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Optimal Distribution System Reconfiguration Using Non-dominated Sorting Genetic Algorithm (NSGA-II)

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ABSTRACT

In this paper, a Non-dominated Sorting Genetic Algorithm-II (NSGA-II) based approach is presented for distribution system reconfiguration. In contrast to the conventional GA based methods, the proposed approach does not require weighting factors for conversion of multi-objective function into an equivalent single objective function. In order to illustrate the performance of the proposed method, 33-bus and 69-bus distribution networks have been employed which have led to the desired results.

KEYWORDS: Distribution System, Load Balancing, Non-dominated Sorting Genetic Algorithm, Power Losses Reduction, Reconfiguration.

1. INTRODUCTION

Distribution networks are generally structured in a mesh but operated in the radial configuration for effective co-ordination of their protective schemes and for reduction of the fault level. The reconfiguration of the distribution system is a process that alters the feeder topological structure by managing the open/close status of sectionalizing and tie switches in the system under contingencies or under normal operating conditions.

Reconfiguration of the radial distribution system is a very effective and efficient means to reduce distribution network losses, improve voltage profile, manage load congestion and enhance system reliability. The aim of distribution network reconfiguration is to find a radial operating configuration that optimizes certain objectives while satisfying all the operational constraints without islanding of any node(s).

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Extensive research work has been carried out in the area of reconfiguration of radial distribution system (RDS).

Merlin *et al.* [1] were the first to report a method for distribution system reconfiguration to minimize line losses. They formulated the problem as integer mixed non-linear optimization problem and solved it by a discrete branch-and-bound technique.

Baran *et al.* [2] developed a heuristic algorithm based on the idea of branch exchange for loss minimization and load balancing. To assist in the search, two approximated load flows for radial networks with different degrees of accuracy were used. They are simple Dist flow method and back and forward update of Dist flow method. The method is very time consuming due to the complicated combinations in large-scale system and converges to a local optimum solution, that is, convergence to the global optimum is not guaranteed.

Martín *et al.* [3] presented a new heuristic approach of branch exchange to reduce the power losses of distribution systems based upon the direction of the branch power flows.

Civanlar [4] developed a branch exchange method. In this method, loss reduction is achieved by exchange operation that corresponds to the selection of a pair of switches, one for opening and the other for closing so that the resulting network has lower line losses while remaining connected and radial. Peponis [5] used a combination of switch exchange method (SEM) and sequential switch opening method (SSOM) for reconfiguration of the network for loss reduction.

Nara *et al.* [6] introduced genetic algorithm (GA) for reconfiguration of RDS with minimum loss. Mendoza *et al.* [7] proposed a new methodology for minimal loss reconfiguration using GA by the help of fundamental loops. Yu and Wu [8] reported an efficient global optimization algorithm named core schema genetic shortest algorithm (CSGSA) for problems of large-scale distribution network reconfiguration. CSGSA changes from branches combination to loads combination. CSGSA has a powerful global optimum using core schema algorithm. Huang [9] proposed an enhanced GA based on fuzzy multi-objectives approach maximizing the fuzzy satisfaction allows the operator to simultaneously consider the multiple objectives of the network reconfiguration to minimize the power loss, deviation of voltage and current constraints as well as switching number, which subject to a radial network structure in which all loads must be energized. Parsad and Ranjan [10] presented a fuzzy mutated GA which overcomes the combination nature of the reconfiguration problem and deals with non continuous multi-objectives optimization.

Guedes *et al.* [11] proposed a new reconfiguration heuristic in order to reduce the total power losses and the maximum current of electrical radial networks. It is based on the branch-and-bound strategy, which is an implicit enumeration method that uses a tree structure and bounds to organize the searching process. Mendoza *et al.* [12] presented a microgenetic algorithm (µGA) for power losses and reliability indices minimization in distribution networks. Fu-Yan [13] suggested non-dominated sorting evolutionary programming in order to solve the multi-objective problems in distribution systems reconfiguration. Hongbin [14] used fuzzy preferences for multi-objective reconfiguration of distribution network. In this work, the multiple objectives are considered including load balancing among the feeders, minimum deviation of the nodes voltage, minimize the power loss and branch current constraint violation. Gupta *et al.* [15] presented an efficient method for the multi-objective reconfiguration of radial distribution systems in fuzzy framework using adaptive genetic algorithm. In [16], Swarnkar introduced an efficient method for the multi-objective reconfiguration of radial distribution networks in fuzzy framework using adaptive particle swarm optimization. The initial population of particle swarm optimization is created using a heuristic approach and the particles are adapted with the help of graph theory to make feasible solutions. Mori and Shimomugi [17] proposed a new method using multi-objective meta-heuristics (MOMH) in order to power losses and voltage deviation minimization in distribution networks.

Mendoza *et al.* [18] evaluated the performance of three multi-objective optimization techniques, microgenetic algorithm (µGA), non-dominated sorting genetic algorithm II (NSGA-II) and strength pareto evolutionary algorithm II (SPEA-II), applied to distribution network reconfiguration problems. The multiple objectives that should be optimized are power losses and reliability index. The results obtained from [18] show that the three above mentioned multi-objective methods are highly efficient in finding the pareto front and they require the evaluation of a reduced number of candidates in order to identify all the solutions belonging to the real front. Additionally, the NSGA-II and the SPEA-II require only half the evaluation and simulation time of those of the µGA, in order to find the same solutions.

Hence, in this study, a non-dominated sorting genetic algorithm-II (NSGA-II) [19] based approach is proposed for solving the reconfiguration problem. The main advantage of this technique is that the multi-objective nature of the reconfiguration problem is retained without the need of any tunable weights or parameters. As a result, the proposed methodology is generalized enough to be applicable to any power distribution network [20]. Rudplph [21] has proved that GAs converge to the global optimal solution in the presence of elitism.

Another important advantage of the proposed algorithm in this paper is that along with convergence, the NSGA-II maintains a good spread of solutions in the obtained set of solutions (called diversity). In this method, the diversity is achieved by the help of the crowded tournament selection operator (CTSO) that does not require any tuning parameter.

2. PROBLEM FORMULATION

The objective functions and the constraints of the reconfiguration problem are described as below:

Objective function:

1- Minimization of power losses:

$$Minimize\ \ f(x)=\sum_{i=1}^{N_l} r_i \frac{P_i^2+Q_i^2}{V_i^2} \qquad (1)$$

2- Load balancing [22, 23]

$$Minimize\ (LBI) \qquad (2)$$

where, $LBI=\mathbf{var}(S_1/S_1^{\max}, S_2/S_2^{\max}, S_3/S_3^{\max}, \ldots, S_{N_l}/S_{N_l}^{\max})$

Constraints:

$$I_i \le I_i^{\max} \qquad ;\forall j \in N_l \qquad (3)$$

$$V_{\min} \le V_j \le V_{\max} \qquad ;\forall j \in N_b \qquad (4)$$

$$\Phi(n)=0 \qquad (5)$$

Equation (1) and (2) present the power losses through the branches and load balancing index of the network, respectively, that should be minimized. In (2), $S_i/S_i^{\max}$ is the load balancing index of branch *i*, if *i*th branch of the network is lightly loaded, the value of $S_i/S_i^{\max}$ is low (less than 1), in critical condition its equal to 1 and in bad condition, when the branch rated capacity is exceeded, its value will be greater than 1. If the loads are unbalanced, the load balancing indices of individual branches will differ widely, whereas, the balanced load will make the load balancing indices of all the branches nearly equal. An effective strategy to reduce the load balancing index of the network is to transfer part of loads of heavily loaded feeders to lightly loaded feeders. Equation (3) corresponds to limit branch current and substation current capacities within permissible limits. Equation (4) considers voltage constraints for each node of the system and (5) deals with the radial topology constraint so that, $\Phi(n)=0$ if *n*th topology of network is radial, otherwise $\Phi(n)=1$.

3. NON-DOMINATED SORTING GENETIC ALGORITHM-II

Non-dominated sorting genetic algorithm is essentially a modified form of conventional GA. Like conventional GA, it also uses selection, crossover and mutation operator to create mating pool and offspring population. The step-by-step procedure of NSGA-II for one generation is described here for ready reference. The basic algorithm of NSGA-II is as follows [20]:

Step 1: Initially a random parent population P_o of size N is created (i.e. N is the number of strings or solutions in P_o). The length of each string is LS (i.e. LS is the number of bits in each string).

Step 2: Create offspring population Q_o of size N by applying usual GA operators (i.e. selection, crossover and mutation) on P_o.

Step 3: Assign $P_t = P_o$ and $Q_t = Q_o$, where P_t and Q_t denote the parent and offspring population at any general '*t*th' generation, respectively.

Step 4: Create a combined population $R_t = P_t$, Q_t. Thus, the size of R_t is $2N$.

Step 5: Perform non-dominated sorting on R_t. Non-dominated sorting divides the population in different fronts. The solutions in R_t, which do not constrained-dominate each other but constrained-dominate all the other solutions of

R_t, are kept in the first front or best front (called set F_1). Among the solutions not in $F = F_1$, the solutions which do not constrained-dominate each other but constrained-dominate all the other solutions, are kept in the second front (called set $F2$). Similarly, among the solutions not belonging to $F=F_1*F_2$, the solutions which do not constrained-dominate each other but constrained-dominate all the other solutions, are kept in the third front (called set F_3). This process is repeated until there is no solution in R_t without having its own front. Subsequently, these generated fronts are assigned corresponding ranks. Thus, F_1 is assigned rank 1, F_2 is assigned rank 2 and so on.

Step 6: To create P_{t+1}, i.e. the parent population in the next or '(t+1)th' generation, the following procedure is adopted. Initially, the solutions belonging to the set F_1 are considered. If size of F_1 is smaller than N, then all the solutions in F_1 are included in P_{t+1}. The remaining solutions in P_{t+1} are filled up from the rest of the non-dominated fronts in order of their ranks. Thus, if after including all the solutions in F_1, the size of P_{t+1} (let it be denoted by 'n') is less than N, the solutions belonging to F_2 are included in P_{t+1}. If the size of P_{t+1} is still less than N, the solutions belonging to F_3 are included in P_{t+1}. This process is repeated until the total number of solutions (i.e. n) in P_{t+1} is greater than N. To make the size of P_{t+1} exactly equal to N, ($n-N$) solutions from the last included non-dominated front are discarded from P_{t+1}. To choose the solutions to be discarded, initially the solutions of the last included non-dominated front are sorted according to their crowding distances and subsequently, the solutions having least ($n-N$) crowding distances are discarded from P_{t+1}.

Step 7: Create the offspring population Q_{t+1} by application of CTSO, crossover and mutation operator on P_{t+1}. In CTSO, the winner (better) solution is selected by comparing two solutions based on their rank and crowding distance. The solution having lower rank is declared winner. If two solutions have the same rank, the solution having higher crowding distance is declared winner. Now, to create offspring, two solutions are picked up randomly from the parents' population, and subsequently the winner of these two solutions is collected. This process is repeated until the number of solutions collected is lesser than size of population. After collecting required number of solutions, crossover and mutation operators are applied on collected solutions.

Step 8: Test for convergence. If the algorithm has converged then stop and report the results. Else, $t \leftarrow (t + 1)$, $P_t \leftarrow P_{t+1}$, $Q_t \leftarrow Q_{t+1}$ and go back to step 4.

4. APPLICATION OF NSGA-II IN DISTRIBUTION SYSTEM RECONFIGURATION

In this work, NSGA-II is implemented for solving the reconfiguration problem of distribution network. Various sections of NSGA-II are discussed below [20]:

4.1. String representation

As the configuration of a network is represented by status of all the switches in the network, the string in the reconfiguration problem represents the status of all the switches in the system. The length of each string (i.e. the number of bits in a string) is equal to the number of switches in the system. In this work, the binary coding system has been adopted. Thus, the status of the 'closed' and 'open' switch in the system is represented by the binary digit '1' and '0', respectively.

4.2. Generation of initial population

As discussed in the first step of Sec. 3, generally the initial population P_o is generated randomly. This is the simplest method, in which no knowledge about the network is required. The bit corresponding to the root switch (*i.e.* the switch directly connected to the substation) would always be fixed as '1' and a string of 'n-1' bits (where 'n' is the number of switches in the system) would be generated randomly.

4.3. Radiality checking

In this study, in order to check the radiality of the system, a breadth-first-traversal of the network, which starts from the root switch and proceeds towards the downstream side of the distribution system, has been employed [20].

The switch at which the traversal starts (*i.e.* the root switch) is called the first level switch. If any switch under consideration is closed, the nodes connected at the downstream side of this switch can be reached and hence is marked 'visited'. On the other hand, if this switch is open, the nodes connected at the downstream side cannot be reached and these nodes are marked 'unvisited'. After all first level switches are considered, nodes marked 'visited' are appended in list *M*. The switches connected at downstream side of the nodes currently appended in list *M* are called second level switches. After considering the second level switches in the same manner as just described, the list *M* is updated. The switches connected at the downstream side of the nodes most recently appended in the list *M* are called 'third level switches'. This process is repeated until there is no switch left in the next level. During this traversal, if any of the nodes is 'visited' more than once, the presence of a loop is detected. To maintain the radiality of the system, the switch currently under consideration is made 'OFF' immediately. After the network traversal is complete (*i.e.* all the network switches are considered), all the nodes marked 'visited' are put in a list EN called "existing nodes". It is to be noted that only the "existing nodes" are actually energized nodes (*i.e.* each of these nodes is connected to the substation via some combination of 'closed' switches).

4.4. Objective function evaluation

After checking the radiality, all strings give radial configuration. Thus, the value of objective functions, power losses and LBI index, of the network are calculated using (1) and (2), respectively.

4.5. String operation

To generate the offspring population, single point crossover method is used. Moreover, the mutation operator is applied randomly in any string. After the offspring population is created, the radiality of all offspring configurations is checked. If any of the offspring configurations is found to be non-radial, it is made radial following the procedure described in Section 4.3. Subsequently, with the help of CTSO, mating pool is created for the next generation. This operator maintains: 1) convergence as the solution having better front is selected and 2) diversity as the solution having higher crowding distance within the same front is selected [20].

4.6. Front formation

The combination of parent and offspring population having length 2*N* is divided in various ranked non-dominated fronts. Because of the front formation from the combination of parent and offspring population, chance is given to the current best solution in parents to compete with the offspring solutions. If no better solution is generated in offspring, the current best solution in parent becomes winner again. In this way, the elitism is maintained and due to the presence of elitism, convergence is improved [21].

N strings for parent population of the next generation from R_t of current generation are selected following the procedure described in step 6 of Section 3.

4.7. Convergence

To check for convergence, at each generation, the candidate configurations in parent P_t and offspring Q_t are compared after they are made radial. If both populations are the same, the convergence is considered to be achieved, otherwise not [20].

4.8. Selection of final solution

After the convergence is achieved, the best solutions are contained in the first front of R_t. If the first front has only one solution, then obviously it is the final solution of the reconfiguration problem [20]. On the other hand, if the first front has more than one solution, the final solution is chosen following a *L* stage (where *L* is the number of objective functions) procedure which uses the knowledge of preference of different objective functions. In the first stage, those solutions (from the first front of R_t) are picked up which have minimum value of the most preferred objective function and put them in a set FS. If FS contains only one solution, this is declared to be the final solution. If not, then in the second stage, those solutions from FS are picked up which have minimum value of the second preferred objective function and FS is updated with these solutions (i.e. FS now contains the solutions obtained after the second stage).

Again, if FS now contains only one solution, it is declared to be the final solution. If not, the above procedure is repeated. In general, at any '*m*th' stage ($m <= L$), those solutions from FS are picked up which have minimum value for the '*m*th' preferred objective function and the set FS is updated with these solutions. If FS contains only one solution at any stage, this is declared to be the final solution and the algorithm terminates. Otherwise, the algorithm proceeds to the next stage.

In this paper, from the point of view of distribution companies benefits, the first objective function (*i.e.* minimization of power losses) is kept on first preference and then the second objective function (i.e. minimization of *LBI*) has been kept on second preference.

The flowchart of the proposed reconfiguration algorithm is shown in Fig. 1.

5. TEST RESULTS AND DISCUSSION

In order to illustrate the validity and effectiveness of the proposed method, it is tested on the 33-bus [2] and 69-bus distribution systems [24]. The values of the crossover probability, mutation probability and the population size for both test system are given in Table 1. The proposed method is programmed in MATLAB on a PC Pentium IV, 2.8-GHz computer with 512 MB of RAM.

5.1. The 33-bus distribution system

The 33-bus distribution system operates at the nominal voltage of 12.66 kV and the base apparent power is 10 MVA and the base network losses and maximum voltage drop are 203.74 KW and 8.7%, respectively. In addition, the maximum current limit of the system branches is selected to be 255 A. This system for reconfiguration consists of 33 buses and 5 tie-lines. The normally open switches are 33-37 represented by the dotted lines and the normally closed switches 1 to 32 are represented by the solid lines as shown in Fig. 2.

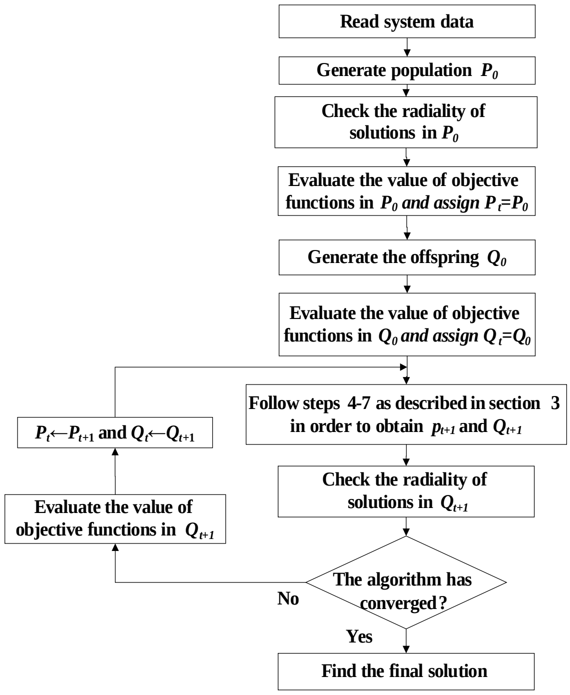


Fig. 1. The flowchart of the proposed NSGA-II

Table 1. NSGA-II parameters.

Test system	Population size	Crossover probability	Mutation probability
39-bus	5	0.8	0.03
69-bus	7	0.67	0.02

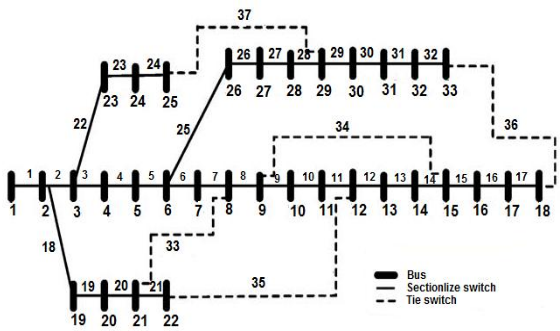


Fig. 2. The IEEE 33-bus distribution system.

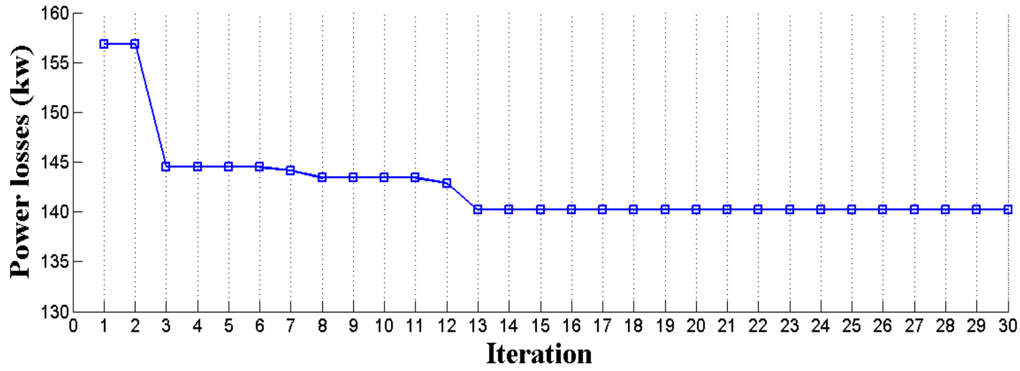
The proposed algorithm is applied to reduce real power losses and to increase the load balancing. The results of this application are depicted in Table 2.

Table 2. The results obtained from reconfiguration on the IEEE 33-bus system.

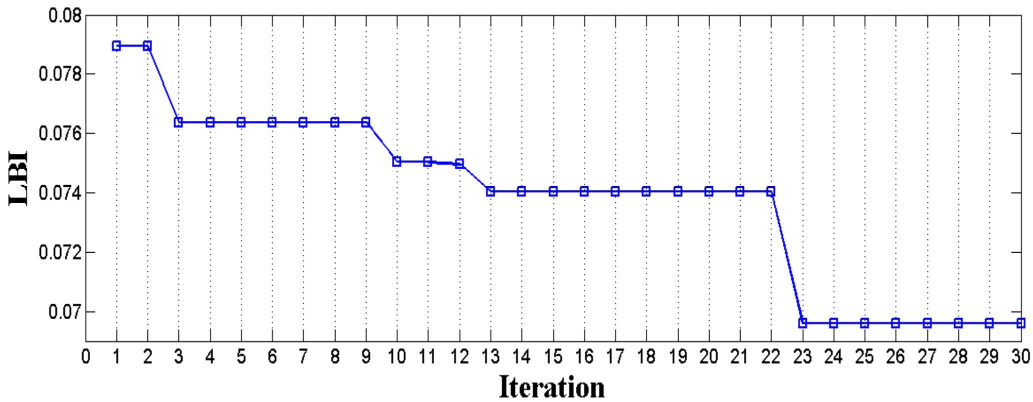
Method	Fuzzy-ACO [25]	Proposed NSGA-II
Base losses (kw)	202.74	203.45
Base LBI	0.119688	0. 125431
Tie-lines	37,32,14,9,6	37,32,14,9,7
Final losses (kw)	139.987	140.17
Final LBI	0.078672	0.083823
Loss reduction (%)	31	32.11
LBI improvement(%)	34.26	33.17
Maximum voltage drop (%)	5.85	6.25

The convergence characteristics of the both objective functions have been shown in Fig. 3. It is observed from Fig. 3 that the optimal solution is found at 23th iteration (which takes 8.34s to achieve) and the algorithm finally, after 12.14 s, converges at 30th iteration.

The proposed algorithm is also compared with the ones Fuzzy-ACO [25], Heuristic [26], DPSO-HBMO [27], SA [28], HBMO [29], HSA [30] and a brute-force routine, in which all possible configurations are tested, is derived from [31] in order to study the capability of all methods to reduce the real power losses. The results of this comparison are shown in Table 3. These results show that the proposed algorithm has got the real power loss in the system compared with the initial configuration by 31.1% reduction in power loss of the system. From Table 3, it can be seen the methods DPSO-HBMO [27] and HBMO [29] as well as proposed method in this paper have all found the global optimum configuration. A near-optimum solution has been found by applying the Heuristic [26], SA [28] and HSA [30] algorithms.



(a). Power losses vs. iteration.



(b). LBI vs. iteration.

Fig. 3. Convergence characteristics of the objective functions.

Table 3. Results obtained from the comparison of proposed method with other methods for the reduction of 33-bus real power losses.

Method	Tie-lines	Base losses (kw)	Final losses (kw)	Losses reduction (%)	Maximum voltage drop (%)
Optimum*	37,32,14,9,7	202.68	136.57	32.6	6.25
Proposed NSGA-II	37,32,14,9,7	203.74	140.17	31.1	6.25
Fuzzy-ACO [25]	37,32,14,10,7	202.74	136.81	32.47	6.25
Heuristic [26]	37,34,11,31,28	210.99	109.59	48.07	5.37
DPSO–HBMO [27]	37,32,14,9,7	202.67	139.53	31.14	6.2
SA [28]	34,33,31,28,11	202.74	140.67	30.64	7.67
HBMO [29]	37,32,14,9,7	202.67	139.53	31.14	6.2
HSA [30]	37,36,14,10,7	202.77	138.06	31.89	6.58

*Obtained with a brute-force algorithm [31].

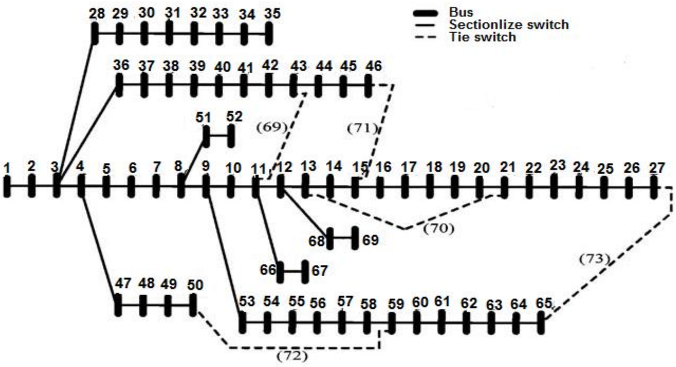


Fig. 4. The IEEE 69-bus distribution system.

It should be noted that what is important in reconfiguration process is the result related to the final tie-lines as proposed method is completely match with optimum tie-lines, and the differences in base and final losses in all methods are due to differences in their load flow algorithms.

5.2. The 69-bus distribution system

The 69-bus distribution system work at the nominal voltage of 12.66 kV and the base apparent power is 10 MVA. This system has 69 nodes and 73 branches, including tie-lines 69-73 as shown in Fig. 4.

This five tie-lines are open under normal operating conditions. Each branch is numbered based on the number of its starting node, the real power loss of the system before reconfiguration is 224.9346 KW and the minimum system voltage is 0.9092 pu.

Table 4 shows the results of reconfiguration by the proposed method. From Table 4, it can be seen that the proposed algorithm provides significant improvement in the system with 56% reduction at real power losses. Although, the SA [32] and fuzzy [23] slightly give the better results compared with the proposed NSGA-II for load balancing, the difference is not appreciable. In this case, the optimal solution is found at 34th iteration, which takes 27.3s to achieve.

Table 4. Results obtained from the reconfiguration for 69-bus distribution system

Method	SA [32]	Fuzzy [23]	Proposed NSGA-II
Base losses (kw)	228.46	228.46	224.93
Base LBI	0.1546	0.1546	0.1714
Tie-lines	69,70,14,56,61	69,70,14,57,61	69,61,58,13,12
Final losses (kw)	92.30	92.30	98.90
Final LBI	0.0907	0.0907	0.1025
Losses reduction (%)	59.62	59.62	56.03
LBI improvement (%)	41.33	41.33	40.20
Maximum voltage drop (%)	5.05	5.05	5.05

6. CONCLUSION

In this paper, an algorithm based on NSGA-II has been proposed for solving the reconfiguration problem in power distribution systems. The advantage of the proposed NSGA-II based technique is that it does not require any weighting factor (as needed in a conventional GA based technique). The simulation results for two typical IEEE distribution power systems showed that a new topology for the open/closed status of the switches was attained. In addition to the optimal reduction of power losses, the load balancing on the branches were also optimally improved. The voltage drop in the system was also reduced to its minimum value.

Nomenclature

N_b	number of nodes
N_l	number of network branches
P_i	active power at sending end of branch *i* (pu)
Q_i	reactive power at sending end of branch *i* (pu)
r_i	resistance of branch *i* (pu)
S_i	the apparent power in the sending bus of the *i*th branch (KVA)
$S_i^{\max}$	maximum capacity of the *i*th branch (KVA)
V_i	voltage at sending end of branch *i* (pu)
V_{max}	upper voltage limit (pu)
V_{min}	lower voltage limit (pu)
var (x)	variance of x
Ø(n)	radiality constraint of *n*th topology of network

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