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Optimal Reconfiguration and Capacitor Allocation in Radial Distribution Systems Using the Hybrid Shuffled Frog Leaping Algorithm in the Fuzzy Framework

M. Sedighizadeh[1,]*, M.M. Mahmoodi[2]

[1]Faculty of Electrical and Computer Engineering, Shahid Beheshti University, Tehran, Iran
[2]Department of Electrical Engineering, College of Engineering, Saveh Branch, Islamic Azad University, Saveh, Iran

ABSTRACT

In distribution systems, network reconfiguration and capacitor placement are commonly used to diminish power losses and keep voltage profiles within acceptable limits. In this paper, the Hybrid Shuffled Frog Leaping Algorithm (HSFLA) has been used to optimize the balanced and unbalanced radial distribution systems using a network reconfiguration and capacitor placement. High accuracy and fast convergence are the major advantages of the proposed approach regarding the result of solving the multi-objective reconfiguration and capacitor placement in a fuzzy framework. These objectives are minimizing the total network real power losses and buses voltage violation, and balancing the load in the feeders. Each objective is transferred into fuzzy domain using its membership function and fuzzified separately. Then, the overall fuzzy satisfaction function is formed and considered as a fitness function. The value of this function has to be maximized to gain the optimal solution. In the literature review, several reconfiguration and capacitor placement methods which had already been implemented separately have been investigated, but there are few studies which simultaneously apply these two methods. The proposed algorithm has been implemented in three IEEE test systems (two balanced and one unbalanced systems).The numerical results obtained by the simulation carried out in this study show that the HSFLA algorithm improves the performance much more than other meta-heuristic algorithms.

KEYWORDS: Artificial intelligence, Distribution systems, Multi-objective optimization, Optimal reconfiguration and capacitor placement, SFLA

1. INTRODUCTION

It is a common application to use capacitors in power systems in order to compensate for reactive power losses as well as to provide a good voltage profile by preventing occurrence of under- or over-voltages. An issue of exploiting maximum advantage of compensation effect of capacitors is the size and location of these components. On the basis of switches used in power systems there are two types of these devices called normally closed switches (sectionalizing switches) and normally open switches (tie switches), which by applying either, topology of system may be changed. The change happens when altering the status of these switches from open or closed, and by this way, feeder is reconfigured due to the change in topology and configuration of distribution systems. Regarding this, the need to optimally reconfigure network and find the optimum placement of capacitors have raised and separately been investigated in many papers. For solving the aforementioned problem associated with reconfiguration of feeder and finding the optimum placement for capacitors, many different methods have been used with various objective functions and optimization theories.

Recently there have been so many algorithms developed for different goals including power loss

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*Corresponding author:
M. Sedighizadeh (m_sedighi@sbu.ac.ir)

reduction and major utilization factors using reconfiguration of distribution systems, most of which based on artificial intelligence methods and heuristic techniques. Examples of studies focused on reconfiguration of network can be mentioned as following: in [1], a new meta-heuristics fireworks algorithm was 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 was presented in [3], which was 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 NR.

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. TS 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 to minimize energy losses was presented in [5], in which radiality and connectivity constraints were considered as well as different load levels for planning the system operation. In [6] an efficient hybrid big bang–big crunch optimization algorithm to solve the multi-objective reconfiguration of balanced and unbalanced distribution systems in a fuzzy framework was rpresented. 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 was reported. The network reconfiguration algorithm is based on the fuzzy multi-objective approach and the max-min principle was adopted for the multi-objective optimization in a fuzzy framework. Multiple objectives were 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 for the reconfiguration of radial distribution systems with minimizing real power loss was used in [8] that conventional ant colony optimization was 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. In [9] size and location of FACTs devices in a power system are calculated and a Dedicated Improved Particle Swarm Optimization (DIPSO) algorithm was developed for decreasing the overall costs of power generation and maximizing of profit.

There are many articles that have presented wide researches on the capacitor placement problem for reduction of losses in power distribution systems. For instance, an approach based on fuzzy method was proposed in [10]. For determining the location, size and number of capacitor banks in distribution systems a mixed integer LP model was reported in [11]. For loss reduction in [12] a two stage method was used for formulation and the optimal operation status of the devices by applying a genetic algorithm. To solve the problem of capacitor placement, Ref. [13] was applied a single objective probabilistic optimal allocation, and in [14] for optimal placement of capacitors in order to reduce harmonic distortion, a honey bee foraging approach was used. In [15] a hybrid optimization algorithm for the optimal placement of shunt capacitor banks in radial distribution networks was used in the presence of different voltage-dependent load models, which the algorithm was based on the combination of genetic algorithm and binary particle swarm optimization algorithm. Optimal capacitor allocation and sizing using big bang big crunch optimization algorithm is represented in [16].

Papers, which work with both capacitor placement and network reconfiguration at the same time, are reviewed now. Zhang et al. in [17] treated capacitor placement and reconfiguration by using Improved Adaptive Genetic Algorithm (IAGA) and a simplified branch exchange algorithm, respectively. Farahani et al. in [18] solved the reconfiguration problem by using simple branch exchange method and the outcome was that loops selection sequence is an affecting factor which has effects on network loss as well as optimal configuration and also proposed a new algorithm for combining improved method of reconfiguration and capacitor placement, in which for optimizing the location and size of capacitors and sequence of loops selection, discrete genetic algorithm (GA) was used. Chung-Fu Chang in [19] worked on ant colony search algorithm and used it as a solver for the problems of feeder reconfiguration optimization and capacitor placement simultaneo-usly. Montoya et al. in [20] by using a minimum spanning tree algorithm determined the minimum losses optimum configuration in reconfiguration problem and utilized GA to obtain the greatest savings through the problem of optimal capacitor problem. Guimara˜es et al. in [21] used a modified dedicated approach based on GA. Development and implementation of this algorithm was successful, as well, it has low computations and was capable of obtaining appropriate configurations. In [22] based on a new Improved Binary PSO (IBPSO) algorithm, some suggestions for planning priority associated with problems of capacitor placement and reconfiguration in distribution systems are being investigated. This suggested method applies a new structure in order to obtain an optimization for the aforementioned problem.

The proposed method is to use an efficient Hybrid Shuffled Frog Leaping Algorithm (SFLA) [23] associated with fuzzy objective function to get a proper solution for the problems of feeder reconfiguration and capacitor placements at the same time. The objective functions which have been considered in this paper are the minimization of total real power losses and bus's voltage violation as well as load balancing in the feeders. One of the commonly used methods to increase loading capability of system, dwindling real power losses and reducing voltage drops is load balancing. The main objectives considered in this paper are to obtain maximum reduction of loss, present an in-limits-maintained voltage profile, and have the current in each branch maintained within the capacity limits of the branch. The first step, is to use trapezoidal fuzzy membership function in order to transfer the objectives to fuzzy domain and fuzzify them separately. The second step is to develop the overall fuzzy satisfaction function. We will see in the next step that this function is considered as an overall fitness function and the value of it will increase until it reaches to maximum value. The test system for the suggested method is a balanced 33 and 94-bus and an unbalanced 25-bus distribution system. In comparison with PSO and IPSO and other various algorithms, the suggested HSFLA has a better efficiency which is verified by numerical results.

2. FUZZY MULTI-OBJECTIVE FORMULATION

Since the objective functions have different dimensions, for easier comparison a fuzzy multi-objective approach is used. In fuzzy domain, a membership function is defined for each objective which represents the degree of fuzzy satisfaction of the objective. The membership value of each objective is a real number between 0 and 1 and in this section is determined by using the trapezoidal fuzzy membership function. In this paper, power losses minimization, minimizing the buses voltage deviation and load balancing in the feeders are considered as the objectives and fuzzified as explained below.

2.1 Membership function for the real power loss (λP_i)

Mathematically, the real power loss in the network can be formulated as follows:

$$P_{loss} = \sum_{i=1}^{N_{br}} R_i \frac{P_i^2 + Q_i^2}{|U_m|^2} \tag{1}$$

The voltage magnitude at each bus must remain within its permissible intervals. On the other hand, the current of each branch must satisfy the branch current limitations. Therefore:

$$U_{min} \le |U_m| \le U_{max} \tag{2}$$

$$|I_i| \le I_{i,max} \tag{3}$$

Where R_i, P_i and Qi are, the branch resistance, real and reactive power flows through branch i respectively, and U_m is the voltage at bus m and N_{br} is the total number of branches in the system. U_{min} and U_{max} are minimum and maximum allowable voltages, respectively, which are considered as $U_{min} = 0.95$ and $U_{max} = 1.05$. The following index `for the power loss minimization is defined as follows [6]:

$$XP_i = \frac{P_{lossi}}{P_{loss0}} \tag{4}$$

where, P_{loss0} represents the initial real power loss before reconfiguration and capacitor placement of the network and P_{lossi} represents the real power loss after reconfiguration and capacitor placement in ith radial system.

The degree of fuzzy satisfaction of power loss objective function can be determined using the membership function as defined in fuzzy domain. The membership function is expressed as follows:

$$\lambda P_i = \begin{cases} 1 & XP_i < XP_{min} \\ \dfrac{XP_{max} - XP_i}{XP_{max} - XP_{min}} & XP_{min} < XP_i < XP_{max} \\ 0 & XP_i > XP_{max} \end{cases} \tag{5}$$

where, XP_{min} and XP_{max} are the lower and upper limits of XP_i index, respectively. To determine the XP_{min} and XP_{max}, the best and the worst system configuration for real power losses is considered. P_{lossi} for the best system configuration is minimum value of the power loss and for the worst system configuration is assumed to be equal with the power loss of the initial configuration.

2.2 Membership function for maximum bus voltage violation (λU_i)

For the purpose of minimizing the bus voltage deviation, the index of XUi is defined as follows:

$$XU_i = max\left(|1 - U_{min}| \, and \, |1 - U_{max}|\right) \tag{6}$$

where, U_{min} and U_{max} are the minimum and maximum values of bus voltage respectively. Membership function of maximum bus voltage deviation index is formulated as follows[6]:

$$\lambda U_i = \begin{cases} 1 & XU_i \le XU_{\min} \\ \dfrac{XU_{\max} - XU_i}{XU_{\max} - XU_{\min}} & \mathrm{XU}_{\min} < XU_i < XU_{\max} \\ 0 & \mathrm{XU}_i \ge XU_{\max} \end{cases} \tag{7}$$

where, XU_{min} and XU_{max} are the lower and upper limits of XU_i index, respectively. To determine the XU_{min} and XU_{max}, the best and the worst system configuration is considered for minimum and maximum bus voltage deviation, respectively.

2.3 Membership function for load balancing index (LBI) (λI_i)

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 [24]:

$$Line Usage\ Index = \frac{I_i}{I_i^{max}} \tag{8}$$

where, I_i^{max} is the maximum current capacity of the *ith* branch of the system. For all the branches of the system LBI index is calculated as follows:

$$Y = \left[\frac{I_1}{I_1^{max}} \; \frac{I_2}{I_2^{max}} \; \frac{I_3}{I_3^{max}} \; \ldots\ldots \; \frac{I_N}{I_{N_{br}}^{max}} \right] \tag{9}$$

$$LBI = Var(Y) \tag{10}$$

where, Var represents the variance operation. However, the smaller value of the LBI index indicates that the load balancing has been conducted more efficiently. In the next stage, the index of XB_i for load balancing is defined as:

$$XB_i = \frac{LBI_i}{LBI_0} \tag{11}$$

where, LBI_0 is the load balancing before network reconfiguration and capacitor placement, calculated in initial power flow for each case study, and LBI_i is the load balancing of the *ith* radial system after reconfiguration and capacitor placement.

Membership function of feeder load balancing index is formulated as follows:

$$\lambda I_i = \begin{cases} 1 & \mathrm{XB}_i \le XB_{\min} \\ \dfrac{XB_{\max} - XB_i}{XB_{\max} - XB_{\min}} & \mathrm{XB}_{\min} < XB_i < XB_{\max} \\ 0 & \mathrm{XB}_i \ge XB_{\max} \end{cases} \tag{12}$$

where, XB_{min} and XB_{max} are the lower and upper limits of XB_i, respectively. To determine the XB_{min} and XB_{max}, the best and the worst system configuration is considered for feeder load balancing.

In the proposed algorithm, the worst system configuration is considered to be the initial configuration of system before reconfiguration and capacitor placement, and the best system configuration after reconfiguration and capacitor placement is obtained by optimizing each objective separately.

2.4 Degree of overall fuzzy satisfaction (λO_i)

The idea of multi objective function is proposed for the following purposes:

- Finding the best and most compatible system configuration satisfying every objectives.
- Satisfying operational limits such as voltage and current constraints and also preventing load islanding.

In this paper, a new operator named “max-geometric mean” is utilized to determine the degree of overall fuzzy satisfaction in the proposed method. This operator is expressed as follows [25]:

$$\lambda O_i = \left(\lambda P_i \times \lambda U_i \times \lambda I_i\right)^{\frac{1}{3}} \tag{13}$$

where, λO_i in the HSFLA is considered as the fitness function, maximized during the optimization process to obtain the best compatible configuration. This operator has several advantages. For instance, if any membership function of each objective reaches the value of zero, λO_i is assigned a value of zero. Furthermore, this function provides correct information as about how to make this algorithm achieving an ideal state, namely a value of 1.

3. SHUFFLED FROG LEAPING ALGORITHM

3.1. Original algorithm

The first thing to do in SFLA is to randomly create initial population of F frogs. Then it is necessary to sort the population of *F* frogs in increasing performance level and separate them into *m* memeplexes each of which containing *n* frogs (i.e. $F=m\times n$); in this sorting the first frog goes to the first memeplex, the second frog goes to the second memeplex, the mth frog goes to the mth memeplex, and the (m+1)th frog goes back to the first [8]. After the previous is done it is time to evaluate each memeplex. In this step, the best frog is a sample from which each frog in the memeplex by learning from it, leaps toward the location which is the optimum. The new position, the worst frog has in the memeplex, is calculated as represented below:

$$x\_worst^{k+1} = x\_worst^{k} + r^{k}\left(x\_sbest - x\_worst^{k}\right) \tag{14}$$

where, *x_worst* is the position of the worst frog in the memeplex, *x_sbest* is the position of the best frog in the memeplex, *r* is a random number between 0 and 1, and k is the iteration number of the memeplex [26].

In case that, this process introduces a better answer (frog), the older frog is being replaced. Otherwise, *x_sbest* is replaced by *x_gbest* in Eq. (14), and the way we calculate the new position is as below:

$$x\_worst^{k+1} = x\_worst^{k} + r^{k}\left(x\_gbest - x\_worst^{k}\right) \tag{15}$$

In a case that, there is no improvement observed, the old frog is replaced by random frog [27].

3.2. Proposed SFLA based hybrid algorithm

The basis of this new method is identification of drawbacks of the basic SFLA, which was initially used on various functions and to mention a critical ones of them can be explained in this way that because some memeplexes have been wasted in local minima, the effective frogs eliminated from the solving procedure. To prevent this as much as possible, enhancement of the guiding particle in each memeplex is necessary; in the SFLA this guiding article in each memeplex is *x_sbest*. So in the suggested method the movement of the frog which has the best position is determined through the search space toward the position which the global best frog has, is given by Eq. (16)

$$x\_best^{k+1} = x\_best^{k} + r^{k}(x\_gbest - x\_best^{k}) \quad (16)$$

4. IMPLEMENTATION OF THE HSFLA

In the proposed algorithm, the number of switch's which should 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 candidate for capacitor placement, is expressed as follows:

$$N_{cv} = N_L + N_{bus} \quad (17)$$

where, N_{cv} is the number of control variables, N_L is the number of tie switches and N_{bus} is the number of network buses that candidate for capacitor placement. The number of tie switches is obtained as follows:

$$N_L = N_{br} - N_{bus} + 1 \quad (18)$$

where, N_{br} is the total number of network branches.

For example, in 33-bus system shown in Fig. 2 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.

Loop vectors1 $= [s_2 s_3 s_4 s_5 s_6\ s_7 s_{33} s_{20} s_{18} s_{19}]$

Loop vectors2 $= [s_8 s_9 s_{10} s_{11} s_{35}\ s_{21} s_{33}]$

Loop vectors3 $= [s_9 s_{10} s_{11} s_{12} s_{13} s_{14} s_{34}]$

Loop vectors4 $= [s_{22} s_{23} s_{24} s_{37} s_{28} s_{27} s_{26} s_{25} s_5 s_4 s_3]$

Loop vectors5 $= [$
$s_{25} s_{26} s_{27} s_{28} s_{29}\ s_{30} s_{31} s_{32} s_{36} s_{17} s_{16} s_{15} s_{34} s_8 s_7 s_6\ ]$

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

Capacitor vector = [0300600900120015001800]

This capacitor vector is repeated for all buses that should be candidate for capacitor placement.

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 HSFLA is applied to the problem of the multi-objective network reconfiguration and capacitor placement as follows:

Step 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 ($P = n \times m$), the number of memeplexes (m), number of frogs in each memeplex (n), and the number of iterations (G).

Step 2: Generating the initial population. For the initialization of each individual (frog), one switch from each fundamental loop or loop vector to be opened and one capacitor from capacitor vector to be placed is randomly chosen.

Step 3: Checking the radiality of the network and all loads being in service for each individual. To check whether radiality is maintained as well as to make sure that all loads are in serviceso as to prevent load islanding, the graph theory can be used. If in a tree the vertices those degree is equal to 1 along all edges connected to them are removed and this procedure is repeated, finally, all vertices will be deleted. If the network graph is not the tree, it means that 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.

Step 4: Performing the load flow. By allocating capacitors that are determined by each individual in candidate buses a direct approach proposed in [28] is used for load flow solution. The value of the fitness function (λO_i) is calculated using the results of distribution load flow for each radial structure (for each individual or frog).

Step 5: Sort the population P in descending order of their fitness and then divide P into m memeplexes;

for each memeplex, determine the best and worst frogs;

Step 6: Improve the worst frog position using Eqs. (14) and (15).

Step 7: Improve the best frog in each memeplex toward the global best using Eq. (16)

Step 8: Combine the evolved memeplexes;

Step 9: Repeating steps 3-8 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. 1. shows the flowchart of the proposed algorithm.

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 PSO and IPSO. These methods have been implemented using MATLAB software.

5.1. Case study 1

Baran and Wu [29] distribution test system is used as first example with 3 feeders which is shown in Fig. 2. 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 kVra, respectively.

The initial power loss is 202.677 kW and minimum bus voltage is 0.913 p.u. To optimize the multi objective fitness function, in this simulation, number of frogs in each memeplex is 5 and number of memeplexes is 6, so the number of population is set $P=m\times n=30$. Maximum iteration to achieve the convergence was set $G=50$. In the first step, the objective functions, 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, 2 and 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 instances of running the proposed method and other algorithms.

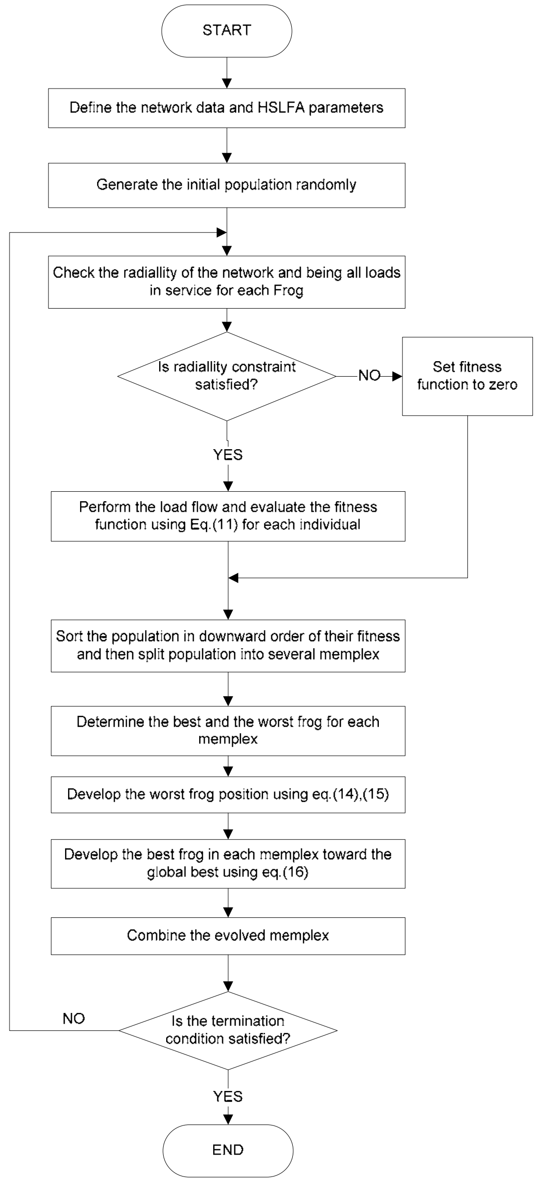

Fig. 1. Flowchart of the proposed HSFLA

As demonstrated in Table. 1, it is observed that the loss reduction ratio obtained by the HSFLA 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 drop of 0.98441544 is not as appropriate as PSO and IPSO algorithms. On the other hand the total used capacitance is equal by the ones used in IPSO method but their arrangement became more distributed.

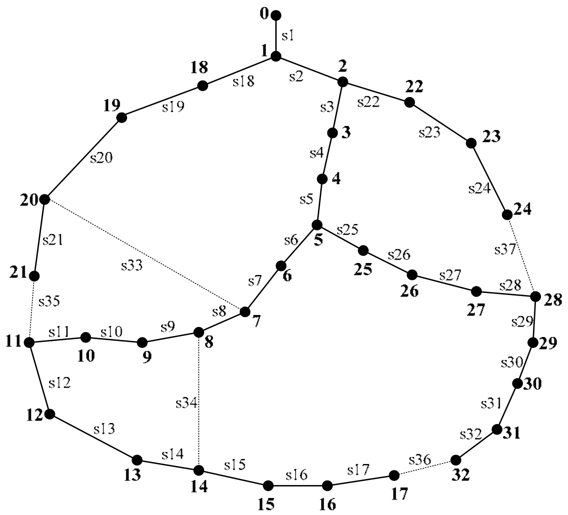

Fig. 2. Baran and Wu distribution test system (33-bus)

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 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 of IPSO algorithm. Table. 4 shows result of multi-objective simulations, it can be seen that for all three objectives, the proposed algorithm has better results than PSO algorithm and very close to IPSO results, but it used less capacitors than IPSO. Figures 3 and 4 show the voltage and branches current profiles before and after optimal reconfiguration and capacitor placement, respectively. As shown in these figures, the voltage and current branches profile is obviously improved by using the HSFLA algorithm.

Fig. 5 indicates the convergence characteristic of the HSFLA for the multi-objective function for case study 1.It is shown that after 19 iterations HSLFA algorithm reaches to full convergence and fitness function value at approximately 0.83 remains constant.

5.2. Case study 2

The second example is a practical distribution network of the Taiwan Power Company [31]. 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. 6 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 [31]. The initial power loss is 531.99 kW and minimum bus voltage is 0.9285 p.u. In this simulation to optimize the multi objective fitness function, number of each cycle frogs and number of memeplexes are considered as 5 and 5, respectively. So, the number of population was $P = m \times n = 25$. By considering the statistical nature of this algorithm, 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 (G=50). The optimal solutions for minimization of total real power losses, the minimization of buses voltage violation, and load balancing and optimal solution for the multi-objective function are illustrated in Table. 5 and 6. The optimal solution for the minimization of total real power losses using the HSFLA and SA, GA and ACSA is shown in Table. 7.

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

Methods	Power losses (kW)	Loss reduction (%)	Minimum voltage (p.u.) at bus#17	LBI	Open switches	Capacitor located at (buses)
Initial state	202.677	-----------------	0.9130905	0.1575671	33-34-35-36-37	--------------------
HSFLA	92.5768	54.32	0.95858645	0.0448181	7-11-14-37-32	300(2-4-10-11-18-24-28-29-30)
PSO	95.38	52.93	0.9635100	0.046994	7-10-14-37-36	300(9-10-31) 600(6-29)
IPSO	98.834	51.23	0.965607	0.0400872	11-28-33-34-36	300(5-13-32) 1200(28)
IBPSO[22]	93.061	54.08	0.9585	0.0433806	7-9-14-32-37	300 (11-24-32) 600 (6-29)
ACO[30]	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.) at bus#17	LBI	Open switches	Capacitor located at (buses)
Initial state	202.677	------------------	0.9130905	0.1575671	33-34-35-36-37	------------------------
HSFLA	187.3621	7.55	0.98441544	0.0946267	6-35-13-37-17	300 (1-2-12-16-17-18-19) 600(13-24) 900 (24) 1200 (30)
PSO	103.1509	49.105	0.96942101	0.0432883	7-11-34-28-36	300(9-14-19-25) 600 (28) 900 (31)
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)

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

Methods	Power losses (kW)	Loss reduction (%)	Minimum voltage (p.u.) at bus#17	LBI	Open switches	Capacitor located at (buses)
Initial state	202.677	------------------	0.9130905	0.1575671	33-34-35-36-37	--------------------------
HSFLA	127.472	37.10	0.96323607	0.039968	7-35-34-37-32	300 (5-19-23) 600 (16-18) 1200 (31)
PSO	149.534	26.22	0.9703912	0.0282468	7-35-34-37-32	300 (7) 600 (29-31) 900 (32)
IPSO	135.541	33.12	0.9601967	0.030369	33-11-34-28-36	300 (25-26-27) 900 (16-32)

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.) at bus#17	LBI	Open switches	Capacitor located at (buses)
Initial state	202.677	------------------	0.9130905	0.1575671	33-34-35-36-37	------------------
HSFLA	98.44	51.45	0.95418297	0.0464747	7-10-14-37-32	300 (10-12-26) 600(3) 900 (29)
PSO	100.05	50.63	0.9616666	0.046695	7-11-34-37-36	300 (16-25-30-32) 600(1-5)
IPSO	101.11	50.11	0.9706953	0.04698	7-10-14-37-36	300 (11-17-25) 600(28-32) 900 (2)

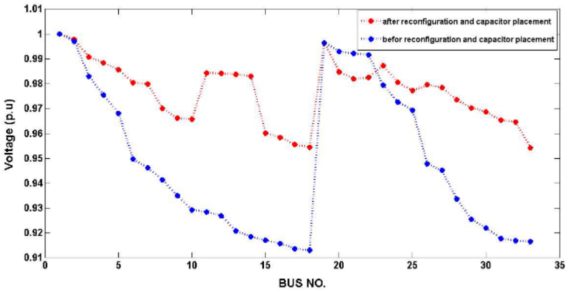

Fig. 3. Voltage profiles before and after optimal reconfiguration and capacitor placement in 33-bus system

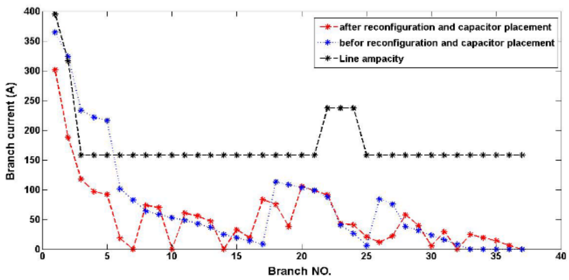

Fig. 4. Branches current profiles before and after optimal reconfiguration and capacitor placement in 33-bus system

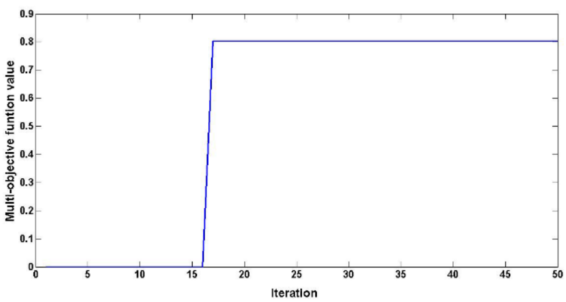

Fig. 5. Convergence characteristic of HSFLA for the multi-objective function for case study 1

As can be seen from Table. 6,the proposed method have better performance compared to the SA algorithm, but GA and ACSA have better perform-ance compared to the HSFLA algorithm. Figures 7 and 8 show the voltage and branches current profiles before and after optimal reconfiguration and capac-itor placement and convergence characteristic of the HSFLA for Case study 2, respectively. As shown in these figures, the voltage and current branches profile are obviously improved by using the HSFLA algorithm.

5.3. Case study 3

The third case study is a 25-bus unbalanced distribution 4.16-kV system consisting of 24 sectio-nalizing 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 [32]. This system is shown in Fig. 9. The initial power loss is 150.13 kW and minimum bus voltage in phase

a, b and c is 0.9284, 0.9284 and 0.9366 p.u respectively. In this simulation to optimize the multi objective fitness function, number of each cycle frogs and number of memeplexes are considered as

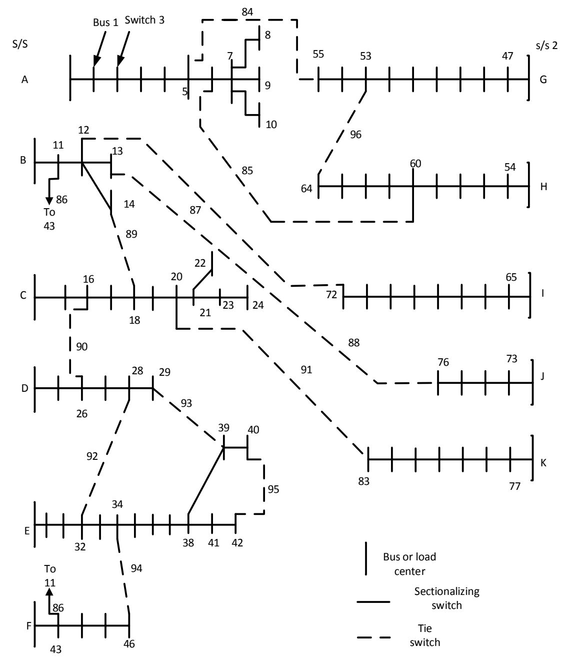

Fig. 6. 94-bus system

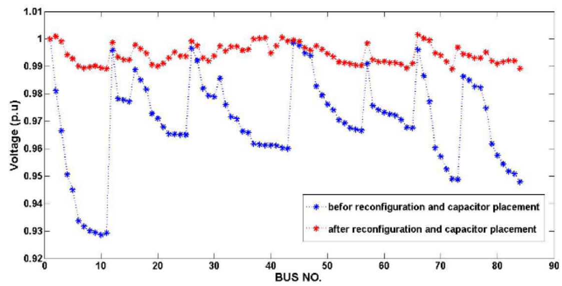

Fig. 7. Voltage profiles before and after optimal reconfiguration and capacitor placement in 94-bus system

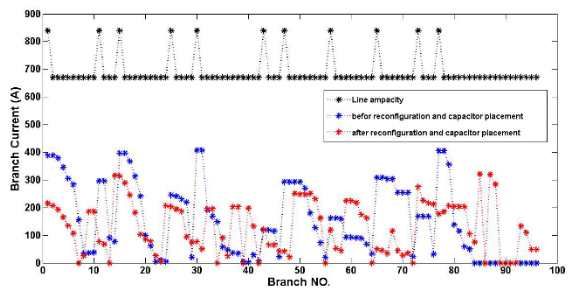

Fig. 8. Branches current profiles before and after optimal reconfiguration and capacitor placement in 94-bus system

4 and 5, respectively. So, the number of population is $P = m \times n = 20$. 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. 8. By considering the statistical nature of this algorithm, 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. 10 shows the voltage profiles in phase a, b and phase c of case study 3 before and after optimal reconfiguration and capacitor placement.

Fig. 11 shows the convergence characteristic of the HSFLA for case study 3. As shown in Fig. 10, fitness function after 35 iterations converges to 0.97 and the voltages profile is obviously improved using the HSFLA algorithm in each phase.

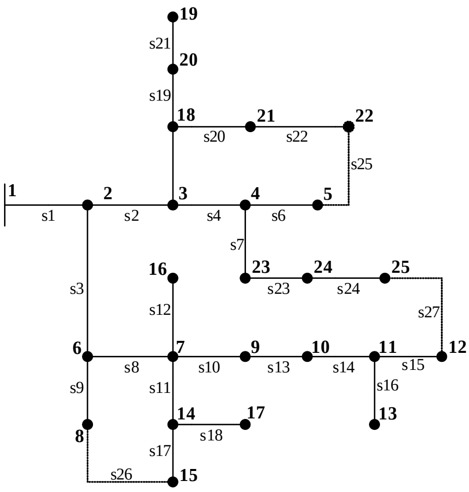

Fig. 9. 25 bus unbalanced distribution system

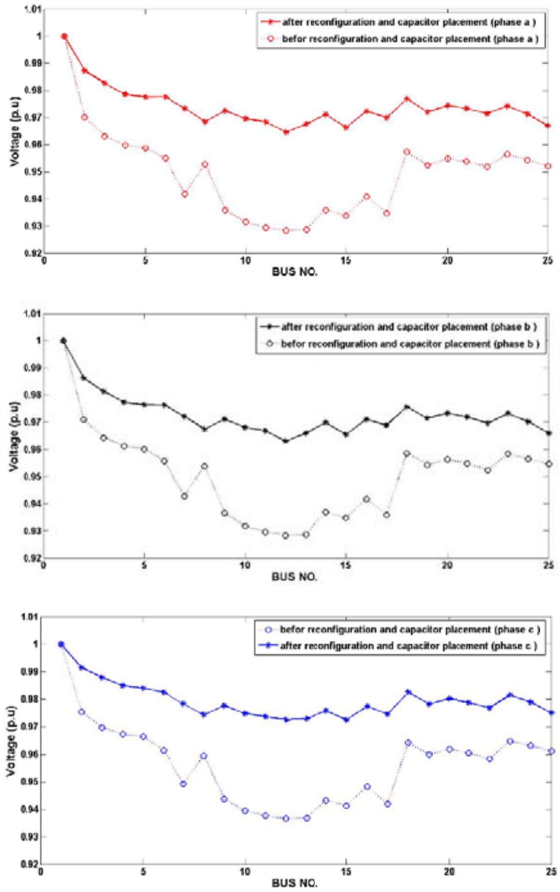

Fig. 10. Voltage profiles before and after optimal reconfiguration and capacitor placement in 25-bus system

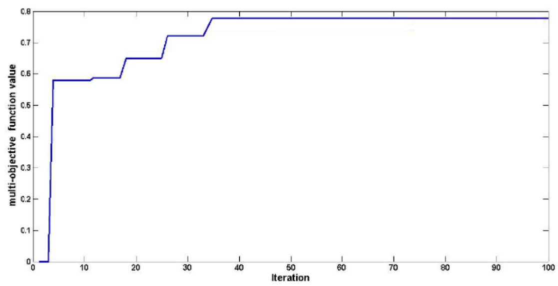

Fig. 11. Convergence characteristic of HSFLA for the multi-objective function for case study 3

Table 5. Results obtained by the HSFLA 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.) at bus#72	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 6. Results obtained for optimal size and location of capacitors by the HSFLA algorithm for case study 2

Bus		Capacitor (KVAr)		Capacitor (KVAr)		Capacitor (KVAr)		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	

Table 7. Results obtained by optimizing real power losses with HSFLA algorithm along in comparison with SA, GA and ACO

Item		Power losses (KW)	Minimum voltage (p.u) at bus#72	LBI
Original configuration		531.99	0.9285191	0.0329944
HSFLA	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 [19]	Best	309.12	---------------------	-----------
	Worst	315.86	---------------------	-----------
	Average	312.30	---------------------	-----------
	Average Loss reduction	41.3	---------------------	-----------
GA [19]	Best	295.39	---------------------	-----------
	Worst	299.13	---------------------	-----------
	Average	297.75	---------------------	-----------

	Average Loss reduction	44.03	---------------------	------------
ACO [19]	Best	295.12	---------------------	------------
	Worst	299.46	---------------------	------------
	Average	296.89	---------------------	------------
	Average Loss reduction	44.19	---------------------	------------

Table 8. Results obtained by the HSFLA algorithm for case study 3

Item	Initial state	Only optimizing real power losses	Only optimizing voltage violation	Only optimizing load balancing	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.) at bus #12	0.9284107	0.9640415	0.9877222	0.9740478	0.964586
Minimum voltage Phase b (p.u.)at bus #12	0.9283703	0.9626266	0.985857	0.9694966	0.963076
Minimum voltage Phase c (p.u.)at bus #12	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)

6. CONCLUSIONS

An HSFLA optimization algorithm as an efficient algorithm for multi-objective reconfiguration and capacitor placement of balanced and unbalanced distribution systems in a fuzzy framework has been introduced in this paper. An important property of the proposed approach is introduced for solving the problem of multi-objective reconfiguration and capacitor placement problem in the fuzzy framework. The minimization of total network real power losses and buses voltage violation as well as balancing the load in the feeders, are the major objectives of this approach. 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 resulting 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 HSFLA has achieved better performance compared to other algorithms. In case study 2, the HSFLA has obtained a better performance compared to the SA, and shown a performance almost similar to that of the GA and ACO. As it 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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