:

$$\text{capacitor vector} = [0, 300, 600, 900, 1200, 1500, 1800]$$

This capacitor vector is repeated for all buses that should be candidate for capacitor placement. For example in 33-bus system the number of capacitor vectors is 32 because capacitor vectors are not considered for slack bus. The main vector consisting of loop and capacitor vectors is expressed as follows:

$$\text{main vectors} = \begin{bmatrix} s_2 s_3 s_4 s_5 s_6 s_7 s_{33} s_{20} s_{18} s_{19} 000000; \\ s_8 s_9 s_{10} s_{11} s_{35} s_{21} s_{33} 000000000; \\ s_9 s_{10} s_{11} s_{12} s_{13} s_{14} s_{34} 000000000; \\ s_{22} s_{23} s_{24} s_{37} s_{28} s_{27} s_{26} s_{25} s_5 s_4 s_3 00000; \\ s_{25} s_{26} s_{27} s_{28} s_{29} s_{30} s_{31} s_{32} s_{36} s_{17} s_{16} s_{15} s_{34} s_8 s_7 s_6; \\ 030060090012001500180000000000; \\ 030060090012001500180000000000; \\ 030060090012001500180000000000; \\ 030060090012001500180000000000; \\ . \\ . \\ . \end{bmatrix}$$

For the initialization of each individual, one switch is randomly chosen from each loop vector to be opened and one capacitor is also chosen from each capacitor vector to be allocated.

The HBB–BC algorithm is applied to the problem of the multi-objective network reconfiguration and capacitor placement as follows:

Table 1 Results obtained by optimizing the real power losses for case study 1.

Methods	Power losses (kW)	Loss reduction (%)	Minimum voltage (p.u.)	LBI	Open switches	Capacitor located at (buses)	CPU time (sec)
Initial state	202.677	–	0.9130905	0.1575671	33-34-35-36-37	–	–
HBB–BC	92.5757	54.32	0.95858745	0.0448190	7-11-14-37-32	300 (2-4-10-11-18-24-28-29-30)	7.125
PSO	95.38	52.93	0.9635100	0.046994	7-10-14-37-36	300 (9-10-31) 600 (6-29)	6.247
IPSO	98.834	51.23	0.965607	0.0400872	11-28-33-34-36	300 (5-13-32) 1200 (28)	7.065
IBPSO [33]	93.061	54.08	0.9585	0.0433806	7-9-14-32-37	300 (11-24-32) 600 (6-29)	–
ACO [47]	95.79	52.73	0.9656	0.0469611	7-9-14-32-37	450 (28) 600 (20-29)	–

Table 2 Results obtained by optimizing the voltage violation of the buses for case study 1.

Methods	Power losses (kW)	Loss reduction (%)	Minimum voltage (p.u.)	LBI	Open switches	Capacitor located at (buses)	CPU time (sec)
Initial state	202.677	–	0.9130905	0.1575671	33-34-35-36-37	–	–
HBB–BC	187.3618	7.55	0.98441113	0.0946266	6-35-13-37-17	300 (1-2-12-16-17-18-19) 600 (13-24) 900 (24) 1200 (30)	7.267
PSO	103.1509	49.105	0.96942101	0.0432883	7-11-34-28-36	300 (9-14-19-25) 600 (28) 900 (31)	6.984
IPSO	183.073	9.67	0.98617336	0.10167143	7-9-34-37-36	300 (1-9-14-15-20-22-32) 1200 (23) 1500 (28) 600 (29)	7.168

Table 3 Results obtained by optimizing the load balancing for case study 1.

Methods	Power losses (kW)	Loss reduction (%)	Minimum voltage (p.u.)	LBI	Open switches	Capacitor located at (buses)	CPU time (sec)
Initial state	202.677	–	0.9130905	0.1575671	33-34-35-36-37	–	–
HBB–BC	127.472	37.10	0.96323607	0.039968	7-35-34-37-32	300 (5-19-23) 600 (16-18) 1200 (31)	7.254
PSO	149.534	26.22	0.9703912	0.0282468	7-35-34-37-32	300 (7) 600 (29-31) 900 (32)	6.342
IPSO	135.541	33.12	0.9601967	0.030369	33-11-34-28-36	300 (25-26-27) 900 (16-32)	7.167

1. Defining the input data. In this step, the input data are defined including the initial network configuration, line impedance, the total number of fundamental loops and capacitor vectors for each bus, the number of switches in each loop, the number of population, the limiting parameter of the size of the search space (α_1), adjustable parameters (α_2, α_3), mutation probability (*Pm*), and the number of iterations.
2. Generating the initial population. For the initialization of each individual, one switch from each fundamental loop or loop vector to be opened and one capacitor from capacitor vector to be placed is randomly chosen.
3. Checking the radiality of the network and all loads being in service for each individual. If the network is not radial or that at least one load has been isolated. In this state, the value of fitness function is considered to be zero.
4. Performing the load flow. By allocating capacitors that are determined by each individual in candidate buses a direct approach proposed in [46] is used for load flow solution. The value of the fitness function (μ_f) is calculated using the results of distribution load flow for each radial structure.

Table 4 Results obtained by optimizing the multi-objective fitness function for case study 1.

Methods	Power losses (kW)	Loss reduction (%)	Minimum voltage (p.u.)	LBI	Open switches	Capacitor located at (buses)	CPU time (sec)
Initial state	202.677	–	0.9130905	0.1575671	33-34-35-36-37	–	
HBB–BC	98.4	51.45	0.95418166	0.0464988	7-10-14-37-32	300 (10-12-26) 600 (3) 900 (29)	7.354
PSO	100.05	50.63	0.9616666	0.046695	7-11-34-37-36	300 (16-25-30-32) 600 (1-5)	6.752
IPSO	101.11	50.11	0.9706953	0.04698	7-10-14-37-36	300 (11-17-25) 600 (28-32) 900 (2)	7.225

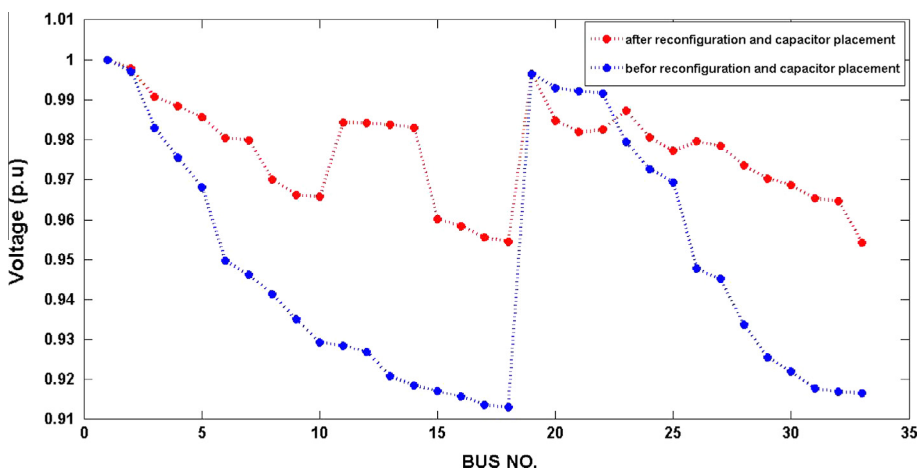

Figure 4 Voltage profiles before and after optimal reconfiguration and capacitor placement in 33-bus system.

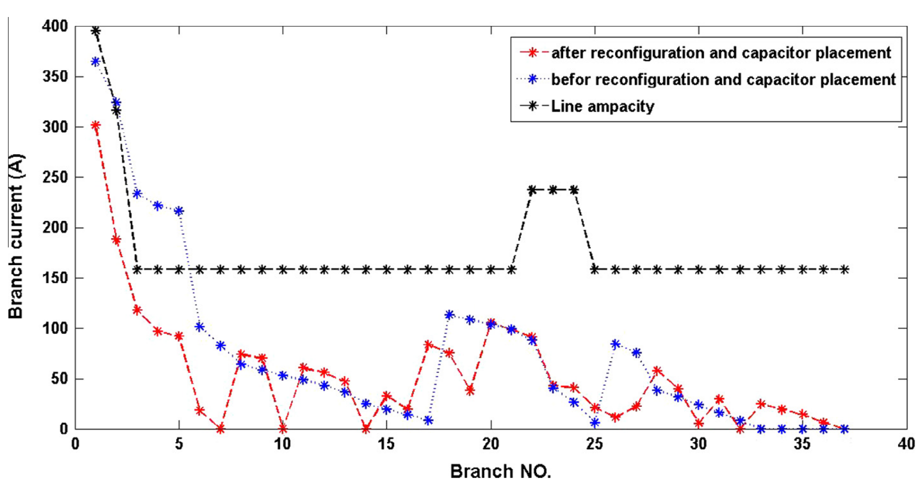

Figure 5 Branches current profiles before and after optimal reconfiguration and capacitor placement in 33-bus system.

5. Calculating the center of mass $(A_i^{c(k)})$ using Eq.(12) and determining the best position of each particle $(A_i^{lbest(k,j)})$ and the best global position $(A_i^{gbest(k)})$.
6. Calculating new candidates according to (17). Then, the mutation operation is used to prevent the HBB–BC from trapping into the local optimum according to (18).
7. Repeating Steps 3–6 until a termination criterion is satisfied. In this paper, the termination criterion is considered to be the number of iterations. Furthermore, if the maximal iteration number is satisfied, the algorithm is terminated.

Fig. 2 shows the flowchart of the proposed algorithm.

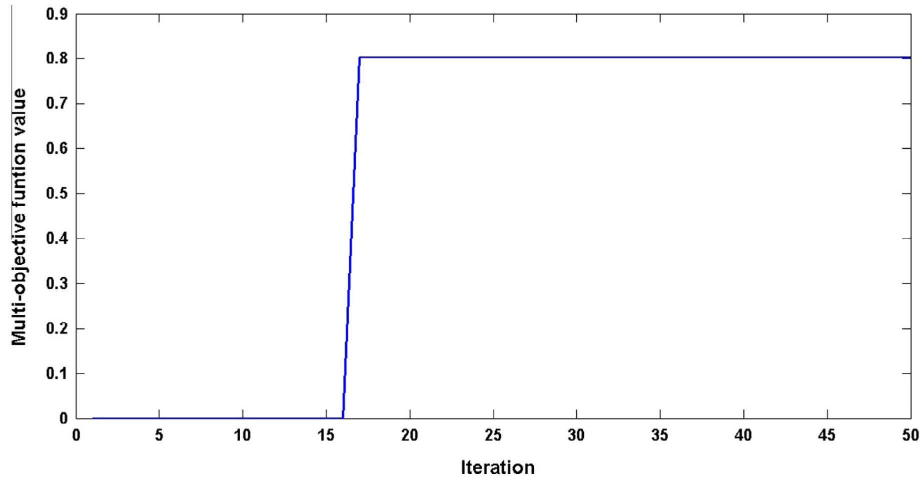

Figure 6 Convergence characteristic of the HBB–BC for the multi-objective function for case study 1.

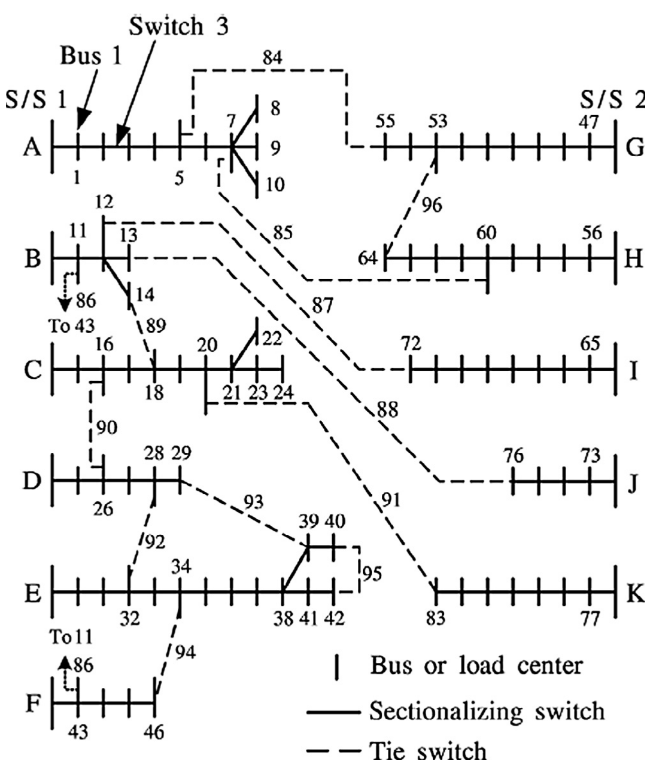

Figure 7 94-bus distribution test system.

5. Simulation results

To demonstrate the performance of the proposed algorithm, three Case study systems consisting of two balanced distribution systems (33-bus system and 94-bus system) and one unbalanced distribution systems (25-bus system) are investigated and numerical results are compared with another algorithm such as the PSO and IPSO. These methods have been implemented using MATLAB 7.10.0 (R2010a; The MathWorks, Natick, Massachusetts, USA) on an Intel(R) Core(TM)2 2.67-GHz PC with 2-GB RAM.

Case study 1: The Baran and Wu [47] distribution test system is used as first example with 3 feeders which is shown in Fig. 3. The system consists 32 sectionalizing switches (normally closed switches), and 5 tie switches (normally open switches) and 37 branches. The total real and reactive power loads on the system are 3715 kW and 2300 kvar, respectively. In this network, different copper cables are used. These cables are 185 mm^2, 120 mm^2, 70 mm^2 and 35 mm^2 [6]. The initial power loss is 202.677 kW and minimum bus voltage is 0.913 p.u. To optimize the multi objective fitness function using HBB–BC algorithm, parameters were selected as follows: the number of population was set at 30 and α_1, α_2 and α_3 were set at 1, 0.4 and 0.8 respectively, and mutation probability and maximum iterations were set at 0.2 and 50 respectively. The parameters for PSO and IPSO algorithms are as follows: the number of population was set at 30 and c_1, c_2 and w were set at 0.6, 0.6 and 1 respectively. In the first step, the objective functions,

Table 5a Results obtained by the HBB–BC algorithm for case study 2.

Item	Initial state	Only optimizing real power losses	Only optimizing voltage violation	Only optimizing load balancing	Optimizing the multi-objective fitness function
Power losses (kW)	531.99	296.47	491.82	474.06	317.836
Loss reduction (%)	–	43.6	7.55	10.89	40.25
Minimum voltage (p.u.)	0.9285191	0.9850667	0.992976	0.9921594	0.9890495
LBI	0.0329944	0.0180701	0.03202964	0.0101664	0.0141092
Open switches	84-85-86-87-88-89-90-91-92-93-94-95-96	55-7-86-72-13-89-90-83-92-39-34-95-63	55-4-86-87-76-89-90-91-28-39-94-40-64	54-7-86-72-13-89-90-91-92-93-34-40-61	55-7-86-72-13-89-90-91-92-39-34-42-64

Table 5b Results obtained by the HBB–BC algorithm for case study 2 (capacitor size).

Bus		Only optimizing real power losses Capacitor (kvar)		Only optimizing voltage violation Capacitor (kvar)		Only optimizing load balancing Capacitor (kvar)		Optimizing the multi-objective fitness function Capacitor (kvar)	
Slack(0)	43	0	0	0	0	0	600	0	0
1	44	300	300	300	0	600	600	300	300
2	45	0	600	300	300	0	0	900	300
3	46	0	0	0	900	0	0	0	0
4	47	300	0	600	900	300	600	300	300
5	48	300	300	0	300	900	300	300	300
6	49	600	300	1200	300	300	0	300	300
7	50	0	0	600	300	300	300	0	0
8	51	300	300	300	300	900	300	600	0
9	52	300	600	300	0	600	0	300	300
10	53	300	300	300	0	900	300	0	600
11	54	0	300	1800	300	900	900	0	0
12	55	300	300	900	0	300	300	600	300
13	56	600	0	600	0	1500	900	900	0
14	57	900	0	300	600	1500	0	0	300
15	58	300	900	300	0	600	0	300	0
16	59	300	0	300	0	300	300	600	600
17	60	300	0	1500	300	0	0	300	0
18	61	600	0	300	0	0	600	0	300
19	62	300	0	0	0	0	600	300	300
20	63	900	0	600	600	600	600	300	0
21	64	600	300	300	1200	300	300	0	600
22	65	0	0	600	300	300	1500	900	1200
23	66	0	300	0	300	300	600	300	300
24	67	0	0	300	300	1500	300	0	600
25	68	0	0	300	900	300	300	0	300
26	69	300	600	600	300	300	1200	300	600
27	70	600	300	300	900	600	300	300	600
28	71	600	900	1800	300	900	300	0	300
29	72	300	300	600	600	1200	1200	300	900
30	73	600	0	600	900	1800	900	0	0
31	74	900	300	300	300	300	300	900	0
32	75	0	600	600	300	900	300	900	600
33	76	600	300	0	600	1500	600	300	300
34	77	600	0	600	300	300	600	600	300
35	78	0	1200	600	600	0	0	0	300
36	79	0	300	0	300	0	600	300	600
37	80	0	300	0	1200	300	600	0	300
38	81	300	300	0	900	300	0	300	900
39	82	0	300	300	300	300	300	0	600
40	83	0	0	300	0	1500	1200	300	0
41		300		0		0		300	
42		0		300		300		600	

including loss reduction, minimization of voltage violation, and load balancing, are separately optimized. The results for these three objectives are respectively shown in Tables 1–3. Results obtained by optimizing the multi-objective fitness function for case study 1 are shown in Table 4. The results indicated for all three objectives and also multi objectives are the best results obtained after 50 times of running the proposed method and other algorithms.

As demonstrated in Table 1, it is observed that the loss reduction ratio obtained by the HBB–BC is more than the PSO, IPSO, IBPSO and ACO algorithms. Thus, the proposed method has a higher performance compared to the other methods. It can be seen from Table. 2, that when the only optimization objective is improving the voltage profile, the proposed algorithm by minimum voltage of 0.98441113 is not as appropriate as IPSO algorithm but it has better performance compared to the PSO algorithm. On the other hand the total used capacitance is equal by the ones used in IPSO method but their arrangement became more distributed. By considering Table. 3, which shows simulations for a load balancing of a single objective case, it is shown that LBI index is 0.039968 for proposed algorithm and does not provide the best result, but is close to PSO and IPSO results. But the weakness of this method is its capacitance (3300 kvar) versus 2700 kvar and 2400 kvar of IPSO and PSO algorithms, respectively. Table 4 shows the results of multi-objective simulations. It can be seen that for power losses and LBI objectives, the proposed algorithm has better results than PSO and IPSO algorithm results, and for the voltage deviation objective, the HBB–BC algorithm gives worse results compared to PSO

Table 6 Results obtained by optimizing real power losses with HBB–BC algorithm along with a comparison with SA, GA and ACSA.

Item		Power losses (kW)	Minimum voltage (p.u)	LBI
Original configuration		531.99	0.9285191	0.0329944
HBB–BC	Best	296.47	0.9850667	0.0180701
	Worst	303.7	0.98378407	0.01724226
	Average	300.08	0.9844253	0.01765618
	Average loss reduction	43.6	–	–
SA [30]	Best	309.12	–	–
	Worst	315.86	–	–
	Average	312.30	–	–
	Average loss reduction	41.3	–	–
GA[30]	Best	295.39	–	–
	Worst	299.13	–	–
	Average	297.75	–	–
	Average loss reduction	44.03	–	–
ACSA [30]	Best	295.12	–	–
	Worst	299.46	–	–
	Average	296.89	–	–
	Average loss reduction	44.19	–	–

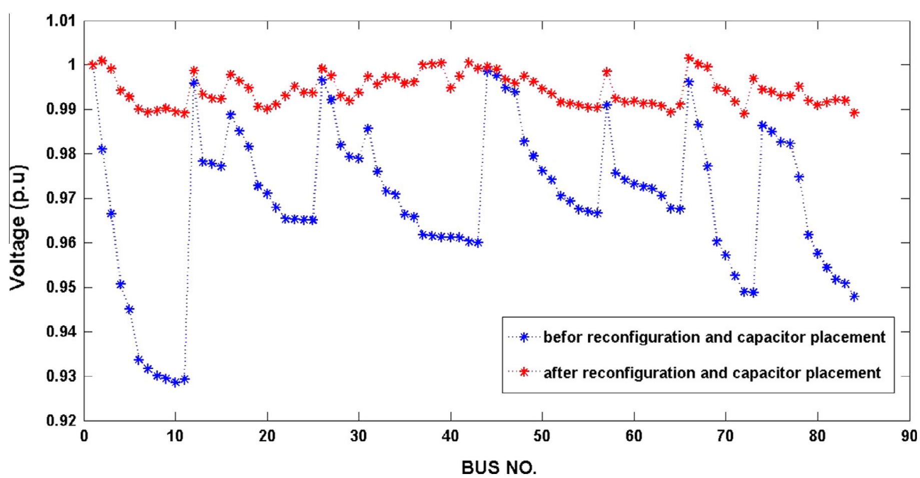

Figure 8 Voltage profiles before and after optimal reconfiguration and capacitor placement in 94-bus system.

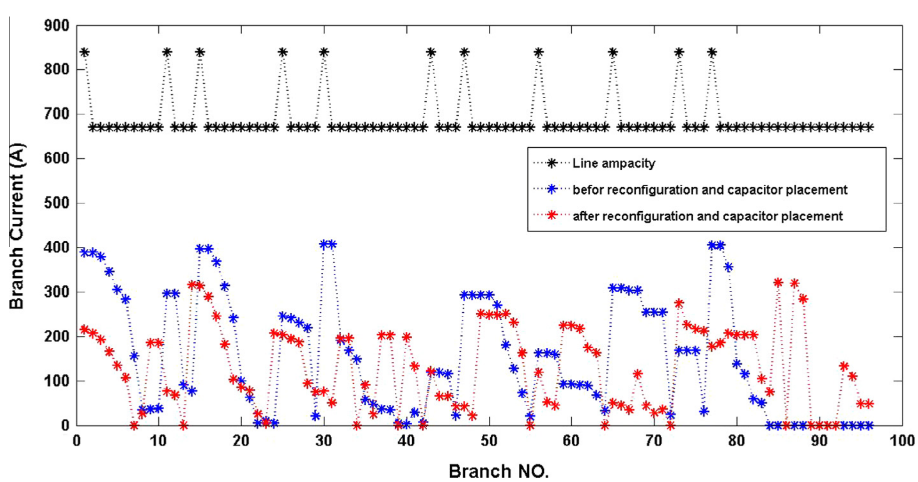

Figure 9 Branches current profiles before and after optimal reconfiguration and capacitor placement in 94-bus system.

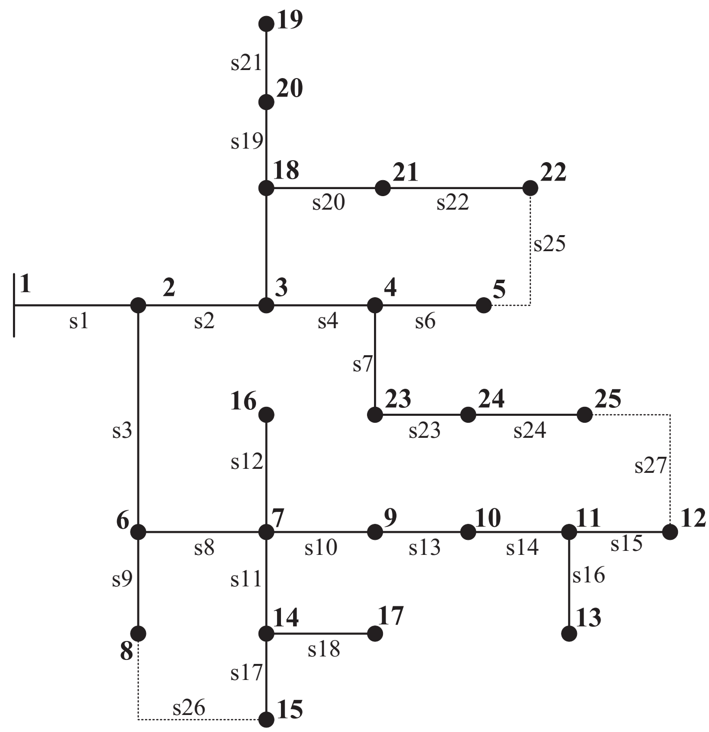

Figure 10 25 bus unbalanced distribution system.

Table 7 Results obtained by the HBB–BC algorithm for case study 3.

Item	Initial state	Only optimizing real power losses	Only optimizing voltage violation	Only optimizing load balancing	Optimizing the multi-objective fitness function
Power losses (kW)	150.13	91.28	146.377	149.973	94.179
Loss reduction (%)	–	39.2	2.5	0.104	37.29
Minimum voltage Phase a (p.u.)	0.9284107	0.9640415	0.9877222	0.9740478	0.964586
Minimum voltage Phase b (p.u.)	0.9283703	0.9626266	0.985857	0.9694966	0.963076
Minimum voltage Phase c (p.u.)	0.9365706	0.9695176	0.9932599	0.9804585	0.9725021
LBI	0.1009584	0.0454020	0.0735533	0.0328862	0.0455454
Open switches	25-26-27	22-17-15	20-17-15	5-11-13	25-17-15
Capacitor (kvar) (bus)	–	300 (3-4-7)	300 (5-8-11-12-14)	300 (10-16-17-19)	300 (2-3-9)

and IPSO algorithm. However, the results are close to those of PSO and IPSO (the minimum voltages in HBB–BC algorithm is within the allowed range). Yet, the proposed and the PSO method use the same installed capacitors (2400 kvar), and they use less capacitors than IPSO method (3000 kvar). Figs. 4 and 5 show the voltage and branches current profiles before and after optimal reconfiguration and capacitor placement, respectively. Fig. 5 shows line capacity for network branches. As shown in these figures, the voltage and current branches profile is obviously improved by using the HBB–BC algorithm. Fig. 6 indicates the convergence characteristic of the HBB–BC for the multi-objective function for case study 1. It is shown that after 18 iterations HBB–BC algorithm reaches to full convergence and fitness function value at approximately 0.83 remains constant.

Case study 2: The second example is a practical distribution network of the Taiwan Power Company [49]. It is a three-phase, 11.4-kV system which consists of 94-bus, 96 branches, 11 feeders, 83 sectionalizing switches (normally close switches), and 13 tie switches (normally open switches). Fig. 7 shows a diagram of this system which has a total load of 28,350 kW and 20,700 kvar. Details of the data of this example can be found in [49]. In this network, an Aluminum Conductor Steel Reinforced (ACSR) 477 kCmil has been employed for the overhead lines and a copper conductor 500 kCmil for the underground lines. The capacities of these conductors are 670 and 840 A, respectively [50].

The initial power loss is 531.99 kW and minimum bus voltage is 0.9285 p.u. To optimize the multi objective fitness function, parameters were selected as follows: the number of population was set at 25, α_1, α_2 and α_3 were set at 1, 0.4 and 0.8 respectively, and the mutation probability and maximum iterations were set at 0.002 and 200 respectively. The results indicated for all the three objectives and also the multi objective function are the best results obtained after 50 times running the proposed method.

The optimal solutions for minimization of total real power losses, the minimization of buses voltage violation, and load

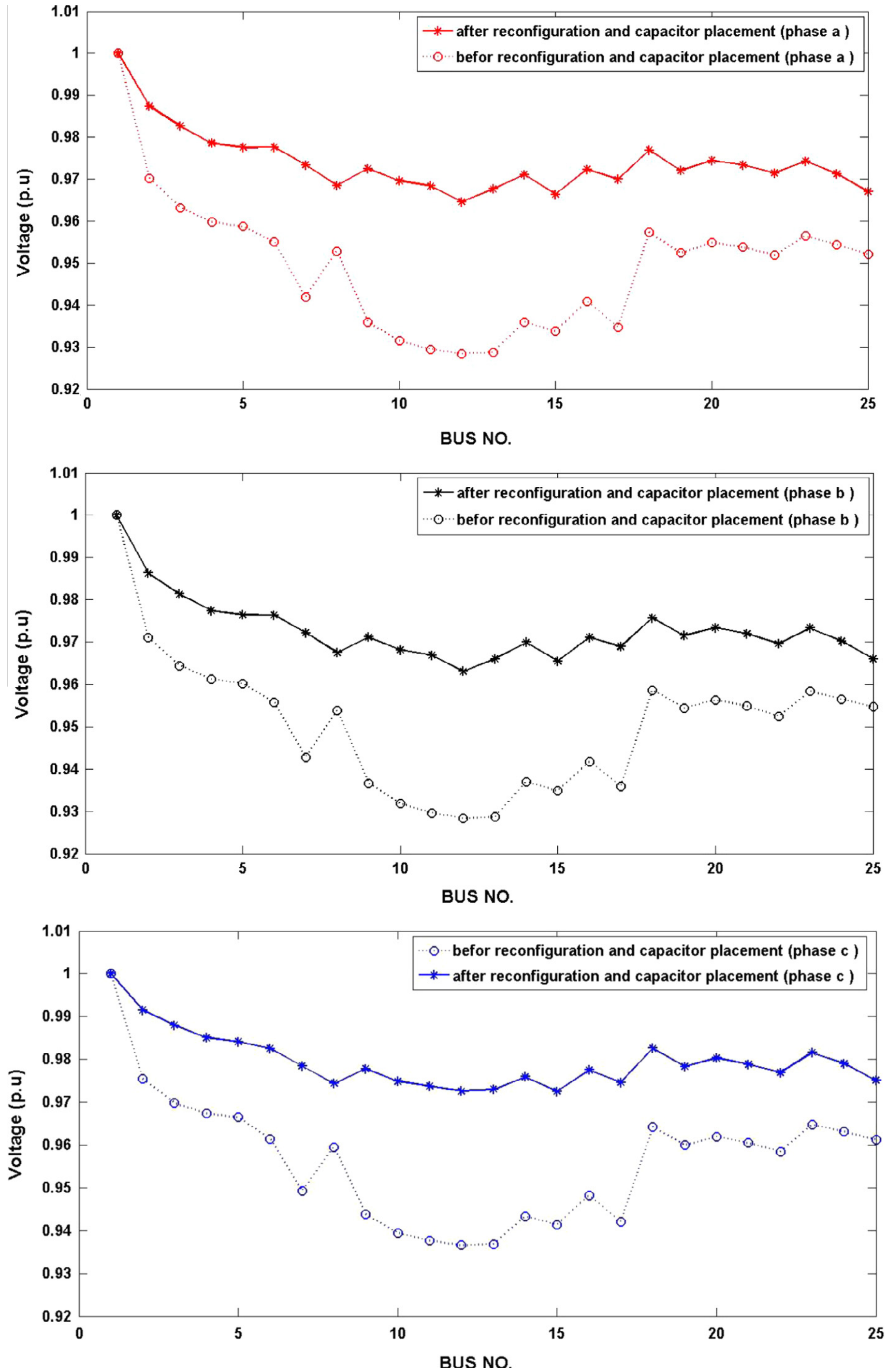

Figure 11 Voltage profiles before and after optimal reconfiguration and capacitor placement in 25-bus system.

balancing and optimal solution for the multi-objective function are illustrated in Table 5. The optimal solution for the minimization of total real power losses using the HBB–BC and SA, GA and ACSA is shown in Table 6 along with a comparison with SA, GA and ACSA. As can be seen from Table 6, the proposed method has better performance compared to the SA algorithm, but GA and ACSA have better performance compared to the HBB–BC algorithm. Figs. 8 and 9 show the voltage and branches current profiles before and after optimal reconfiguration and capacitor placement for Case study 2, respectively. Fig. 9 shows line capacity for network branches. As shown in these Figures, the voltage and current branches profile is obviously improved by using the HBB–BC algorithm.

Case study 3: the third case study is a 25-bus Unbalanced Distribution 4.16-kV System consisting of 24 sectionalizing switches (normally close switches) and 3 tie switches (normally open switches). Details for the line and load data of the system can be found in [51]. This system is shown in Fig. 10. The initial power loss is 150.13 kW and minimum bus voltage in phases a, b and c is 0.9284107, 0.9283703 and 0.9365706 p.u. respectively. To optimize the multi objective fitness function, the parameters were selected as follows: the number of

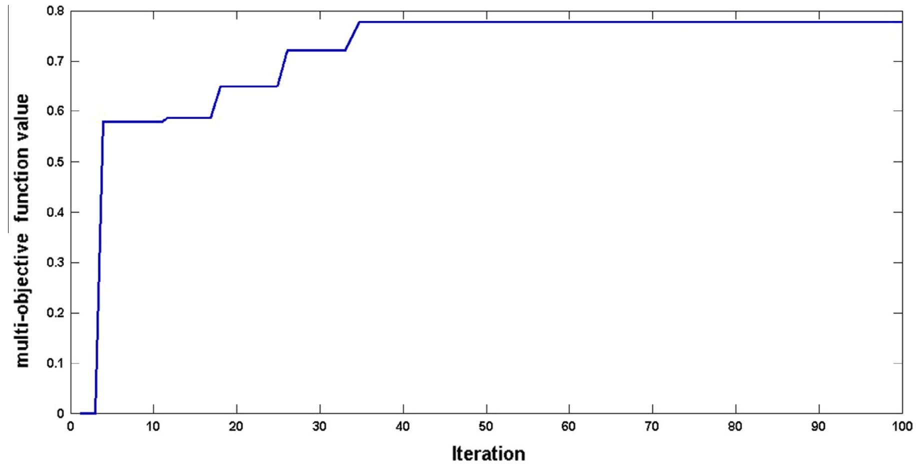

Figure 12 Convergence characteristic of HBB–BC for the multi-objective function for case study 3.

population was set at 20, and α_1, α_2 and α_3 were set at 1, 0.4 and 0.8 respectively, and the mutation probability and maximum iterations were set at 0.01 and 100 respectively. The optimal solutions for only minimizing the total real power losses, only minimizing the buses voltage violation, only load balancing and the optimal solution for the multi-objective function are presented in Table 7. The results indicated for all the three objectives and also the multi-objective function are the best results obtained after 50 instances of running the proposed method. Fig. 11 shows the voltage profiles in phase a, phase b and phase c of case study 3 before and after optimal reconfiguration and capacitor placement. Fig. 12 shows the convergence characteristic of the HBB–BC for case study 3. As shown in Fig. 12, fitness function after 35 iterations converges to 0.79 and the voltages profile is obviously improved using the HBB–BC algorithm in each phase.

6. Conclusions

An HBB–BC optimization algorithm as the combination of the BB–BC algorithm and the capability of the PSO algorithm for multi-objective reconfiguration and capacitor placement of balanced and unbalanced distribution systems in a fuzzy framework has been introduced in this paper. In fact, this algorithm utilizes the PSO's capabilities to improve the search ability and also uses a mutation operator to reduce the problem of the algorithm being trapped into the local optimum problem. An important property of the proposed approach is solving the multi-objective reconfiguration and capacitor placement problem in the fuzzy framework. The objectives considered are the minimization of total network real power losses, the minimization of buses voltage violation, and load balancing in the feeders. To obtain the optimal solution for the multi-objective fitness function, first each objective is transferred into the fuzzy domain using the membership function and then the resultant overall fuzzy satisfaction function is considered as a fitness function, which is maximized during the optimization process. The proposed method has been successfully tested in three case studies (consisting of two balanced and one unbalanced system). In case study 1, the HBB–BC has shown better performance compared to PSO and IPSO algorithms for power losses and LBI objectives. However, it gives less minimum voltage compared to PSO and IPSO algorithms. In case study 2, the HBB–BC has shown a better performance compared to the SA, and has shown a performance almost similar to that of the GA and ACSA. As can be seen from simulation results, the proposed algorithm is an effective method for finding the optimal solution. It is also a powerful method for solving optimization problems in the fuzzy framework for balanced and unbalanced distribution networks.

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