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A New Hybrid Algorithm for Multi-objective Distribution Feeder Reconfiguration Considering Reliability

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Abstract

Reducing electricity losses is the main objective in distribution feeder reconfiguration (DFR) problem. Distribution feeder reconfiguration is an optimization problem in power system which is performed through changing switching state. In this study, distribution feeder reconfiguration is optimized in the presence of distributed generators (DGs). In common DFR problems, reliability constraint is not satisfied and power losses or voltage deviation of buses is selected as the objective function. In this study, multi-objective problem is considered as a combination of reliability along with power losses. By adding reliability, the problem becomes more complex and requires an accurate method for solving multi-objective optimization problem. For this purpose, in this paper proposed a new hybrid evolutionary algorithm for solving the DFR problem. The proposed hybrid evolutionary algorithm is the combination of PSO (particle swarm optimization) and SFLA (shuffled frog leaping algorithm), called Improved particle swarm optimization (IPSO). In order to investigate efficiency of the proposed method, two 33-bus and 70-bus test systems are tested and the results are compared with GA and PSO algorithms

Keywords: distribution feeder reconfiguration (DFR), distributed generators (DGs), Improved particle swarm optimization (IPSO), multi-objective optimization, Energy not supplied (ENS)
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1. Introduction

Distribution networks, which are mostly exploited radially, have high line losses and their voltage drop is comparable with transmission networks. Several methods are proposed to reduce losses in distribution networks, where many of them require installing new equipment in the system. Such equipment not only impose financial load to companies but also their costs might be much higher than their social benefits, and they might result in new faults, which interrupts service. There are switches in distribution network which provide the ability to feed buses through different paths. System reconfiguration means changing state of these switches such that the objective is achieved. Investigating all states for reconfiguration is almost infeasible, because there are many states in a network with two-state switches (on or off), and the following constraints should be satisfied after reconfiguration:

– The new network should be radial
– The new network should include all buses.

Loads should not exceed generation capacity of the network.

Voltage of buses and network equipment should be in the allowed range, Current of lines and network equipment should be in the allowed range.

Therefore, DFR is a complicated optimization problem which requires fast and efficient methods to be solved. In recent years, many meta-heuristic algorithms have been proposed to solve the DFR problem; researches in this context are divided into two categories: one group have not considered effect of DGs [1-12], and second group have considered the effect of (DGs) on DFR problem [13-16].

In [1], a Honey Bee Mating Optimization (HBMO) algorithm is presented for DFR problem, objectives in this study include reducing power losses, number of switching operation and voltage deviation of buses. In [2] an evolutionary algorithm is proposed for DFR problem, the proposed algorithm is modified shuffled frog leaping algorithm (MSFLA). In [3], the combination of Harmony Search algorithm and Dynamic Planning is presented to solve DFR problem in order to reduce power losses and improve reliability. In [4], a new hybrid algorithm is presented for multi-objective DFR which combination of self-adaptive PSO and shuffled frog leaping algorithm (SFLA). In [5], a new hybrid method based on combination of Discrete PSO, Ant Colony Optimization (ACO) and fuzzy approach is suggested to solve multi-objective DFR problem. In [6], a hybrid evolutionary algorithm based on PSO and (ACO) is proposed to solve multi-objective DFR problem. In [7], a new hybrid fuzzy algorithm is presented for DFR problem in order to reduce power losses. In [8], a binary PSO algorithm is suggested for solving DFR problem and capacitor location in order to reduce voltage deviation. In [9], a genetic algorithm (GA) is presented for multi-objective DFR in order to reduce power losses and improve reliability. In [10], a PSO algorithm is proposed for multi-objective DFR in order to reduce power losses. In [11], an evolutionary algorithm is suggested for multi-objective DFR in order to reduce power losses and improve power quality. In [12], a modified honey bee optimization algorithm is presented for multi-objective DFR in order to reduce power losses and voltage deviation. With the development of distribution networks, and the appearing of DGs, Distribution network operators are pursuing various purposes, such as reducing power losses and improving reliability,etc. In [13], a genetic algorithm is suggested for multi-objective DFR problem in the presence of DGs.In this study, annual distribution feeder reconfiguration is presented aiming to reduce switching cost and power losses for each season of year. In [14], a harmony search algorithm is proposed for multi-objective DFR problem considering DGs, in order to reduce power losses and improve voltage profile. In [15], an ant colony algorithm is presented for simultaneous dynamic scheduling of DFR problem and switching of Capacitor Banks in presence of DG. In [16], an enhanced gravitational search algorithm is suggested for multi-objective DFR problem considering DGs. The literature survey shows that most of the papers use power losses reduction as objective function of distribution feeder reconfiguration problem, But fewer articles have used network reliability as an objective function. The main purpose of this paper is to use the distribution feeder reconfiguration problem in order to improve the reliability of the distribution network. For this reason, the objective function is a combination of reliability index along with power losses. In this study of two parameters u and u / that relate to the repair and restoratuin times of the upstream and downstream branches of the affected area is used to accurately calculate the energy not supplied index. In this paper proposed a new hybrid evolutionary algorithm, which is combination of particle swarm optimization (PSO) and shuffled frog leaping algorithm (SFLA) for solving the DFR problem, the main reason for using this proposed method is to resolve the convergence problem of the conventional PSO algorithm. In the proposed algorithm, the particles are divided into several memeplexes and search the optimal solution, in the process of optimizing, particles in different memeplexes search whole space, and then the optimal solution is chosen by exchanging information among the memeplexes. Considering the multi-objective problem, the proposed algorithm utilized the concept of Pareto optimality. In this study, an external repository has been considered to storage of Pareto solutions during the search process. In order to control the size of the repository, a fuzzy-based clustering has been utilized .In the proposed method; the system operator can apply his/her personal preference in choosing any one of those solutions

Rest of this article is organized as follows. Section 2 describes formulation of the problem including objective function and constraints. PSO, SFLA and PSO-SFLA algorithms are introduced in section 3. Multi-objective optimization problem has been investigated in section 4. Sections 5 and 6 present the application of the proposed hybrid algorithm for solving the multi-objective DFR problem and simulation results, respectively. Section 7 concludes the article

2. Problem formulation

In distribution feeder reconfiguration , there are different objective functions including power losses, voltage deviation of buses, load balance on transformers, load balance on feeders. In this study, objective functions include minimizing power losses, energy not supplied

A) *Objective function*

*Minimization of the Power Losses:*The minimization of the total power losses can be calculated as follows [1]:

$$f1(x) = \sum_{i=1}^{N_{branch}} R_i \cdot I_i^2 \tag{1}$$

$$X = \begin{bmatrix} Tie_1, Tie_2, \ldots . Tie_{N_{Tie}}, SW_1, SW_2, \\ \ldots . SW_{N_{Tie}}, P_{dg1}, P_{dg2}, \ldots . P_{dgN_{dg}} \end{bmatrix} \quad (2)$$

Where R_i and I_i are resistance and actual current of the ith branch, respectively. N_{br} is the number of the branches. X is the control variables vector. Tie_i is the state of the *i*th tie switch. Swi is the sectionalizing switch that forms a loop with Tie_i. N_{tie} is the number of the tie switches. N_{DG} is the number of DG.

Minimization of the Energy Not Supplied:The Energy Not Supplied (ENS) at the node can be calculated as follows [17]:

$$ENS_i = P_i \sum_{i,j \in V, i \neq j} (U_{i,j} + U'_{i,j}) \quad (3)$$

In the above equation, V is the set of buses, which are fed by one feeder and include bus i, also. Ui,j is the service unavailability related to the reparation time of all the branches connected to the bus i, U'ij is the service unavailability related to the restoration time of all the branches connected to the bus i. Ui, j and U'i,j are defined as follows [17]:

$$U_{i,j} = \lambda_{i,j} * d_{i,j} * t_{i,j} \quad (4)$$

$$U'_{i,j} = \lambda_{i,j} * d_{i,j} * t'_{i,j} \quad (5)$$

$\lambda_{i,j}$: Failure rate (fail/km-year), $t_{i,j}$: average reparation time (h/fail), $t'_{i,j}$: average restoration time (h/fail), $d_{i,j}$: Length of line (km).

The ENS of whole distribution network is calculated without considering the reference node as follows:

$$f_2(x) = \sum_{i=2}^{N_{BUS}} ENS_i \quad (6)$$

A simple distribution system shown in Fig.1 is used as an example. The ENS_3 can be determined as follows: if there is a fault in $branch_{1,2}$ and $branch_{2,3}$, after the average reparation time t_{1-2} or t_{2-3} the energy supply will be returned to the Bus 3, if there is a fault in $branch_{3,4}$ after the average restoration time t_{3-4} the energy supply will be returned to the Bus 3. The energy-not-supplied can be formulated as:

$$ENS_3 = P_3 \times (U_{1,2} + U_{2,3} + U'_{3,4}) \quad (7)$$

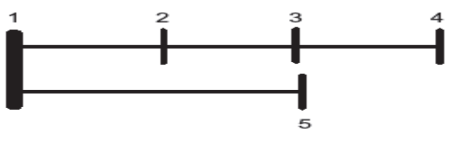

Fig. 1. Simple single line distribution network

B) Constraints

– *Distribution line limits:*

$$\left|P_{ij}^{line}\right| \leq P_{ij,Max}^{line} \quad (8)$$

P_{ij}^{line} and $P_{ij,Max}^{line}$ are the power flowing over the distribution branches and the maximum power transmitted between the nodes i and j ,respectively.

– *Power flow equations:*

$$P_i = \sum_{i=1}^{Nbus} V_i V_j Y_{ij} \cos(\Theta_{ij} - \delta_i + \delta_i) \quad (9)$$

$$Q_i = \sum_{i=1}^{Nbus} V_i V_j Y_{ij} \sin(\Theta_{ij} - \delta_i + \delta_i) \quad (10)$$

P_i and Q_i are the net injected active and reactive powers at the *i*th bus. V_i and δ_i are the amplitude and angle of the voltage at the *i*th bus, Yij and Θij are the amplitude and angle of the branch admittance between the *i*th and *j*th buses.

– *Radial structure of the network:*

$$N_{branch} = N_{bus} - N_{source} \quad (11)$$

N_{Bus} and N_{Source} are the number of buses and number of substations

– *Bus voltge limit:*

$$V_{min} \leq V_i \leq V_{max} \quad (12)$$

Where V_{min} and V_{max} are the minimum and maximum acceptable voltage value of the *i*th node. And V_i is the voltage magnitude of the *i*th node

– *Limit on the current of feeders:*

$$\left|I_{f,i}\right| \leq I_{f,i}^{Max} \quad i = 1,2, \ldots, N_{feeder} \quad (13)$$

Where $I_{f,i}$ and $I_{f,i}^{Max}$ are the the current amplitude and maximum current of the *i*th feeder, respectively. N_f is the number of feeders.

– *Limit on the current of transformers:*

$$\left|I_{t,i}\right| \leq I_{t,i}^{Max} \quad i = 1,2, \ldots, N_t \quad (14)$$

Where $I_{t,i}$ and $I_{t,i}^{Max}$ are the current amplitude and maximum current of the *i*th transformer, respectively. N_t is the number of transformers.

3. Proposed approach

Intelligent optimization algorithms have many advantages compared with classical methods. Therefore, using these algorithms have been increased in various engineering problems. The following meta-heuristic algorithms, particle swarm and shuffled Frog-leaping, briefly have been introduced.

A) Particle swarm optimization (PSO)

Particle swarm is one of the best methods for population-based evolutionary. PSO is inspired by the social behavior of some animals such as flocking behavior of birds and the schooling behavior of fish. In this algorithm, each particle is a potential solution for the optimization problem in which particles reach the best location using best previous experience and best person of the group. This algorithm is applicable to almost all the problems in multiple-dimensional, complex constrained and nonlinear programming [18]. The position of each particle is determined using two vectors in the search space: position vector $X=[x_1,x_2,\dots,x_n]$ and velocity vector $V=[v_1,v_2,\dots,v_n]$. In each iteration, velocity and position of sample particle *i*th by using equation (15,16) are updated:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1\left(pb_i^k - x_i^k\right) + c_2 r_2(gb_i^k - x_i^k) \tag{15}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{16}$$

Personal best (pbest): Best position achieved so far by particle. Global Best (gbest): It is the best position among all the individual pbest of the particles achieved so far.

C_1 and C_2 are Acceleration factors and r_1 , r_2 are normally distributed random values, ω is inertia weight. Using inertia weight makes a compromise between the ability to explore global and local. Often the inertia weight factor is set in the implementation of the algorithm and during learning. In this paper inertia weight, subject to equation (17), linearly decreasing from 1 to approximately zero [19].

$$ENS_3 = P_3 \times (U_{1,2} + U_{2,3} + U'_{3,4}) \tag{17}$$

Iter is the current iteration number and $iter_{max}$ is the maximum iteration number. Amount of velocity V_i (Velocity vector) in each dimension between [-Vmax +Vmax].

B) Shuffled frog leaping algorithm (SFLA)

Shuffled frog leaping algorithm is one of the algorithms inspired by nature which has been developed by Lansy and Eusuff [20].In this algorithm,an initial population of frogs (a set of solutions) is generated randomly. Then, by calculating the objective function for each frog, their fitness is determined, after that frogs are sorted in a descending order according to their fitness value and are divided into K memeplexes. Each memeplex holding M frogs. So the first frog belongs to the first memeplex, second frog belongs to the second memeplex and *M*th frog belongs to the *Mth* memeplex and frog M+1 belongs to the first memeplex. The worst frog and the best frog are shown by X_{worst} and X_{best} in each memeplex. In each memeplex, the frogs with the best and worst fitness are shown by X_b and X_w respectively, also the frog with best fitness among all memplexes is specified as X_G. improving the position of worst frog in each memeplex is done by equations (18,19).

$$D_i = rand \cdot (X_{b-}X_w) \tag{18}$$

$$X_w^{new} = X_w + D_i \tag{19}$$

Where rand is a random number between (0,1). and D is the displacement boundaries of frog.

If changing position produces a better frog, new frog is replaced with worst frog. Otherwise, the calculations in equation (19) are repeated with respect to the global best frog (i.e. Xg replaces Xb), and the new frog is generated. If improvement does not occur in this step, then a new frog is generated randomly and it is replaced with the worst frog. After internal evolution of several generations, all memeplexes are combined and frogs on the basis of their fitness in descending order are divided into several memeplexes and evolution procedure continues until the stopping criterion is reached.

C) Improved Particle Swarm Optimizatiom (IPSO)

PSO algorithm is widely used in optimization of power system problems. One of the main advantages of using SFLA compared to other evolutionary algorithms is its simplicity and minimum storage requirement. The main drawback of the PSO algorithm is its premature convergence. In PSO algorithm, particles tend to reach at local optimum or close to local optimum, therefore Particles may concentrate to a small region of space and do not have global exploration ability. In the SFLA, frogs are divided into several Memeplexes and search the different parts of space. Thus, by combining these algorithms, SFLA resolves the drawback of PSO through dividing particles into several Memeplexes, in other words by this proposed method several PSO algorithms will be implemented in different parts of the solution space. So the IPSO algorithm is suitable for multi-objective and non-convex DFR problem.

4. Multi-objective optimization problem

In a multi-objective optimization problem where objectives are in contradiction and constraints should be satisfied, the problem is as follows [21]:

$$Min\ f(x) = [f_1(x), f_2(x), \dots . f_n(x)]^T \tag{20}$$

Where $f_i(x)$ is the *i*th objective function and $h_i(x)$ and $g_i(x)$ are equal and unequal constraints. n is the number of objective functions and x is the optimization variables vector

A) Pareto optimal method

Solutions of multi-objective optimization problem are a set of Pareto points. In the multi-objective optimization problem, the vector X_1 dominates X_2 if:

$$\forall j \in \{1,2,\dots,N_{obj}\}, f_i(x_1) \ll f_i(x_2) \tag{21}$$

$$\exists j \in \{1,2,\dots,N_{obj}\}, f_j(x_1) < f_j(x_2) \tag{22}$$

Where N_{obj} is the number of objective functions.

B) Fuzzy based clustring

Since the objective functions are imprecise and are not in a similar range fuzzy based clustering is used for to control size of the repository. In this method, fuzzy membership function is used to identify the best compromise solution, in other words, this decision is made when the repository gets filled [4].For each particle in the repository,membership function for each objective function is defined as below. Objective function F_i is described by membership function U_i [1].

$$\boldsymbol{\mu_i(x)} = \begin{cases} \mathbf{1} & \boldsymbol{if} \quad \boldsymbol{F_i(x) \ll F_i^{min}} \\ \mathbf{0} & \boldsymbol{if} \quad \boldsymbol{F_i(x) \gg F_i^{max}} \\ \frac{\boldsymbol{F_i^{max} - F_i(x)}}{\boldsymbol{F_i^{min} - F_i(x)}} & \boldsymbol{if} \quad \boldsymbol{F_i^{min} \le F_i(x) \ll F_i^{max}} \end{cases} \tag{23}$$

F_i^{min} and F_i^{max}: lower and upper bounds of the objective function. These values are obtained through optimizing each objective function separately. The normalized membership value for each individual in the repository is evaluated by using [1]:

$$N_\mu(j) = \frac{\sum_{k=1}^{n} W_k . \mu_{fk}(X_j)}{\sum_{j=1}^{m}\sum_{k=1}^{n} W_k . \mu_{fk}(X_j)} \tag{24}$$

Where m is the number of non-dominant solutions, n is the number of objective functions, W_k is weight of the *k*th objective function. Value of W_k is selected by the operator based on importance of the objective function.

5. Application of proposed IPSO algorithm

The steps of the IPSO algorithm for DFR problem are as follows:

– Define the input data. The input data including distribution network information and algorithm parameters.
– Transfer the constrained multi-objective problem to an unconstrained one by the following equation:

$$F_1(x) = f_1(x) + k_1 \sum_{j=1}^{N_{eq}} (h_j(x))^2 + k_2 \sum_{j=1}^{N_{ueq}} \left(Max[0, -g_j(x)]^2\right) \tag{25}$$

$$F_2(x) = f_2(x) + k_1 \sum_{j=1}^{N_{eq}} (h_j(x))^2 + k_2 \sum_{j=1}^{N_{ueq}} \left(Max[0, -g_j(x)]^2\right) \tag{26}$$

$F_1(x)$ and $F_2(x)$ are the values of the augmented $f_1(x)$ and $f_2(x)$.

K_1 and K_2: penalty factors which are used to resolve constraints, value of penalty factor in this study is 10000. N_{eq} and N_{ueq} are the number of equality and inequality constraints, respectively, $h_j(x)$ and $g_j(x)$ are the equality and inequality constraints.

– An initial population Xi is generated randomly as follows:

$$Initial\ Population = \begin{bmatrix} X_1 \\ X_2 \\ . \\ X_N \end{bmatrix} \tag{27}$$

$$X_i = \begin{bmatrix} Tie_1, Tie_2, \dots . Tie_{N_{Tie}}, SW_1, SW_2, \\ \dots . SW_{N_{Tie}}, P_{dg1}, P_{dg2}, \dots . P_{dgN_{dg}} \end{bmatrix} \tag{28}$$

Where Xj is the ith control variable, N is the number of initial population.

– Evaluate the objectives function by Equations 1, 3
– Evaluate the membership function of each objective function by Equation (23)
– Use the Equation (24) to calculate the normalized membership value for all particles
– Using Pareto optimality method to obtain the normalized objective functions from previous step and storing set of non-dominant solutions in the repository.
– Divide the particles into K memeplexes based on descending order of fitness value
– Determine the XPbesti and XGbesti in the jth memplex
– Update the ith particle in the jth memplex based on (29, 30), this method should be repeated for all memeplexes.

$$D_{i,j}^{iter+1}=w.D_{i,j}^{iter}+c_1\cdot rand_1(0)\left(X_{Pbesti}-X_{i,j}^{iter}\right)+c_2\cdot rand_2(0)\left(X_{Gbesti}-X_{i,j}^{iter}\right) \quad (29)$$

$$X_{i,j}^{iter+1}=X_{i,j}^{iter}+D_{i,j}^{iter+1} \quad (30)$$

D: plays velocity role in the proposed algorithm and X denotes position of particles in this algorithm. C1 and C2 are acceleration factors and rand1 and rand2 are random values with normal distribution at interval (0, 1) and W is the inertia parameter.

- At this step, information is exchanged among all memeplexes. for this purpose, all Memeplexes are combined together and categorized again, all non-dominated solutions are extracted and stored this repository.
- Check the convergence criteria, If the current iteration number reaches the predetermined maximum iteration number, the search procedure stops, otherwise, it goes to Step 8.

6. Simulation Results

In order to investigate efficiency of the proposed method, it is applied to 33-bus and 70-bus test systems. Additionally, in order to validate the proposed method, it is compared with other algorithms such as genetic algorithm and PSO. Results of each network are given in 2 parts. In part 1, DGs are not considered but in part 2, the effect of DGs is also considered. Parameters of the IPSO algorithm are as follows: initial population is 300, maximum number of iterations is 200 and number of groups is 5. c1= c2=1.4 and W= [0.4-.09].

A) 33-bus radial distribution network

This test system is a 12.66kV network with a two-feeder substation, 32 buses and 5 looping branches [21]. The total active power losses for the initial configuration are 202.67 Kw. In this study, 4 DGs are used: 2 DGs with 300 kW capacity located at buses 7 and 14 and 2 DGs with 500kW capacity at buses 24 and 30

- *Power losses optimization:*

Table 1 shows the results of optimizing power losses in the absence of DGs employing GA, PSO and IPSO algorithms for 33-bus distribution system and compared with other optimization method from other references. The Best solution for all three algorithms in 30 iterations is shown in table 1.From this table, it is clear that results of IPSO algorithm are better than GA and PSO algorithms, also results of proposed algorithm are similar to other references or even better than them. In order to investigate effect of DGs on power losses, Table 2 shows results of GA, PSO and IPSO algorithms. As can be seen in the results, DGs can play a significant role in power losses decreasing with respect to Table 1. In addition, IPSO algorithm gives better results compared to other algorithms. Also, the amount of power losses in the presence of DGs has reduced from 139.53 Kw to 72.22 Kw. Figures 2 and 3 show convergence curve of the IPSO algorithm compared to PSO and GA for power losses optimization in the presence and absence of DGs

- *Energy Not Supplied optimization:*

Tables 3 and 4, show the results of optimizing Energy Not Supplied (ENS) in the absence and presence of (DGs) using GA, PSO and IPSO algorithm, respectively. From these tables, it is clear that the proposed algorithm can obtain better results with respect to other algorithms Furthermore, considering the effect of DGs in the 33-bus test system reduces the Energy Not Supplied index compared to Table 3, the amount of ENS in the presence of DGs has reduced from 53299.33 Kwh/year to 306056.96 Kwh/year).

- *Multi-objective optimization:*

Since main purpose of this study is to solve multi-objective distribution feeder reconfiguration, Tables 5 shows set of non-dominant solutions obtained for simultaneous optimization of two objective functions include minimizing power losses and ENS using IPSO algorithm in the presence of DGs associated to 33-bus test system. Pareto front for optimization of different objective functions in solving complex multi-objective distribution feeder reconfiguration using proposed IPSO algorithm in the presence of DGs is shown in Figure 4. Simulation results in Table 5 show that depending on priorities of the distribution system, if operator needs a configuration with minimum power losses in the network, configuration 5 is selected and if configuration with minimum ENS is required, configuration 8 is selected.

As can be seen in Figures 2 and 3, the convergence curve of the proposed IPSO algorithm for 33-bus system shows that in the absence of DGs, before fifth iteration and in the presence of DGs after fifth iteration, the proposed algorithm has converged towards the optimal solution, in other words, the proposed algorithm can obtain better results in less time compared to other algorithms.

B) 70-bus radial distribution network

This test system is a 11kV network has two substations, four feeders, 70 buses and 78 branches [23]. The total active power losses for the initial configuration are 227.53 Kw. This test system consists of seven DGs with 500 kW capacity at buses 9, 16, 24, 33, 43, 54 and 66

- *Power losses optimization:*

Table 6 shows the results of optimizing power losses in the absence of DGs employing GA, PSO and IPSO algorithms for 70-bus distribution system. The obtained results are compared with other optimization methods. The Best solution for all three algorithms in 30 iterations is shown in table 6.From this table, it is clear that results of IPSO algorithm are better than GA and PSO algorithms. In order to investigate effect of DGs on power losses, Table 7 shows results of GA, PSO and IPSO algorithms. As can be seen in the results, DGs can play a significant role in power losses decreasing with respect to Table 6.

In addition, IPSO algorithm gives better results compared to other algorithms and this shows effectiveness of the proposed algorithm for finding the optimal solution in the search space of the optimization problem. The amount of power losses in the presence of DGs has reduced from 227.53 Kw to 202.148 Kw. Figures 5 and 6 show convergence curve of the IPSO algorithm compared to PSO and GA for power losses optimization in the presence and absence of DGs.

– *Energy Not Supplied optimization*

Tables 8 shows the results of optimizing Energy Not Supplied (ENS) in the presence of (DGs) using GA, PSO and IPSO algorithm. From these tables, it is clear that the proposed algorithm can obtain better results with respect to other algorithms, which shows the ability of the proposed algorithm for solving the complex Distribution Feeder Reconfiguration problem. The value of the ENS before the presence of DGs was 150905 Kwh/year. Considering the effect of DGs in the 70-bus test system reduces the Energy Not Supplied index. The amount of ENS in the presence of DGs has reduced from 150905 Kwh/year to 30256.072 Kwh/year).

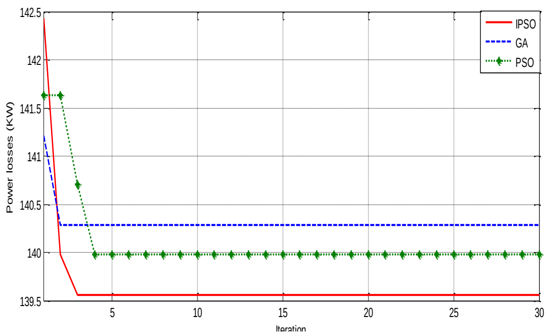

Fig. 2. Convergence curve for power losses objective function without DGs

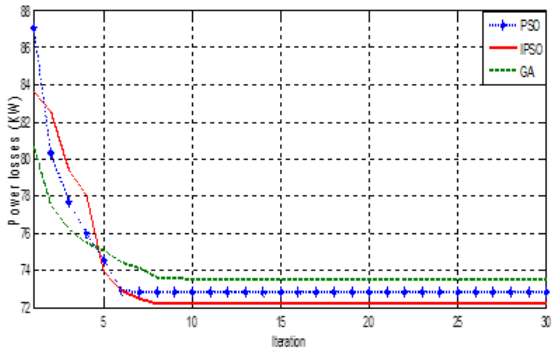

Fig. 3. Convergence curve for power losses objective function with DGs

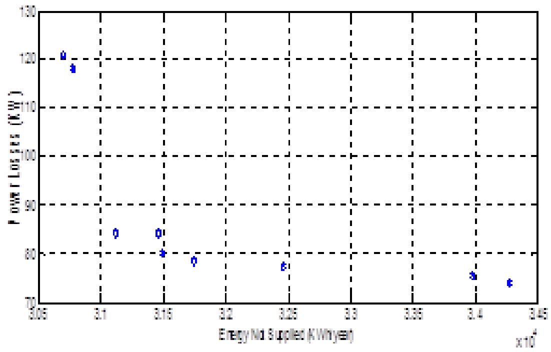

Fig. 4. Pareto front for multi-objective optimization using IPSO algorithm with DGs

Table.1.
Power Losses optimization without DGs

Open Switches	*Saving (%)*	*Power Losses (KW)*	*Method*
S7,S14,S9,S32,S37	31.14	139.53	HBMO [7]
S7,S14,S9,S32,S37	31.14	139.53	DPSO- HBMO [5
S7,S14,S9,S32,S37	31.14	139.53	PSO-ACO [6]
S7,S14,S9,S32,S37	31.14	139.53	DPSO-ACO [22]
S7,S14,S10,S32,S37	30.78	140.28	GA
S7-S14-S9-S32-S28	30.98	139.98	PSO

Table.2.
Power Losses optimization with DGs

Open Switches	*Power Losses (KW)*	*Generated power by DGs*	*Method*
S33,S34,S32 ,S28,S8	73.8	Bus7-300,Bus14-300,Bus24-500,Bus 30-500	GA
S37,S34,S 32,S6,S11	72.8	Bus7-300,Bus14-300,Bus24-500,Bus 30-500	PSO
S33,S34,S32 ,S28,S11	72.2	Bus7-300,Bus14-300,Bus24-500,Bus 30-500	IPSO

Table.3.
ENS optimization without DGs

Open Switches	*ENS (KWh/year)*	*Method*
S37,S35,S19,S15,S13	53798.1995	GA
S37,S35,S34,S19,S15	53299.6255	PSO
S37,S35,S34,S19,S17	53299.3375	IPSO

Table.4.
ENS optimization with DGs

Open Switches	*ENS (KWh/year)*	*Generated power*	*Method*
S37,S35,S19 ,S17,S13	30796.23	Bus7-300,Bus14 300,Bus24-500,Bus 30-500	GA
S37,S35,S34 ,S19,S17	30702.09	Bus7-300,Bus14-300,Bus24-500,Bus 30-500	PSO
S37,S35,S29 ,S19,S13	30656.96	Bus7-300,Bus14-300,Bus24-500,Bus 30-500	IPSO

– *Multi-objective optimization*

Tables 9 shows set of non-dominant solutions obtained for simultaneous optimization of two objective functions include minimizing power losses, ENS using IPSO algorithm in the presence of DGs associated to 70-bus test system. Pareto front for optimization of different objective functions in solving complex multi-objective distribution feeder reconfiguration using proposed IPSO algorithm in the presence of DGs is shown in Figure 7. Simulation results in Table 9 show that depending on priorities of the distribution system, if operator needs a configuration with minimum power losses in the network, configuration 3 is selected and if configuration with minimum ENS is required, configuration 7 is selected. As can be seen in Figures 5 and 6, the convergence curve of the proposed IPSO algorithm for 70-bus system shows that in the absence of DGs, after fifth iteration and in the presence of DGs after fifth iteration, the proposed algorithm has converged towards the optimal solution.

7. Conclusion

In this paper, a powerful evolutionary algorithm is proposed to solve multi-objective distribution feeder reconfiguration problem based on the combination of PSO and SFLA, called IPSO. In order to resolve convergence problem of the conventional PSO algorithm and improve quality of solutions, PSO and shuffled frog leaping algorithms are combined. Objective functions in this study include minimizing power losses and Energy Not Supplied. Constraints of the problem are associated to radial structure of the network, voltage of the buses, current of lines and capacity of transformers. The proposed algorithm is tested on 33-bus and 70-bus test systems. According to the results obtained in this paper, the proposed method has given better results compared to other algorithms employed in this paper. Comparison of the results obtained from the proposed method with other references shows superiority and accuracy of the proposed method compared to other algorithms. In addition, the proposed method can be used in networks with higher dimensions.

Table.5.
Obtained values using proposed IPSO algorithm with DG

M.	Open Switches	ENS (KWh/year)	Power Losses (KW)	Generated power by DGs
1	S19,S34, S8,S29,S28	32457.74	77.34929	Bus7-300,Bus14-299.96,Bus24-475.72,Bus30-500
2	S18,S34, S21,S15,S4	33981.01	75.40254	Bus7-285.96,Bus14-299.97,Bus24-500,Bus30-488.31
3	S18,S34, S35,S17,S22	31465.52	84.12741	Bus7-285.51,Bus14-300,Bus24-500,Bus30-500
4	S7,S34, S35,S16,S22	31120.08	84.29465	Bus7-279.2,Bus14-299.6,Bus24-493.9,Bus30-496.67
5	S7,S12, S35,S16,S37	34271.84	**73.9426**	Bus7-300,Bus14-300,Bus24-483.66,Bus 30-488.28
6	S2,S34, S35,S36,S37	31746.04	78.45434	Bus7-300,Bus14-294.14,Bus24-500,Bus 30-500
7	S18,S34, S11,S15,S22	31497.16	80.07617	Bus7-300,Bus14-300,Bus24-500,Bus 30-478.62
8	S19,S34, S35,S15,S37	**30702.39**	121.0324	Bus7-299.66,Bus14-277.65,Bus24-500,Bus 30-499.7
9	S33,S34, S35,S15,S37	30783.23	118.2597	Bus7-300,Bus14-300,Bus24-500,Bus 30-499.64

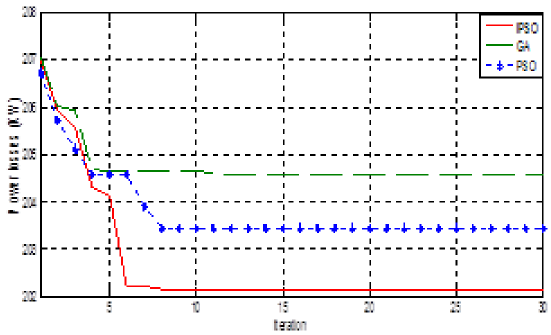

Fig. 5. Convergence curve for power losses objective function without DGs

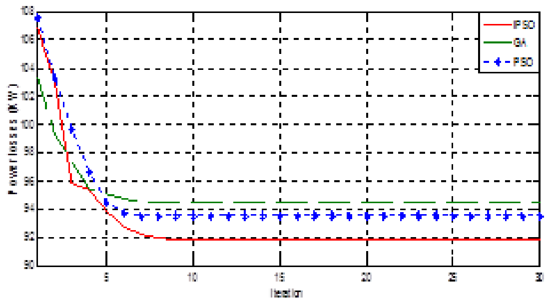

Fig. 6. Convergence curve for power losses objective function with DGs

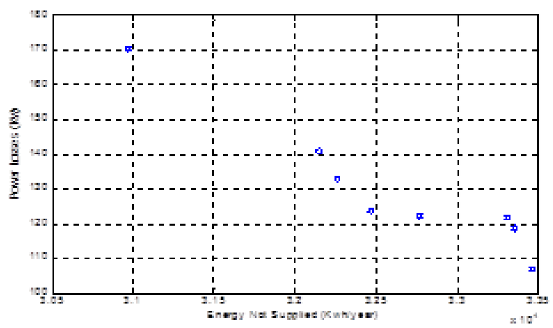

Fig. 7. Pareto front for multi-objective optimization using IPSO algorithm with DG

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