Multi-objective Reconfiguration of Distribution Network Using a Heuristic Modified Ant Colony Optimization Algorithm

Seyed Hasan Mirhoseini, Seyed Mehdi Hosseini, Mehdi Ghanbari, and Majid Gandomkar

Abstract

In this paper, a multi-objective reconfiguration problem has been solved simultaneously by a modified ant colony optimization algorithm. Two objective functions, real power loss and energy not supplied index (ENS), were utilized. Multi-objective modified ant colony optimization algorithm has been generated by adding non-dominated sorting technique and changing the pheromone updating rule of original ACO. By proposed algorithm, a group of the best solutions can be obtained that called pareto front. None of these solutions are completely better than others among this pareto front. Furthermore, another objective function, i.e., voltage profile index has been separately considered to have better comparison between pareto front members. Simulations have been performed on two standard IEEE 16-bus and 33-bus test systems. The results show that the proposed heuristic modified algorithm generates well-distributed Pareto optimal solutions for the multi-objective reconfiguration problem.

Keywords**—**Network reconfiguration, Ant colony optimization, Non-dominated sorting technique, Power loss, Energy not supplied

I. INTRODUCTION

The most common way of solving multi-objective optimization problems is converting multi objective function problem into single-objective problem by summing all objective functions after allocating a weight to each of them. This approach is known as weighted sum method [1-3]. In this approach, finding the appropriate weights is the most important problem. This classical method has three main drawbacks. First, this method could not search all feasible areas of the problem. Second, this method is not individually known as an intelligent approach. Finally, all objective functions, need to be normalized to sum with each other in this method. On the other hand, better methods optimize the objective functions independently. Many optimum solutions can be discovered, instead of a single one [4-5].

The distribution system is a final link between the supply and loads. Therefore, it seems to be a very important section of the power network. Thus, lots of methods have been generated to improve operation of distribution network. One of the more basic and popular approach to enhance operation capability of distribution network is known as a network reconfiguration. There are two types of switches, sectionalizing switches (normally closed) and tie switches (normally open) in distribution feeders. The status of these switches are determined by network reconfiguration to achieve a new topological structure to bring about some goals such as loss reduction, load balancing, voltage profile improved, service restoration, power quality improvement, etc. The first research in reconfiguration distribution network has been done for loss reduction by Merlin and Back, based on a branch-and-bound-type optimization by a spanning tree structure [6]. After that, many research have been done on network reconfiguration with different heuristic techniques, such as interesting heuristic algorithm proposed by Shirmohammadi and Hong [7]. In this method, at first, all switches are kept closed. Then, the switches open one by one, in order to handle an optimum power flow in network. Civanlar has proposed another heuristic algorithm based on the branch exchange [8]. Then, Baran and Wu improved this method [9]. An improved mixed-integer linear program has been presented to determine the tree of minimum active power losses in balanced large medium voltage systems [10]. On the other hand, some researchers have been done different intelligent algorithms to achieve considered purposes such as Simulated Annealing, Genetic Algorithm, Differential Evolution Algorithm, Bacterial Foraging Optimization Algorithm, Ant Colony Algorithm, Particle Swarm Optimization [11-16]. In addition, Juan Carlos Cebrian et al. presented a computational implementation of an evolutionary algorithm (EA) in order to tackle the problem of reconfiguring radial distribution systems with considering power quality indices, due to voltage sags, by using the Monte Carlo simulation method [17].

The reconfiguration problem is usually formulated as a nonlinear, multi-objective and multi-constrained problem. For this problem, some multi-objective algorithms were applied such as multi-objective genetic algorithm (MOGA), NSGA, NPGA, PAES, NSGA-II and SPEA2.

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This paper presents a new multi-objective algorithm based on a non-dominated sorting technique. The procedure of reconfiguration is based on an approach, known as a loop eliminating method that consider opened switches as variables, instead of finding the configuration of closed switches.

II. PROBLEM FORMULATION

The purpose of distribution network reconfiguration is to find a radial operating structure that minimizes both real power losses and energy not supplied index simultaneously while satisfying operating constraints. The first objective function is the real power loss which is formulated as follows:

$$\min LP_{loss} = \sum_{i=1}^{n_b} r_i \frac{P_i^2 + Q_i^2}{V_i^2} \tag{1}$$

Where, n_b , r_i , P_i , Q_i and V_i are total number of branches, resistance of branch i, real power of branch i, reactive power of branch i and voltage of the head node of branch i respectively.

The second objective function relates to the energy not supplied index that can be expressed as

$$Min \quad ENS = \sum_{i=1}^{N_C} P_i \cdot U_i \tag{2}$$

$$U_i = \lambda_i \cdot r_i \tag{3}$$

where P_i , U_i , λ_i and r_i are real power, unavailability, failure rate and repair time for each load point respectively.

Also, an objective function related to voltage profile index can be considered for comparing obtained solutions as pareto front. This objective function can be presented as:

$$Min \quad V_S = \sqrt{\frac{1}{m_b} \sum_{i=1}^{m_b} (v_i - v_p)^2} \tag{4}$$

$$v_p = \frac{1}{m_b} \times \sum_{i=1}^{m_b} v_i \tag{5}$$

Where, V_S is voltage profile index, v_i is the voltage of node i, m_b is the number of nodes.

Constraint:

1) Radial network constraint:

The distribution network should operate in radial structure

2) Node voltage constraints

Voltage magnitude at each node must satisfy permissible ranges.

$$v_{i\min} \le v_i \le v_{i\max} \tag{6}$$

$v_{i\min}$, $v_{i\max}$ are the minimum and maximum voltage limits for node *i*, respectively.

3) Branch current constraints:

$$i_\ell \prec i_{\ell\max} \tag{7}$$

Current magnitude of each branch (feeder, laterals and switches) must satisfy allowable ranges.

4) Isolation constraint

All of the nodes should be energized.

III. NON-DOMINATED SORTING TECHNIQUE

The most important part of all optimization algorithms is the selection part. A suitable selection criterion can be brought about to obtain a good convergence behavior for algorithm. Non-dominated sorting approach is a suitable method for multi-objective problems. This approach provides a suitable selection criterion for algorithm to distinguish between solutions in muti-objective problems. In each cycle of the algorithm, all solutions will be sorted by assigning a rank to each of them. This rank will be obtained by non-dominated sorting technique. For the sake clarity of this approach, it is necessary to explain some subjects [4].

A. Concept of Domination

In a multi-objective minimization problem, the comparison between two solutions is defined:

$$X \le Y\,(X\,dom Y) \Leftrightarrow \forall i : X_i \le Y_i \ \wedge \ \exists i_0 : X_{i0} \prec Y_{i0} \tag{8}$$

Where X and Y are two solutions of a multi-objective problem, i is the number of objective-functions and i_0 is one of objectives [4].

B. Effectiveness of presence of other available solutions

Some solutions can be compared with each other after introducing concept of domination. But during the comparison, we confront with some solutions that cannot be compared with each other by concept of domination. Because, some solutions may be better according to one objective function while they are worse according to another objective function. Therefore, the effectiveness of presence of other solutions can help us to overcome this problem. This concept will be explained by an example from fig.1. In this figure, problem space has been divided to 4 region A, B, C and D, by considering point x as a goal. Also, some solutions 'a, b, c, d, e and x', have been specified from all possible solutions of an artificial minimization problem. As shown in fig.1, these solutions have two values by the two objective functions f_1 and f_2 . We want to compare point 'x' with other points in this problem. The point 'x' dominates all points in region A. It means that values of f_1 and f_2 for the point 'x' are less than values of f_1 and f_2 for the all points in this region A. For example, $f_1(x) \prec f_1(c)$ and $f_2(x) \prec f_2(c)$, therefore x dominates 'c'. Also, all points of region C dominate 'x'. It means that f_1 and f_2 of the all points of region C have less values than f_1 and f_2 of the point 'x'. On the other hand, comparing points of region B and D with point 'x' is difficult. The values of f_1 from all points of the region B are less than value of f_1 from point 'x', but the value of f_2 from point 'x' is less than values of f_2 from all points of the region B. Furthermore, the values of f_2 from all points of the region D are less than value of f_2 from point 'x', but the value of f_1 from point 'x' is less than values of f_1 from all points of the region D. Therefore, the best point cannot be specified by concept of domination between 'x' and points of region B and D. In this situation, we use effectiveness of presence of other available solutions to compare. At first, we assume that there is no point in region C. We want to compare point 'x' with point 'b' in region B. As seen, we have $f_1(x) \succ f_1(b)$ and $f_2(x) \prec f_2(b)$ for these two points. Therefore, it is not possible to compare points 'x' with 'b' at first. On the other hand, there is point 'a' that $f_2(a) \prec f_2(b)$ and $f_1(a) \prec f_1(b)$, it means that point 'b' is dominated by point 'a'. But there is no point that dominates '*x*'. Therefore, effectiveness of presence of point 'a' could help to compare point 'x' with 'b'. Thus, point 'x' is better than point 'b'. Also, we have the same difficulty to compare point 'x' with point '*d*'. It means that, $f_2(x) \succ f_2(d)$ and $f_1(x) \prec f_1(d)$ and then there is the point 'e' that $f_2(e) \prec f_2(d)$ and $f_1(e) \prec f_1(d)$, but there is no point that dominates 'x'. Therefore, effectiveness of presence of point 'e' could help to compare point 'x' with point '*d*'. Thus, point 'x' is better than point '*d*'. Finally, there is the same difficulty to compare between point 'x' with point 'e' and point 'a' with each other. In this situation, we cannot compare these points with concept of domination and effectiveness of presence of other available solutions. Therefore, there is no point that dominates these points completely. Thus, these points known as a pareto front of this cycle of algorithm [4].

C. Perform non-dominated sorting

Non-dominated sorting divides the solutions of each cycle to different fronts (level). After producing concept of domination and explaining the effectiveness of presence of other available solutions in comparing between each couple of them, non-dominated sorting will be performed by algorithm in each cycle. At first, we compare each couple of solutions with the concept of domination, separately.

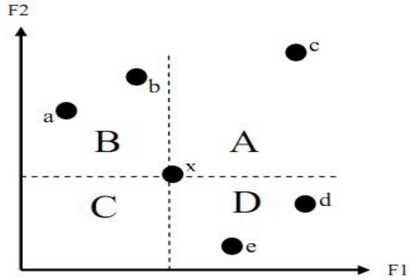

Fig. 1: some solutions from all possible solutions of an artificial minimization problem

The solutions, which were not dominated by others, are kept in the first front or best front (called set F_1). Then Among, the solutions which were not dominated by others without considering the effectiveness of front F_1, are kept in the second front (called set F_2). Similarly, the solutions which were not dominated by others without considering the effectiveness of front $F_1 \cup F_2$, are kept in the third front (called set F_3). This process is repeated until there is no solution in this cycle without having its own front. Subsequently, these generated fronts are assigned their corresponding ranks. Thus, F_1 is assigned rank 1, F_2 is assigned rank 2 and so on [4].

IV. ANT COLONY OPTIMIZATION

The ACO is an algorithm which based on swarm intelligence. Thus, colony of ants with swarm intelligence rules tries to find shortest way between the nest and food [18].

A. Behaviour of real ants

The ACO is a meta-heuristic optimization technique inspired from the foraging behavior observed in real ant colonies. Ants spray a substance that is called pheromone along the path. In fact, the pheromone is a track to guide other ants for selecting paths. Also, there is another fact about pheromone. It immediately starts to evaporate after spraying. As a result, if a path is a short one, the density of pheromone will be more. Thus, other ants follow the shorter path because of high density of pheromone. In this method, the longer paths will be disappeared during the time due to low density of pheromone.

At first, each ant that is placed on a starting state, builds a full path from the beginning to the end state. Selecting next state among all possible state is an important problem. All facts about ants are used for assigning a selection probability to all stations. Selection chance is formulated by:

$$P^k_{i\to j} = P^k_{ij} = \begin{cases} \dfrac{(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}}{\sum_{m \in N_i^k} (\tau_{im})^{\alpha}(\eta_{im})^{\beta}} & , j \in N_i^k \\ 0 & , j \notin N_i^k \end{cases} \qquad (9)$$

Where, P_{ij}^{k} is selection probability of stations, τ_{ij} and η_{ij} are, sprayed pheromones and heuristic data (distance) from i to j respectively, N_{i}^{k} consists of all nodes that k[th] ant were not there, α *and* β are coefficients of τ *and* η respectively. However, α *and* β are usually between 0 and 1.

B. Pheromone updating rule

For updating pheromone we have two formulations as follow:

$$\tau_{ij\,new} = \tau_{ij\,old} + \sum_{k} \Delta\tau_{ij}^{k} \tag{10}$$

$$\tau_{ij\,new} = (1-\rho) \times \tau_{ij\,old} \tag{11}$$

Where $\Delta\tau_{ij}^{k}$, is obtaining by:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{J(\psi^{K})} & , l_{ij} \in \psi^{k} \\ 0 & , l_{ij} \notin \psi^{k} \end{cases} \tag{12}$$

Where, ρ is evaporating coefficient, Q is a constant coefficient, ψ^{k} is path that is traversed by k[th] ant and $J(\psi^{K})$ is cost of k[th] ant.

C. Converting single-objective ACO to multi-objective ACO

Difference between single-objective and multi-objective algorithms is related to value of objective functions. In single-objective ACO, we have value of objective function as denominator in formula $\Delta\tau_{ij}^{k}$. In multi-objective ACO, we have more than one value of objective functions. Therefore, we cannot use this form of formula. In this paper, a new approach is proposed to overcome this problem. Rank of each solution that obtained by non-dominated sorting method is used instead of values of objective functions. Since the objective function is going to be minimized, solutions with lowest rank are better. Therefore, if this rank replace in denominator of formula, we will have better simulation of pheromone trails in formula $\Delta\tau_{ij}^{k}$. Also, we multiply a constant number to rank of each solution to have more resolution between solutions with different ranks. Therefore, $\Delta\tau_{ij}^{k}$ is formulated in multi-objective ACO by follow

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{K \cdot R(\psi^{K})} & , l_{ij} \in \psi^{k} \\ 0 & , l_{ij} \notin \psi^{k} \end{cases} \tag{13}$$

Where, $R(\psi^{K})$ is rank of each solution and k is a constant number.

V. Loop Eliminating Method for Reconfiguration Problem

Every configuration of the distribution network can be presented by the status of all available switches. In this algorithm, an approach known as loop eliminating method is used for reconfiguration problem that is a popular method because of decreasing the number of variables in each solution. The opened switches are considered as variables instead of specifying the status for all switches in this method. Therefore, each solution is modeled by these opened switches. All switches are considered to be closed at the beginning. In this situation, *K* loops are appeared. Because of the design of the network, these loops are numbered from 1 to *K* respectively. Then, one switch from every *K* loops is opened to keep the network radial with considering constraints of system. These opened switches are considered as variables of solutions [19].

A. Radial test of solutions

The most important part of reconfiguration problem is how to handle infeasible solutions. Ant colony optimization has an important precedence than other algorithms. In ACO, all solutions are constructed variable by variable. But in other algorithms like GA, the solutions are collectively generated. With this Characteristic, ACO can handle radial constraint during the building solutions. Therefore, infeasible solutions are not be created and the speed of ACO does not reduced when the algorithm precedes. Thus, it can be done with considering some rules during constructing solutions. These rules are:

1- In each configuration, none of the switches are selected more than one time.
2- At most one switch from each common path can be existed in each configuration.
3- At least one variable of all configurations must be selected from independent path of loops.
4- After providing radial constraints, each individual will be checked to provide branch current constraints and node voltage constraints.

B. Modeling construction of solution by ants movement

As mentioned above, all solution will be created via one by one movement of some ants. It is modeled by some layers instead of loops and stations instead of switches of loops, in order to find each solution in ACO by each ant for reconfiguration problem. All ants should pass these layers to nail food by pattern as follow:

1- In each cycle of algorithm, ants move toward food one by one
2- In each layer, only one station should be selected by each ant to achieve food.

3- Some loops are common in some lines, together. Therefore, there are some common stations in some layers. Thus, in forming a solution of ant's movement toward food, if one of these stations is selected, not only selected station will be omitted from next layers, but also other common stations related to this selected station will be omitted from next layers.

For instance, this pattern has shown in fig.2 for moving an ant for the sake of generating one solution for IEEE 33-bus system.

VI. Non-dominated sorting ant colony optimization (NSACO)

Non-dominated sorting ant colony optimization is a modified form of conventional ACO. The step-by-step procedure of the NSACO for one generation can be summarized as follows:

Step 1: initializing and assigning values of control parameters of algorithm and constructing initial solutions.

Step 2: calculating values of all cost functions for all solutions

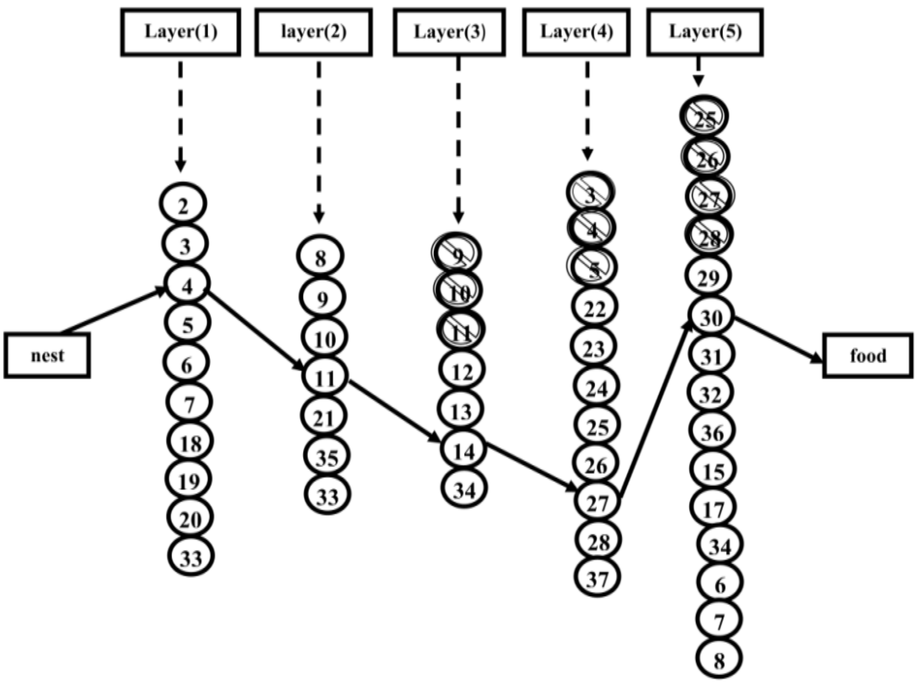

Fig. 2: constructing one feasible solution by moving

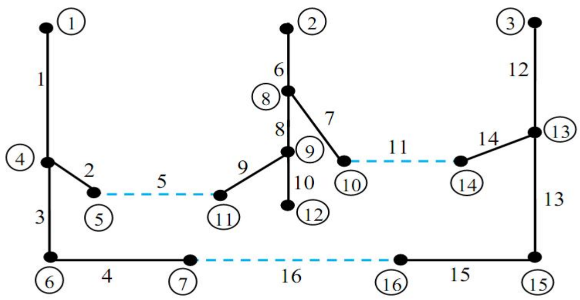

Fig. 3: IEEE 16-bus standard system (Civanlar)

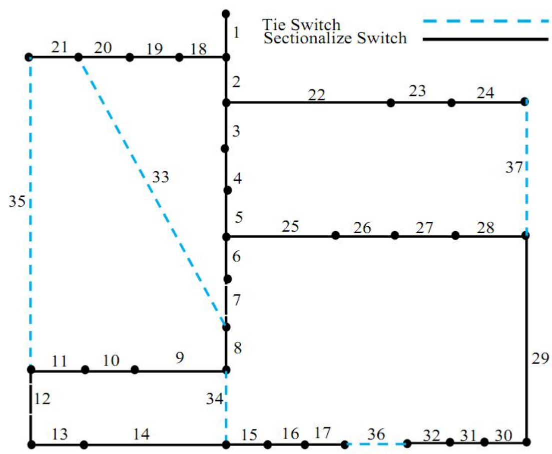

Fig. 4: IEEE 33-bus standard

Step 3: Performing non-dominated sorting technique and determining rank of all solutions

Step 4: deposit of pheromone based on rank of each solution

Step 5: updating pheromone and evaporating some part of pheromone

Step 6: specifying selected probability for all switches of each layer based on density of deposited pheromone

Step 7: constructing new solutions based on selection probability from step 6. (if termination criteria don not satisfy go to step 2)

VII. ANALYSIS OF RESULTS

The proposed algorithm has been implemented through two 16-bus and 33-bus test networks. These networks are shown in fig.3 and fig.4 respectively. All loops of these two networks with their switches are brought in Tables I and II. Only some possible solutions have been evaluated by non-dominated sorting technique instead of evaluating all solutions. Therefore, number of function evaluation is reduced by applying an intelligent algorithm and efficient technique. Also, values of these parameters can be different in each problem. In this problem, the optimal values of controlling parameters of the algorithms have been obtained by running the algorithms at different times that given in Table III.

A. The 16-Bus Test System

The first test system that is called the Civanlar system is a three-feeder distribution system [8], as shown in Fig. 3. Input data of this example system are shown in Table IV. The system consists of three feeders, 13 normally closed switches, and three normally open switches which are considered as dashed lines of 5, 11 and 16. This system has an installed power of 28.47 MW and 5.9 MVAR and $S_{base} = 100MVA$. Real power losses and the energy not supplied index of initial configuration of this system are 511.89 (KW) and 113.089 (MWh/yr) respectively. The pareto-optimal front of the non-dominated sorting ant colony optimization algorithm for the best optimization runs with considering real power losses and the energy not supplied index for the Civanlar system are shown in Fig. 5. Also, the obtained numerical results of applying algorithm in this system are brought in Table V.

It can be observed in fig.5 that 6 points are obtained as pareto front of problem. Having a single solution for problem among pareto front points, it can be obtained by several approaches. One way for presenting a solution for the problem is determining a logical region for objective functions and chooses a point in that region. Another way is chooseing a solution located in the middle of the set. Finally, a heuristic way that applied in this paper is using another objective function separately for all obtained solutions. Therefore, voltage profile index is considered in this paper for implementing it. Thus, six values of voltage profile index are obtained for six points of pareto front. Among these points, point number 4 with a reduction of 3.58% in losses and a reduction of 4.05% in ENS and with lowest value of voltage profile index, i.e., 0.07583 is obtained as a single solution of problem. Also, for giving the better view, voltage profile index for four cases (points) of pareto front is compared together. Case-1 and case-2, are the first and last points of pareto front that each of them is the best solution for each of two considered objective functions, case-3 is related to initial configuration and case-4 is related to the selected point as the best solution. Numerical results of this comparison for this

TABLEI
Switches Number of Loops of 16-Bus System

Loop Number	Switch Number
Loop-1	1, 2, 5, 9, 8, 6
Loop-2	6, 7, 11, 14, 12
Loop-3	2, 5, 9, 8, 7, 11, 14, 13, 15, 16, 4, 3

TABLE II
Switches Number of Loops of 33-Bus System

Loop Number	Switch Number
Loop-1	2, 3, 4, 5, 6, 7, 33, 20, 19, 18
Loop-2	33, 8, 9, 10, 11, 35, 21
Loop-3	14, 13, 12, 11, 10, 9, 34
Loop-4	22, 23, 24, 37, 28, 27, 26, 25, 5, 4, 3
Loop-5	25, 26, 27, 28, 29, 30, 31, 32, 36, 17, 16, 15, 34, 8, 7, 6

TABLE III
Summary of total features of applied algorithm

Some features of applied algorithms in 16-bus system for reconfiguration	Some features of applied algorithms in 33-bus system for reconfiguration
$\alpha = 0.59, \beta = 0.15$, number of ants=8, $\rho = 0.04, Q = 7$, number of variables=3 , η_{ij} = distance of i to j , k=5	$\alpha = 0.66, \beta = 0.12$, number of ants=70 , $\rho = 0.06, Q = 10$, number of variables=5, η_{ij} = distance of i to j , k=8

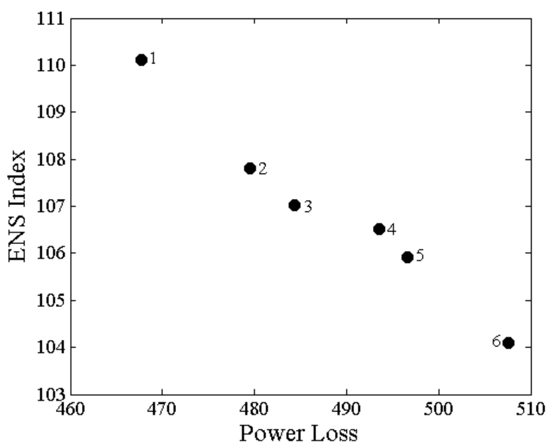

Fig. 5: parato-front for IEEE 16-bus

test network and next test network is brought in Table VI. As it seen, case-4 as a selected solution has the best value after case-1. Furthermore, plot of voltage profile for these four cases is drown in fig.6.

B. The 33-Bus Test System

The second test system that called Baran system is a 12.66 kV radial distribution system. The schematic diagram of the initial configuration is shown in Fig. 4. Input data of this example system are shown in Table VII. The system consists of one source transformer, 32 bus-bars, and 5 tie switches. The total active and reactive power for the whole system loads are 5048.26 kW and 2547.32 kVAR, respectively. In addition, the dashed line s33, s34, s35, s36, and s37 signify the original normal open tie switches. Real power losses and the energy not supplied index of initial configuration of this system are 202.496 kW and 6.689 MWh/yr respectively. The best compromise of Pareto-front for this system with considering power losses and the energy not supplied index is depicted in Fig. 7.

The results obtained of multi-objective reconfiguration on this system is reported Table VIII. It can be seen that the best pareto front of this study is formed by 10 points. If we consider, that pareto frontier selection criterion presents a solution which is located in the middle of the set, such as topology 7-11-14-17-37, a reduction of 26.82% in losses and a reduction of 4.39% in ENS is obtained, comparing to the initial configuration. This configuration has value of 0.01937 for voltage profile index that is almost average between all values. Also voltage profile index for four cases is compared together. Case-1 and case-2 are the first and last points of pareto front that each of them is the best solution for each of two considered objective functions, case-3 is related to the initial configuration and case-4 is related to the selected point as the best solution the same as first network. As it can be seen in table 6, case-4 as a selected solution has the best value of voltage profile index. Furthermore, plot of voltage profile for these four cases is drown in Fig. 8.

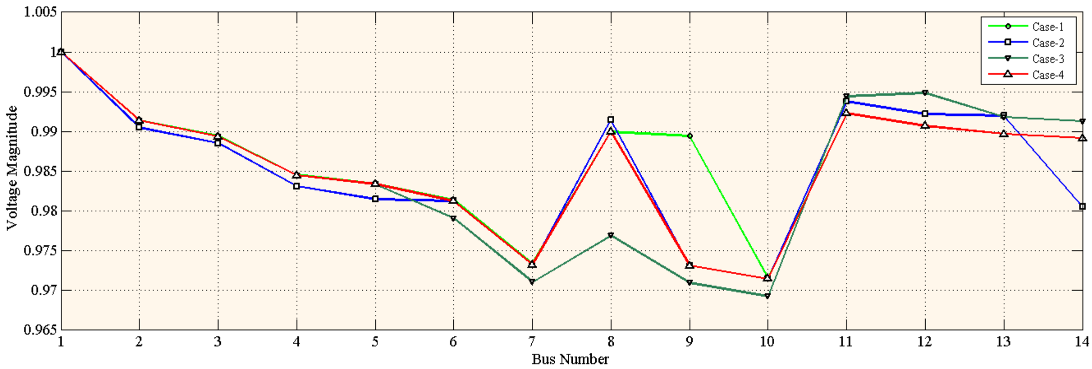

Fig. 6: Comparison of voltage profile of 16-bus network for four considered cases

TABLE IV
Civanlar system data

Line Number	Start Node	End Node	R(h)	$\lambda(f/yr)$	EMP	X(p.u)	R (p.u)	MW	MVAR
1	1	4	1	3.5	22	0.1	0.075	2	1.6
2	4	5	1	3	333	0.11	0.08	3	0.4
3	4	6	1	1.5	3	0.18	0.09	2	-0.4
4	6	7	1	3.5	3	0.04	0.04	1.5	1.2
5	5	11	1	0.4	222	0.04	0.04	0	0
6	2	8	1	1.1	222	0.11	0.11	4	2.7
7	8	10	1	1.1	2	0.11	0.11	1	0.9
8	8	9	1	2.8	2	0.11	0.08	0.5	1.8
9	9	11	1	0.8	222	0.11	0.11	0.6	-0.5
10	9	12	1	2	1	0.11	0.08	4.5	-1.7
11	10	14	1	5	222	0.04	0.04	0	0
12	3	13	1	0.5	0	0.11	0.11	1	0.9
13	13	15	1	1.5	3	0.11	0.08	1	-0.9
14	13	14	1	1	3	0.12	0.09	1	-1.1
15	15	16	1	4.4	2	0.04	0.04	2.1	-0.8
16	7	16	1	1	222	0.12	0.09	0	0

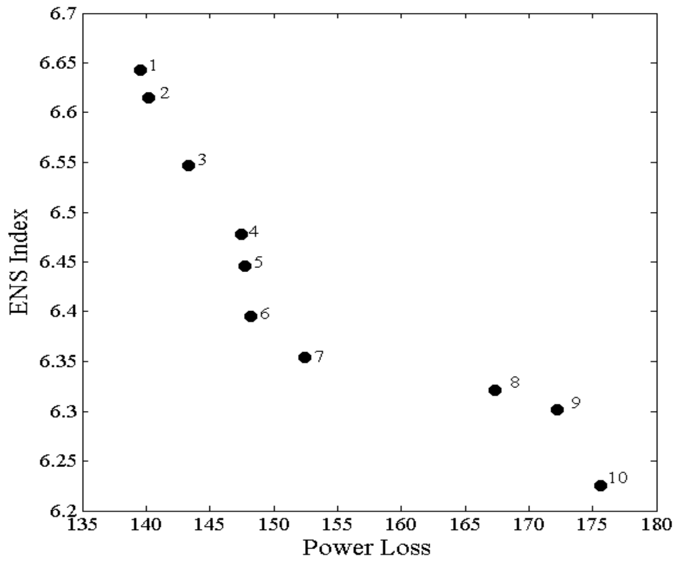

Fig. 7: Pareto-front for IEEE 33-bus

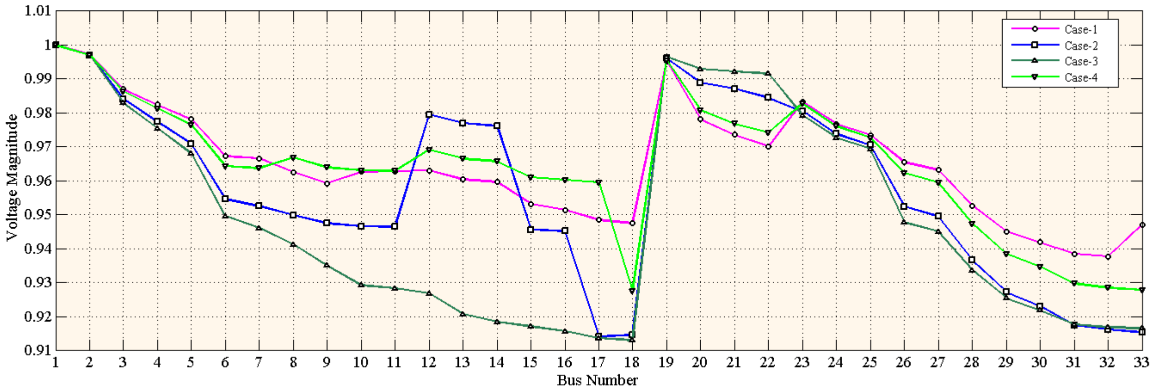

Fig.8 Comparison of voltage profile of 33-bus network for four considered cases

TABLE V
The details of pareto-front of 16-bus system

Number of Point	Number of Switch	Power Loss (kw)	Energy Not Supplied Index	Lowest Bus Voltage (p.u)	Voltage Profile Index
1	7-9-16	467.758	110.111	0.9715	0.07645
2	4-7-9	479.487	107.816	0.9715	0.07596
3	5-7-16	484.327	107.018	0.9714	0.07653
4	7-9-15	493.518	106.508	0.9715	0.07583
5	4-5-7	496.574	105.918	0.9714	0.07602
6	7-5-15	507.536	104.093	0.9714	0.07591

The same problem is solved in [20], but with different objective functions that are the construction cost of the network and the non-supplied energy. This problem is solved using the original non-dominated sorting genetic algorithm (NSGA) and the Pareto archived evolution strategy (PAES). They focused on distribution network design. Therefore, the objective functions associated to the reliability costs and power losses are evaluated in an approximated way. In our work, reconfiguration problem also has been solved by pareto envelope-based selection algorithm 2 (PESA 2) to have a comparison with NSACO. Table IX shows performance of NSACO compare with PESA2. According to table IX, in all items, NSACO has better performance in comparison with PESA2.

TABLE VI
Voltage Profile Index

Case Number	16-Bus System	33-Bus System
Case-1	0.07645	0.01632
Case-2	0.07591	0.02641
Case-3	0.07688	0.02984
Case-4	0.07653	0.01937

VIII. CONCLUSION

In this paper, a multi-objective reconfiguration problem considering to the real power losses and the energy not supplied index was studied simultaneously by a modified ant colony algorithm. The original ACO was converted to a multi-objective one by adding Non-dominated sorting technique. It was implemented on standard IEEE 16 and 33-bus test systems. The results show that implementing non-dominated sorting technique on an intelligent algorithm like ACO is an effective tool for solving multi-objective optimization problem. Also, this approach has three important benefits compared to other approaches like weighted-sum method. First, our approach could search all feasible areas of the problem. Second, in multi objective intelligent problems, time spending is crucial. In this paper best solution are obtained by 1.63 and 109 seconds for 16-bus and 33-bus systems respectively. Therefore, this approach is known as an intelligent method individually. Third, objective functions do not need to be normalized in this approach. Also, for obtaining a single solution between pareto front points, a heuristic way that is used in this paper is applying another objective function separately for all obtained solutions. Therefore, voltage profile index is considered in this paper for implementing it. Obtained results of two considered networks show that selected points reduce both selected objective function, i.e., 3.58% and 26.82% in losses and 4.05% and 4.39% in energy not supplied index for 16 and 33 bus systems respectively. Also, about comparison of obtained solutions as pareto front, especially for 16 bus system shows that voltage profile index is a suitable way for selecting the best solution among possible range of solutions.
Furthermore, ACO has a good preference in solving the reconfiguration problem because of having ability on constructing solutions without violation in radial constraint. Therefore, it is a suitable algorithm to solve the reconfiguration problem in large systems.

TABLE VII
Baran system data

Line Number	Start Node	End Node	R(h)	$\lambda(f/yr)$	EMP	X(P.U)	R (P.U)	MW	MVAR
1	1	2	1	0.5	1	0.0029	0.0058	100	60
2	2	3	1	0.3	3	0.0157	0.0308	90	40
3	3	4	1	0.22	2	0.0116	0.0288	120	80
4	4	5	1	0.23	0	0.0121	0.0238	60	30
5	5	6	1	0.51	0	0.0441	0.0511	60	20
6	6	7	1	0.11	3	0.0386	0.0117	200	100
7	7	8	1	0.44	2	0.0147	0.0444	200	100
8	8	9	1	0.64	2	0.0462	0.0643	60	20
9	9	10	1	0.65	333	0.0462	0.0651	60	20
10	10	11	1	0.12	2	0.0041	0.0123	45	30
11	11	12	1	0.23	2	0.0077	0.0234	60	35
12	12	13	1	0.91	2	0.0721	0.0916	60	35
13	13	14	1	0.33	222	0.0445	0.0338	120	80
14	14	15	1	0.36	2	0.0328	0.0369	60	10
15	15	16	1	0.46	333	0.0340	0.0466	60	20
16	16	17	1	0.8	2	0.1074	0.0804	60	20
17	17	18	1	0.45	2	0.0358	0.0457	90	40
18	2	19	1	0.1	3	0.0098	0.0102	90	40
19	19	20	1	0.93	2	0.0846	0.0939	90	40
20	20	21	1	0.25	2	0.0298	0.0255	90	40
21	21	22	1	0.44	2	0.0585	0.0442	90	40
22	3	23	1	0.28	333	0.0192	0.0282	90	50
23	23	24	1	0.56	2	0.0442	0.0560	420	200
24	24	25	1	0.55	0	0.0437	0.0559	420	200
25	6	26	1	0.12	3	0.0065	0.0127	60	25
26	26	27	1	0.17	0	0.009	0.0177	60	25
27	27	28	1	0.66	2	0.0583	0.0661	60	20
28	28	29	1	0.5	333	0.0437	0.0512	120	70
29	29	30	1	0.31	333	0.0161	0.0317	200	600
30	30	31	1	0.6	2	0.0601	0.0608	150	70
31	31	32	1	0.19	2	0.0226	0.0194	210	100
32	32	33	1	0.21	2	0.0331	0.0213	60	40
33	8	21	1	1.24	333	0.1248	0.1248	-	-
34	9	15	1	1.24	333	0.1248	0.1248	-	-
35	12	22	1	1.24	33	0.1248	0.1248	-	-
36	18	33	1	0.31	333	0.0312	0.0312	-	-
37	25	29	1	0.31	2	0.0312	0.0312	-	-

TABLE VIII
The details of pareto-front of 33-bus system

Number of Point	Number of Switch	Power Loss (kw)	Energy Not Supplied Index	Lowest Bus Voltage (p.u)	Voltage Profile Index
1	7-9-14-32-37	139.5101	6.643	0.9378	0.01632
2	7-10-14-32-37	140.2369	6.615	0.9378	0.01661
3	7-11-14-36-37	143.3604	6.547	0.9336	0.01738
4	7-9-14-17-37	147.4812	6.478	0.9275	0.01933
5	7-10-14-17-37	147.7053	6.446	0.9275	0.01934
6	7-11-14-17-37	148.1849	6.395	0.9275	0.01937
7	7-11-14-16-37	152.4777	6.354	0.9233	0.02166
8	11-14-32-33-37	167.3544	6.321	0.9249	0.02351
9	10-14-16-33-37	172.1783	6.302	0.9152	0.02585
10	11-14-16-33-37	175.6537	6.225	0.9143	0.02641

TABLE IX
Comparative table of 16 and 33-bus system

		16-bus system			33-bus system		
Algorithms	Performance	Number of fitness evaluations	Iterations	Time(s)	Number of fitness evaluations	Iterations	Time(s)
NSACO	average	48	38	2.33	127	231	480
	best	42	14	1.68	109	108	382
	worse	60	58	2.97	173	528	669
PESA2	average	77	60	4.04	185	543	651
	best	70	19	1.75	120	313	573
	worst	83	80	5.21	340	832	736

REFERENCES

[1] Hooshmand R., Soltani S.H. Simultaneous optimization of phase balancing and reconfiguration in distribution networks using BF–NM algorithm. *Electrical Power and Energy Systems* 2012; 41: 76–86.

[2] Saffar A, Hooshmand R., Khodabakhshian A. A new fuzzy optimal reconfiguration of distribution systems for loss reduction and load balancing using ant colony search-based algorithm. *Applied Soft Computing* 2011; 11:4021–4028.

[3] Gupta N, Swarnkar A, Niazi K.R, Bansal R.C. Multi-objective reconfiguration of distribution systems using adaptive genetic algorithm in fuzzy framework. *IET Gener Transm. Distrib* 2010; 12:1288–1298.

[4] Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm:NSGA-II. *IEEE Trans. Evolutionary Computation* 2002; 6:182-197.

[5] Coello A, Pulido G.T, Lechuga M.S. Handling Multiple objectives with particle swarm optimization. *IEEE Trans. Evolutionary Computation* 2004; 8:256-279.

[6] Merlin A, Back G. Search for minimum-loss operational spanning tree configuration for an urban power distribution system. in Proc. 5th Power System Conf. Cambridge, 1975; 1–18.

[7] Shirmohammadi D, Hong H.W. Reconfiguration of electric distribution networks for resistive line losses. *IEEE Trans. Power Del*, Apr 19891492–1498.

[8] Civanlar S, Grainger J, Yin H, Lee S. Distribution feeder reconfiguration for loss reduction. *IEEE Trans. Power Del*, Jul 1988; 1217–1223.

[9] Baran M.E, Wu F.F. Network reconfiguration in distribution systems for loss reduction and load balancing. *IEEE Trans. Power Del*, Apr. 1989; 1401–1407.

[10] Iborra F.L, Santos J.R, Ramos E. Mixed-integer linear programming model for solving reconfiguration problems in large-scale distribution systems. *Electric Power Syst. Res* 2012; 88:137-145.

[11] Chang H.C, Kuo C.C. Network reconfiguration in distribution systems using simulated annealing. *Electric Power Syst. Res* 1994; 29:227-238.

[12] Enacheanu B, Raison B, Caire R, Devaux O, Bienia W, HadjSaid N. Radial network reconfiguration using genetic algorithm based on the matroid theory. *IEEE Trans. Power Sys* 2008; 186-195.

[13] Jazebi S, Vahidi B. Reconfiguration of distribution networks to mitigate utilities power quality disturbances. *Electric Power Syst. Res* 2012; 91:9-17.

[14] Sathish Kumar K, Jayabarathi T. Power system reconfiguration and loss minimization for a distribution systems using bacterial foraging optimization algorithm. *Int. J. of Electrical Power Energy Syst* 2012; 36:13-17.

[15] Swarnkar A, Gupta N, Niazi, K.R. Adapted ant colony optimization for efficient reconfiguration of balanced and unbalanced distribution systems for loss minimization. *Swarm and Evolutionary Computation* 2011; 1:129-137.

[16] Niknam T, Azadfarsani E, Jabbari M. A new hybrid evolutionary algorithm based on new fuzzy adaptive PSO and NM algorithms for Distribution Feeder Reconfiguration. *Energy Conversion and Management*, Feb. 2012; 54:7-16.

[17] Cebrian J.C, Kagan N. Reconfiguration of distribution networks to minimize loss and disruption costs using genetic algorithms. *Electric Power Syst. Res* 2010; 80: 53-62.

[18] Dorigo M and Maniezzo V and Colorni A. Ant System: Optimization by a Colony of Cooperating Agents. *IEEE Trans. On Sys.*, Vol. 26, No. 1, 1996, pp. 29-41.

[19] Mirhoseini S.H, Hosseini S.M, Ghanbari M, Ahmadi M, A new improved adaptive imperialist competitive algorithm to solve the reconfiguration problem of distribution systems for loss reduction and voltage profile improvement. *Int. J. Electr Power Energy Syst* 55 (2014) 128–143.

[20] Mendosa F., Bernal-Agustin J., Dominguez-Navarro J. NSGA and SPEA applied to multiobjective design of power distribution systems. *IEEE Trans. Power Syst*., 2006, 21, (4), pp. 1938–1945.