Journal of Operation and Automation in Power Engineering

Vol. 7, No. 2, Oct. 2019, Pages: 148-156

http://joape.uma.ac.ir

Multi-objective Grasshopper Optimization Algorithm Based Reconfiguration of Distribution Networks

M.A. Tavakoli Ghazi Jahani[1], P. Nazarian[1], A. Safari[2,], M.R. Haghifam[3]*

[1]*Department of Electrical Engineering, Zanjan Branch, Islamic Azad University, Zanjan, Iran*
[2]*Department of Electrical Engineering, Azarbaijan Shahid Madani University, Tabriz, Iran*
[3]*Department of Electrical and Computer Engineering, Tarbiat Modares University, Tehran, Iran*

Abstract- *- Network reconfiguration is a nonlinear optimization procedure which calculates a radial structure to optimize the power losses and improve the network reliability index while meeting practical constraints. In this paper, a multi-objective framework is proposed for optimal network reconfiguration with the objective functions of minimization of power losses and improvement of reliability index. The optimization problem is solved by multi-objective grasshopper optimization algorithm (MOGOA) which is one of the most modern heuristic optimization tools. To solve an optimization problem, the suggested algorithm mathematically mimics and formulates the behavior of grasshopper swarms. The modifying comfort zone coefficient needs grasshoppers to balance exploration and exploitation, which helps the MOGOA to find an exact approximation of global optimization and not trapped in local optima. The efficiency of the suggested technique is approved regarding the 33-bus and 69-bus test systems. Optimization results expressed that the suggested technique not only presents the intensified exploration ability but also has a better solution compared with previous algorithms.*

Keyword: Reconfiguration, Powe loss, Reliability, Multi-objective grasshopper optimization algorithm, Multi-objective optimization.

1. INTRODUCTION

Distribution system giving the electric energy to the customers under a low voltage level is the last part of a power system. In distribution networks, the equipment failure is the main reason that energy does not deliver to the customers. There are some useful strategies to enhance reliability indices in the distribution networks. Some of these strategies as: utilizing highly reliable equipment for protection, reclosing and switching, automation, acceleration of restoration processes by employing faster crew, employing faster fault detection techniques and some equipment to avoid contingencies [1-2]. One of the most important strategies to improve the system reliability is distribution feeder reconfiguration. Network reconfiguration can be implemented by two types of switches, i.e. sectionalizing switches and tie switches, which are installed in the distribution network along the feeders. The healthy part of system can be electrically supplied while a sectionalizing switch separates a faulted section of the system. A tie switch brings the loads that have been disconnected by transferring some of the load to other supporting distribution feeders. The process of reconfiguration includes changing the open/close state of sectionalizing and tie switches in a way that radial structure of system is preserved [1]. Since the status of these switches has a vital effect on branch power flows as well as interruption durations in the event of a system failure, power losses and reliability of a distribution network can be effectively improved by optimal reconfiguration [1]. As the cost of active power losses is usually considerable, even a lower reduction in power losses is so beneficial for electric power utilities. In this respect, major action is performed in literatures about distribution network reconfiguration with the active power loss reduction as the objective function. In Ref. [2], a multi-objective optimization model has been used for reconfiguration of distribution networks equipped with fuel cells using probabilistic power flow. In Ref. [3], the gravitational search algorithm has been provided to solve the network reconfiguration problem with fitness functions of optimizing power losses and loads equilibration in feeders subject to technical and practical constraints. In Ref. [4], network reconfiguration has

Received: 06 Mar. 2019
Revised: 30 May 2019
Accepted: 13 Jun. 2019
∗Corresponding author:
E-mail: asafari1650@yahoo.com (A. Safari)
Digital object identifier: 10.22098/joape.2019.5841.1437
Research paper

been performed for power loss reduction and reliability enhancement with the limitations of bus voltages and network radiality. The genetic algorithm (GA) has been exploited to solve the optimization problem. The basis for this work is the information of a single loop and development of crossover and mutation operations of GA. In Ref. [5], quantum-inspired binary firefly algorithm has been exploited for the reconfiguration problem of distribution system to minimize the number of distributed voltage stages and reliability indices. This problem has been solved subject to constraints of voltage profile and network radiality. The self-adaptive modified optimization algorithm based on the bat algorithm has been used in Ref. [6] for distribution network reconfiguration with considering several objectives like average interruption frequency index, average energy not supplied, total power losses and cost. In order to perceive the effect of distributed generation on the reliability of electrical networks, wind generation has been also considered in the mentioned method. The formulated optimization problem has been solved subject to constraints of voltage profile, feeder ratings and network radiality. In Ref. [7], an efficient GA has been proposed to optimal distribution system reconfiguration. The objectives of the optimization problem are feeder power losses and system's node voltage deviation reduction and improvement of reliability index such as ENS. The authors in Ref. [8] have presented a new reliability-oriented algorithm for distribution system reconfiguration problem. This method maximizes the possibility of reliability enhancement and loss reduction and uses the interval analysis techniques to cover data uncertainties. Network reconfiguration has been formulated as a non-linear programming optimization problem that can be solved by a variety of methods. From viewpoints of optimality and accuracy, intelligent algorithms such as GA, ant colony optimization and particle swarm optimization may give better solutions compared to the classical methods such as lagrangian methodology. In literatures, some evolutionary algorithms have been used to solve the reconfiguration problem in distribution systems like GSA in Ref. [3], and shuffled frog leaping algorithm in Ref. [9].

The presented technique mathematically formulates the behavior of grasshoppers in nature for solving optimization problems. The GOA is able to effectively improve the initial random population of grasshoppers and enhance the average fitness of grasshoppers. By solving challenging problems considering composite objective functions, GOA correctly balances exploration and exploitation [10-12]. Considering the features reviewed above, the contribution of this paper is to perform the optimal reconfiguration of distribution networks using a multi-objective GOA to enhance the reliability index and reduce the power losses. The considered objective functions are minimization of power losses and improvement of reliability index. The optimal reconfiguration of distribution system would be obtained while the power losses are minimized and reliability is enhanced at the same time. It should be noted that the MOGOA is designed by using the unified framework proposed in Ref. [13] in which the primary steps are initialization, selection, generation and replacement. The contributions of the paper are:

• Bi-objective model for minimizing power loss and improving reliability.

• MOGOA solving proposed for bi-objective model.

• Results show that the proposed algorithm is computationally efficient.

Other sections are categorized as follows: In Section 2, the multi-objective reconfiguration problem is formulated as an optimization problem with the objective functions and constraints. In Section 3, the MOGOA are introduced to solve the optimization problem. Simulation results obtained from two test systems are presented in Section 4 and the results are compared with those of other approaches. Finally, the paper concludes in Section 5.

2. PROBLEM FORMULATION

2.1 Reliability index

Reliability is the ability of a device or a system to function adequately under planned conditions for the intended time periods [14]. In distribution system, reliability is defined as the impact of system performance on consumer's and component's operation under normal conditions. So, some reliability indices are defined to evaluate the efficiency of distribution network in order to provide uninterruptible electrical energy to the customers [15-17]. The energy not supplied to customers is measured by the ENS index as presented by Eq. (1) [18-20]:

$$F_1 = ENS = \sum_{i=1}^{N} L_{avg(i)} U_i \tag{1}$$

Where, $L_{avg(i)}$ is the average load connected to the load point i, U_i is the annual unavailability for each load point and N is the total number of load points.

2.2 Power loss minimization

Minimizing power loss is usually the purpose of reconfiguring distribution networks. In system reconfiguration, each switch is operated many times in a day and each operation is associated with some operating costs. Hence, it is significant to select the comprehensive cost minimization as the fitness function. This cost consists of operation cost of switches and the power loss cost and it is calculated by Eq. (2) [21]:

$$\boldsymbol{F_2 = K_1 P_{Loss} + K_s A_s} \tag{2}$$

Where, $\boldsymbol{P_{Loss}}$ is the active power loss of distribution network (kW), $\boldsymbol{K_1}$ is the cost per kilowatt-hour, $\boldsymbol{A_S}$ is the total operation number of all controllable switches, $\boldsymbol{K_S}$ is the cost of one ON/OFF switching operation. Based on the active power curve of distributed generators (DGs) and forecasted segmented-time load curve, the whole control plans of all the switches and distributed generators should be considered in advance. During each small segment, a concrete control decision is executed. Here, load prediction and active power curves of DGs are all considered to be departed into $\boldsymbol{N_L}$ small segments. Hence, the total decision is presented as [21]:

$$X = [X_1, X_2, \dots, X_t, \dots, X_{NL}] \tag{3}$$

Each X_t can be further presented as:

$$X_t = [S_t, Q_t] \tag{4}$$

Where, S_t and Q_t are the status vector of all controllable switches and the reactive power vector of all controllable DGs during the time segment t respectively. Suppose that N_S is the number of all controllable switches and the number of all controllable DGs is N_g, then S_t and Q_t are represented as [21]:

$$S_t = [S_{t,1}, S_{t,2}, \dots, S_{t,N_s}] \tag{5}$$

$$Q_t = [q_{t,1}, q_{t,2}, \dots, q_{t,N_g}] \tag{6}$$

From Eqs. (3)-(7), it can be observed that the dimension variable of X is $N_L.(N_S + N_g)$. Based on the settings of S_t and Q_t, the calculation of power flow during time part is fulfilled by the back/forward sweep technique. Then, the power loss of studied distribution network during time part can be calculated as follows [21]:

$$P_{Loss.t} = \Delta T \sum_{i=1}^{N_b} (I_{i.t}^2 . R_i) \tag{7}$$

Where, ΔT_t is the length of time segment t, N_b is the branch number of the whole system, R_j is the resistance of branch i and $I_{i,t}$ is the current of branch i in time segment t. With the same procedures, the power flow computations of all time segments are finished and the total power loss P_{Loss} in Eq. (2) is calculated as:

$$\mathrm{P_{Loss.t}} = \sum_{t=1}^{N_L} P_{Loss.t} = \sum_{t=1}^{N_L} \Delta T_t \sum_{i=1}^{N_b} (I_{i.t}^2 . R_i) \tag{8}$$

On the other hand, the operation number of switches n in one day is calculated as [21]:

$$\Delta_{t.n} = \sum_{t=1}^{N_L} \left| S_{n.t} - S_{n.(t-1)} \right| \tag{9}$$

2.3 Constraints

2.3.1 *Radial network constraint*

$$\sum_{l=1}^{N_b} \alpha_l = N_{Load} \tag{10}$$

$$\beta_{ij} + \beta_{ji} = \alpha_l, \qquad l = 1, \dots, N_b \tag{11}$$

$$\sum_{j \in N(i)} \beta_{ij} = 1, \qquad i = 1, \dots, N_{Load} \tag{12}$$

$$\sum_{f \in R(k)} \beta_{kf} = 0, \qquad k = 1, \dots, N_{Root} \tag{13}$$

$$\beta_{ij} \in \{0,1\} \qquad i = 1, \dots, N_{Load},\ j \in N(i) \tag{14}$$

In Eq. (10) and Eq. (11), α_l is a binary variable and it shows the status of the line l. α_l equals to 1 when line l is connected to the radial distribution network. $\alpha_l = 0$ means that the line l is not connected to any radial distribution network. In Eqs. (11), (12) and (14), β_{ij} and β_{ji} are two binary variables, respectively. β_{ij} is set to 1 if the node j is the parent of the node i while β_{ji} is set to 1 if the node i is the parent of the node j. In Eq. (11), the node i and the node j are the terminals on line l. In Eq. (12) and Eq. (13), N_{Load} and N_{Root} are the number of load nodes and root nodes, respectively. N_i is the set of nodes connected to the load node i by a line and $R(k)$ is the set of nodes connected to the root node k by a line. In Eq. (13), β_{kf} is exploited to show if node f is the parent of the root node k. Eq. (10) assures that all the load nodes connect to the radial distribution networks; Eq. (12) indicates that each load node has only one parent and Eq. (13) indicates that each root node has no parent. Constraints (10)-(14) assure that the concerned networks are radial and all the load nodes are energized.

2.3.2 Active power balance constraint

Active power balance constraint is presented as follows:

$$\sum_{j \in N(i)} \left[V_{i.t} V_{j.t} \left(G_{ij.t} \cos\theta_{ij.t} + B_{ij.t} \sin\theta_{ij.t} \right) \right] = P_{DG.i.t} - P_{D.i.t} \tag{15}$$

Where, $N(i)$ is the subset of adjacent nodes connected to the node i by corresponding lines, $\theta_{ij,t}$ is the voltage angle difference between the nodes i and j during the time segment t, calculated as ($\theta_{i.t} - \theta_{j.t}$), $G_{ij.t}$ is the real term of elements i and j in the node admittance matrix during the time part t, $B_{ij.t}$ is the imaginary term of elements i and j in the node admittance matrix during the time part t, $P_{DG.i.t}$ is the active power injected by generating unit at the node i during the time part t, $P_{D.i.t}$ is the active load demand at the node i during the time part t and $V_{i.t}$ and $V_{j.t}$ are the voltage amplitudes of the nodes i and j during the time part t , respectively.

2.3.3 Voltage constraint

Voltage constraint can be formulated as:

$$V_{Min} \leq V_{i.t} \leq V_{Max}, \forall \ i \in (1 \sim N_b) \ \& \ \forall \ t \in (1 \sim N_L) \quad (16)$$

Where, V_{Min} is the lower voltage limitation and V_{Max} is the upper voltage limitation and $V_{i,t}$ is the voltage amplitude of the node i during the time part t.

2.3.4 Capacity limit constraint of reactive power of distributed generator

$$q_{Min.g.t} \leq q_{g.t} \leq q_{Max.g.t}, \forall \ g \in (1, N_{g)} \quad (17)$$

Where, $q_{g.t}$, $q_{Min.g.t}$, and $q_{Max.g.t}$ are the control output, the lower limitation and the upper limitation of the reactive power of distributed generator g during the time part t, respectively.

$\boldsymbol{q_{Min.g.t}}$ and $\boldsymbol{q_{Max.g.t}}$ are subject to physical/hardware constraints of different DGs [23].

3. OPTIMIZATION APPROACH

The grasshopper optimization algorithm (GOA) is firstly introduced in this section and then the proposed multi-objective version of the grasshopper optimization algorithm (MOGOA) is presented.

3.1 Grasshopper optimization algorithm

Nature-inspired, the population-based algorithm is the most well-liked among stochastic optimization algorithms. The GOA has been established as a global optimization algorithm which is inspired by the life of grasshopper. Due to GOA's efficiency in solving real-world optimization problems, it can be used to minimize or maximize a target function. The optimization algorithm should find the best values for the decision variables. Slow movement and small steps of the grasshoppers are the main characteristics of the population in the larval phase. In other side, immediate movement and long range are the vital characteristics of the swarm in maturity. Another imperative characteristic of the swarming of grasshoppers is food source seeking. The search procedure is separated into two trends: exploitation and exploration. In the exploration stage, the search factors are influenced to move suddenly while grasshoppers want to move locally during exploitation state [10]. These two goals are achieved by the natural grasshoppers. Simulation of swarming behavior of grasshoppers is presented as:

$$X_i = T_i + G_i + A_i \quad (18)$$

Where, X_i is i^{th} grasshopper; G_i is the gravity force on the i^{th} grasshopper, T_i is the social interaction and A_i shows the wind advection. Notice that in order to make random behavior, the aforementioned equation can be written as:

$$X_i = r_1 T_i + r_2 G_i + r_3 A_i \quad (19)$$

Where, r_1, r_2 and r_3 are random numbers [0,1].

$$T_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} t(d_{ij})\, \hat{d}_{ij} \quad (20)$$

$$d_{ij} = |X_j - X_i| \quad (21)$$

$$t(r) = f e^{\frac{-r}{l}} - e^{-r} \quad (22)$$

Where, d_{ij} is the distance between the i^{th} and the j^{th} grasshopper [10]. Also, $\hat{d}_{ij} = \frac{X_j - X_i}{d_{ij}}$ is a unit vector from the i^{th} to the j^{th} grasshoppers. f introduces the intensity of gravitation and l is the absorptive length scale. The G component in Eq. (18) can be formulated as:

$$G_i = -g\hat{e}_g \quad (23)$$

Where, $\hat{e}_g$ and g indicate unity vector toward the center of the earth and gravitational constant. The A_i parameter in Eq. (18) is calculated as:

$$A_i = u\hat{e}_w \quad (24)$$

Where, u and $\hat{e}_w$ are constant drift and unit vector in the direction of wind. Substituting T, G and A in Eq. (18), this equation can be rewritten as follows [11]:

$$X_i = \sum_{j=1}^{N} t(|X_j - X_i|) \frac{X_j - X_i}{d_{ij}} - g\hat{e}_g + u\hat{e}_w \quad (25)$$

Where, N is the number of grasshoppers in the population. The GOA was prepared with a factor to reduce the comfort zone of grasshoppers and create a balance between exploration and exploitation. As a final point, the optimal solution achieved so far by the swarm was considered as an objective to be looked for and enhanced by the grasshopper population. The implementation steps of GOA can be summarized as follows:

Step 1: Initialize the parameters of algorithm;

Step 2: Produce the population of grasshopper randomly;

Step 3: Assess the position of each grasshopper and calculate its merit;

Step 4: Identify the best grasshopper as the target;

Step 5: Repeat Steps 6 to 12 until the stop condition is established;

Step 6: Repeat steps 7 to 11 for each grasshopper;

Step 7: $\mathrm{C} = \mathrm{C}_{\max} - I\,\frac{C_{\max}-C_{\min}}{L}$

Step 8: Update the value of C;

Step 9: Update it for each grasshopper;

Step 10: Calculate the merit of the new grasshopper;

Step 11: If the new grasshopper's merit is better than the target, set the new grasshopper as the target;

Step 12: If the stop condition is not met, go to step 5, otherwise go to end;

Step 13: End

3.2 Multi-objective grasshopper optimization algorithm

A multi-objective algorithm follows two aims for solving multi-objective problems. First, it should find very accurate approximations of the true Pareto optimal solutions and second, the optimal solutions should be well-distributed across all the objectives in the search space. This is necessary in a posteriori method for the intention making is performed after the optimization process. Furthermore, there is more than one solution for a multi-objective problem. Pareto optimal dominance is exploited to compare the obtained solutions in MOGOA. The Pareto optimal solutions are also reserved in an archive. The purpose is the fundamental component that leads the search agents towards promising areas of the search space, which the purpose is the main challenge in modeling MOGOA. In the past section, the similar equations were applied in the MOGOA and the primary discrepancy is the process of updating the purpose. By choosing the optimal solution captured so far, the target can be chosen easily in a single-objective search space while in the MOGOA, the target should be selected from a set of Pareto optimal solutions. Clearly, the archived value can be updated by the Pareto optimal solutions and the optimization target must be one of them in the archive. The challenge here is to obtain a target to enhance the distribution of the solutions in the archive. For this reason, the number of neighbouring solutions in the neighbourhood of every solution is firstly obtained considering a fixed distance [12]. Then, the number of neighbouring solutions is computed and supposed as the quantitative metric to evaluate the crowdedness of the area in the Pareto set. The probability of choosing the target from the archive can be expressed as:

$$P_i = 1 - N_i \tag{26}$$

Where, N_i is the number of solutions in the neighborhood of the i^{th} solution. With this probability, a roulette wheel is exploited to select the target from the archive list.

3.3 MOGOA for optimal reconfiguration e

In this paper, a MOGOA is utilized for calculating the optimal performance of distribution network under reconfiguration. Each grasshopper is supposed to be a solution containing switches to be opened. Initial population generation is similar to all other evolutionary algorithms. The objective function in MOGOA technique for network reconfiguration includes reliability index improvement and minimization of active power loss which are evaluated for each feasible solution. In the next step, the population is classified by using non-dominated sorting method and other optimal solutions are produced using GOA approach. Then, the feasibility of each solution is investigated and analyzed. The parameter values of the MOGOA are presented in Table 1. It should be noted that the MOGOA was utilized about supposing the unified framework suggested in [23, 24] in which the primary steps are initialization, selection, generation and replacement. Actually, the MOGOA is able to obtain the Pareto solutions, reserve them in the archive list and ameliorate their distribution.

Table 1. MOGOA parameters

Iteration	10
Grosshopper number	100
Archive size	100
$C_{\min}$	0.00004
$C_{\max}$	1

4. SIMULATION RESULTS

In this paper, the suggested approach is validated on 33-bus [15] and 69-bus [19] radial distribution networks and analytical results are presented to assess its efficiency. For all these systems, the substation voltage is assumed to be 1 Pu. Also, all sectionalizing and tie switches are supposed to be candidate switches for network reconfiguration. In this paper, the MOGOA is performed in MATLAB R2013a with DELL Core i5 M430 2.26 GHz.

Table 2. Simulation results on 33-bus distribution system

	Before reconfiguration	After reconfiguration
Tie switches	33, 34, 35, 36, 37	7, 9, 14, 32, 37
Power loss	208.4592 kW	138.9275 kW
Power loss reduction	-	33.355 %
Minimum voltage	0.91075 Pu	0.94234 Pu

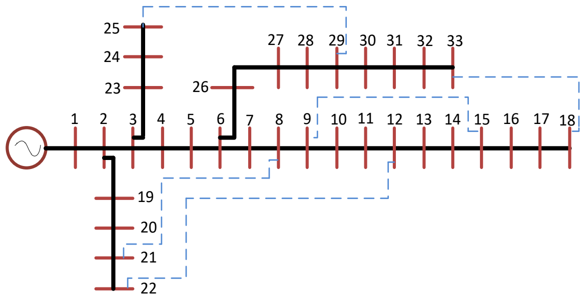

Fig. 1. Single line diagram of 33-bus radial distribution system

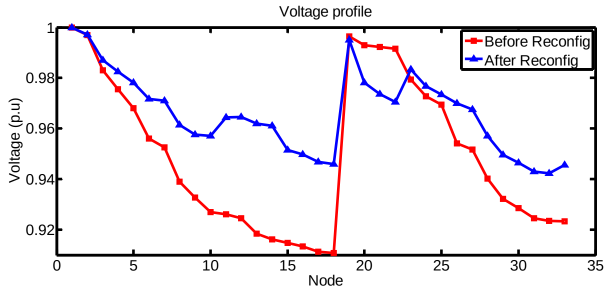

Fig. 2. Voltage profile on 33-bus distribution network before and after reconfiguration

4.1 Test case- 33 bus

The first system is a 33-bus, 12.66 kV, radial distribution network [15] which is illustrated in Figure 1. It consists of 32 sectionalizing and 5 tie-lines switches. The normally closed switches are 1 to 32 and the normally open switches are 33 to 37. The network information is obtained from Ref. [15]. The total real and reactive power loads on the network are 3715 kW and 2300 Kvar, respectively. The initial power loss of the network is 208.4592 kW. The lowest bus-bar voltage is 0.91075 Pu, which happens at bus 18. The optimal result for system reconfiguration acquired by the proposed methodology is 7, 9, 14, 32 and 37 in whi-

Table 3. Node voltages and angles on 33-bus distribution network

Bus	Voltage before reconfiguration		Voltage after reconfiguration	
	Mag (Pu)	Ang (deg)	Mag (Pu)	Ang (deg)
1	1.000	0.000	1.000	0.000
2	0.997	0.013	0.997	0.013
3	0.983	0.089	0.987	0.094
4	0.976	0.154	0.983	0.160
5	0.968	0.216	0.978	0.225
6	0.956	0.643	0.972	0.518
7	0.953	0.414	0.971	0.479
8	0.939	0.263	0.963	-0.686
9	0.933	0.189	0.959	-0.738
10	0.927	0.126	0.963	-0.626
11	0.926	0.133	0.963	-0.626
12	0.925	0.145	0.963	-0.628
13	0.918	0.053	0.960	-0.643
14	0.916	-0.026	0.960	-0.659
15	0.915	-0.064	0.953	-0.894
16	0.913	-0.087	0.951	-0.917
17	0.911	-0.165	0.949	-1.009
18	0.910	-0.174	0.947	-1.020
19	0.996	0.002	0.995	-0.024
20	0.993	-0.065	0.978	-0.307
21	0.992	-0.085	0.974	-0.427
22	0.992	-0.105	0.970	-0.517
23	0.979	0.058	0.983	0.063
24	0.973	-0.030	0.977	-0.025
25	0.969	-0.074	0.973	-0.068
26	0.954	0.682	0.970	0.555
27	0.952	0.737	0.968	0.608
28	0.940	0.819	0.957	0.692
29	0.932	0.896	0.950	0.770
30	0.929	0.999	0.946	0.868
31	0.924	0.916	0.943	0.796
32	0.924	0.893	0.942	0.777
33	0.923	0.886	0.947	-1.024

-ch the real power loss and minimum node voltage are 138.9275 kW and 0.94234 Pu. (at bus 32), respectively. To verify the efficiency of suggested algorithm, the problem was repeatedly solved 120 times. The best and the minimum values among the best solutions as well as the average values of these 120 runs are presented in Table 2. A smaller standard deflection indicates that the most of optimal solutions are close to the average value. The voltage magnitudes and their angles at each bus are presented in Table 3. The voltage profiles of the distribution network before and after reconfiguration are illustrated in Fig. 2. The real power flows in each branch of the system before and after reconfiguration is presented in Fig. 3. It can be seen from Fig. 3, that the power flow in each branch is decreased after network reconfiguration. Actually, feeder capacity is relieved from the overloading condition which makes it possible to load the feeders further. The power loss in every branch before and after reconfiguration is presented in Fig. 4. It is considered that the losses in almost each branch are reduced, except at 16, 17, 18, 19, 20, 21, 25, 26 and 30 where the losses are increased because of displacement of loads.

Table 4. Comparison of simulation results in 33-Bus system

Item	Initial configuration	Final configuration		
		HSA[4]	ITS[18]	MOGOA
Tie switches	33, 34, 35, 37, 36	7, 10, 14, 37, 36	7, 9, 14, 37, 36	7, 9, 14, 32, 37
Power loss reduction (%)	-	31.89	31.29	33.355
Minimum voltage (Pu)	0.91075	0.9342	0.9315	0.94234
ENS (MW)	3.846	-	-	3.3268

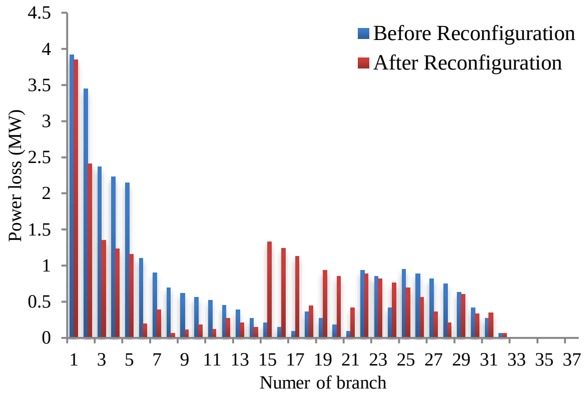

Fig. 3. Power flow in 33-bus distribution network before and after reconfiguration

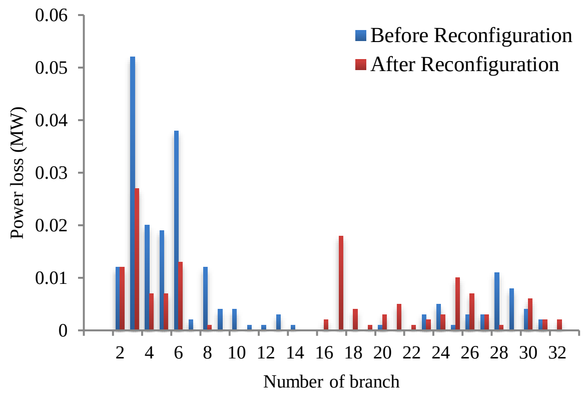

Fig. 4. Power loss in 33-bus distribution network before and after reconfiguration

To compare with the proposed method, improved TS [18] and HSA [4] are exploited to solve this optimization problem. For the HSA, population size, crossover and mutation rates are selected to be 85, 0.8, and 0.05, respectively, and for ITS, the parameters are chosen from Ref. [18]. Power losses in 33-bus system before and after reconfiguration for these 120 runs are compared with the best objective function values obtained by the HAS, ITS, and MOGOA which are listed in Table 4. It can be observed from Table 4 that the optimal power loss obtained by the suggested approach is 2.06% and 1.46% less than that of ITS and HSA, respectively.

5.2 Test case-69 bus

To prove the applicability and performance of the suggested algorithm in large-scale distribution networks, the studied problem was investigated in 69-bus system [18] as presented in Fig 5. It includes 5 tie-switches (normally opened) and 68 sectionalizing switches (normally closed). The network information is obtained from [18]. The initial real power loss is 414.6595 kW. The lowest bus-bar voltage is 0.843 Pu. In this case, the MOGOA parameter and maximum number of iterations are considered to be 38 and 106. The other values of the algorithm are the similar as the first test case. The optimal configuration is calculated which is 45, 59, 69, 70 and 72. The optimal power loss after reconfiguration is 158.4283 kW. Actually, after reconfiguration, the percentage of reduction in active power loss is approximately 61.7931%. The minimum voltage is enhanced to 0.9509 Pu. Simulation results of

Table 5. Simulation results of the 69-bus distribution network

	Before Reconfiguration	After Reconfiguration
Tie switches	69, 70, 71, 72, 73	45, 59, 69, 70, 72
Power loss (kW)	414.6595	158.4283
Power loss reduction (%)	-	61.7931
Minimum voltage (Pu)	0.843	0.9509
ENS (MW)	-	0.96363

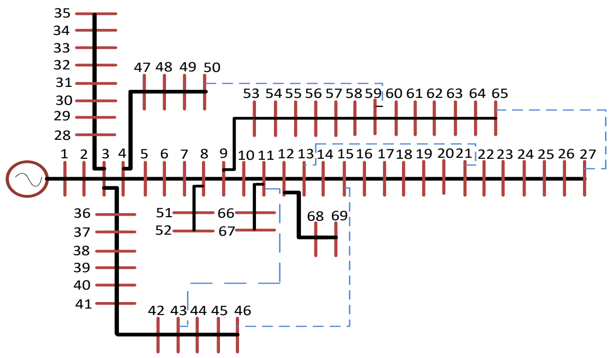

Fig. 5. Single line diagram of the 69-bus radial distribution network

69-bus distribution network are presented in Table 5. To test this case, Fuzzy [9], PSO [17] are exploited to solve this optimization for comparison and simulation results are illustrated in Table 6. It can be seen from the Table 6 that the proposed algorithm has a better performance. The optimal response is determined after 120 iterations. The bus voltages and their angles are presented in Table 7.

Table 6. Comparison of base case and optimal solution of the 69-bus distribution system

	Base case	Optimal reconfiguration		
		Fuzzy [9]	PSO[17]	MOGOA
Open branches	69, 70, 71, 72, 73	56, 70, 63, 69,14	59, 71, 62, 70,15	45, 59, 69, 70, 72
Minimum voltage (Pu)	0.843	0.9483	0.94247	0.9509
Real power loss (kW)	414.6595	183.596	183.66	158.4283

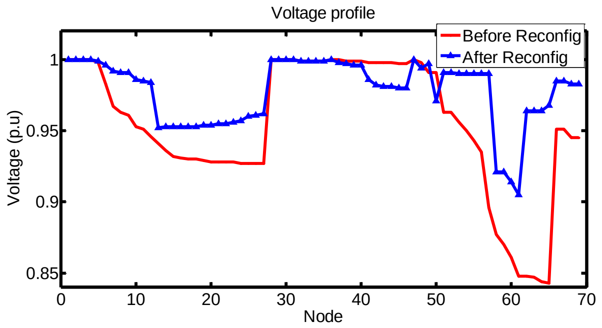

Fig. 6. Voltage profile on 69-bus distribution network

Table 7. Node voltages and angles on 69-bus distribution system

Bus	Voltage before reconfiguration		Voltage after reconfiguration	
	Mag (Pu)	Ang (deg)	Mag (Pu)	Ang (deg)
1	1.000	0.000	1.000	0.000
2	1.000	-0.002	1.000	-0.002
3	1.000	-0.004	1.000	-0.004
4	1.000	-0.010	1.000	-0.008
5	0.998	-0.034	0.999	-0.014
6	0.983	0.064	0.996	0.014
7	0.967	0.169	0.992	0.042
8	0.963	0.195	0.991	0.049
9	0.961	0.208	0.991	0.051
10	0.953	0.333	0.986	0.127
11	0.951	0.360	0.985	0.143
12	0.946	0.435	0.984	0.176
13	0.941	0.492	0.952	-0.489
14	0.936	0549	0.953	-0.491
15	0.932	0.606	0.953	-0.494
16	0.931	0.616	0.953	-0.494
17	0.930	0.633	0.953	-0.499
18	0.930	0.633	0.953	-0.499
19	0.929	0.641	0.954	-0.509
20	0.928	0.646	0.954	-0.516
21	0.928	0.653	0.955	-0.528
22	0.928	0.653	0.955	-0.529
23	0.928	0.651	0.956	-0.539
24	0.927	0.648	0.957	-0.561
25	0.927	0.644	0.960	-0.604
26	0.927	0.643	0.961	-0.622
27	0.927	0.642	0.962	-0.632
28	1.000	-0.005	1.000	-0.004
29	1.000	-0.008	1.000	-0.008
30	1.000	-0.006	1.000	-0.006
31	1.000	-0.006	1.000	-0.005
32	0.999	-0.004	0.999	-0.004
33	0.999	0.001	0.999	0.001
34	0.999	0.013	0.999	0.013
35	0.999	0.015	0.999	0.015
36	1.000	-0.005	1.000	-0.008
37	1.000	-0.015	0.998	-0.064
38	0.999	-0.019	0.997	-0.090
39	0.999	-0.020	0.996	-0.098
40	0.999	-0.020	0.996	-0.098
41	0.998	-0.038	0.986	-0.270
42	0.998	-0.045	0.982	-0.344
43	0.998	-0.046	0.981	-0.354
44	0.998	-0.047	0.981	-0.357
45	0.997	-0.050	0.980	-0.387
46	0.997	-0.050	0.980	-0.388
47	1.000	-0.013	1.000	-0.016
48	0.998	-0.085	0.994	-0.210
49	0.991	-0.309	0.976	-0.862
50	0.991	-0.341	0.971	-1.018
51	0.963	0.195	0.991	0.049
52	0.963	0.195	0.991	0.049
53	0.956	0.242	0.990	0.052
54	0.950	0.283	0.990	0.053
55	0.943	0.340	0.990	0.054
56	0.935	0.396	0.990	0.054
57	0.896	1.085	0.990	0.054
58	0.877	1.447	0.951	-1.529
59	0.870	1.593	0.951	-1.529
60	0.861	1.784	0.954	-1.394
61	0.848	1.911	0.950	-1.305
62	0.848	1.916	0.964	-0.499
63	0.847	1.923	0.964	-0.500
64	0.844	1.956	0.964	-0.503
65	0.843	1.966	0.968	-0.537
66	0.951	0.362	0.985	0.145
67	0.951	0.362	0.985	0.145
68	0.945	0.445	0.983	0.185
69	0.945	0.445	0.983	0.185

The voltage profiles of the test case before and after reconfiguration are presented in Figure 6. After reconfiguration, the minimum voltage in the network is improved 2.6%. The real power flow in each branch before and after network reconfiguration is presented in Figure 7. It can be seen from Figure 7 that the power flow is decreased in each branch after reconfiguration. Also, the power loss in every branch before and after reconfiguration is presented in Figure 8. It can be observed that the losses in almost each branch are reduced except at 40, 42, 45, 48, 50, 51, 72 and 73, where the losses are increased because of displacement of loads.

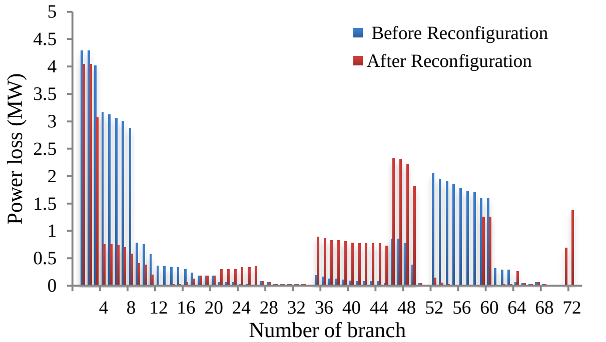

Fig. 7. Power flow in 69-bus distribution network before and after reconfiguration

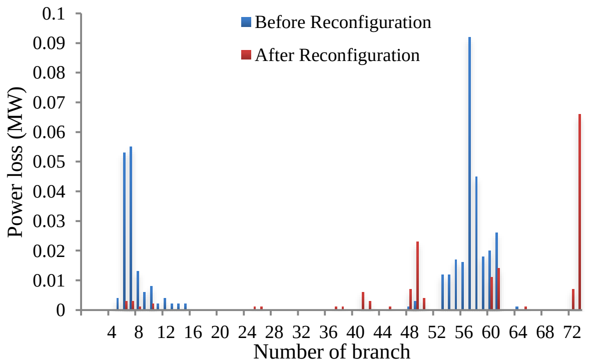

Fig. 8. Power loss in 69-bus distribution network before and after reconfiguration

6. CONCLUSIONS

In this study, a multi-objective framework for optimal reconfiguration problem in distribution networks is presented. The objective functions include minimization of power losses and reliability index (energy not supplied). A non-dominating sorting technique is employed to adopt GOA for solving the multi-objective problem. Results obtained from testing the proposed reconfiguration problem on 33-bus and 69-bus test systems are analyzed and compared with other previous algorithms. The simulation results show that the suggested algorithm is so efficient to obtain the global optimum configuration and it can produce a Pareto set solution containing high quality results.

REFERENCES

[1] I. Ziari, G. Ledwich, A. Ghosh and G. Platt, "Integrated distribution systems planning to improve reliability under load growth", *IEEE Trans. Power Delivery,* vol. 27, no. 2, pp. 757-765, 2012.

[2] A. Abdelaziz, F. Mohamed, S. Mekhamer and M. Badr, "Distribution system reconfiguration using a modified tabu search algorithm", *Electr. Power Syst. Res.,* vol. 80, no. 8, pp. 943-953, 2010.

[3] N. Gupta, A. Swarnkar, K. Niazi and RC. Bansal, "Multi-objective reconfiguration of distribution systems using adaptive genetic algorithm in fuzzy framework", *IET Gener. Transm. Distrib.,* vol. 4 no. 12, pp. 1288-1298, 2010.

[4] R. R. Srinivasa, S. L. Narasimham, R. M. Ramalinga and R. A. Srinivasa, "Optimal network reconfiguration of large-scale distribution system using harmony search algorithm", *IEEE Trans. Power Syst.,* vol. 26, no. 3, pp. 1080-1088, 2011.

[5] T. Niknam, A. Kavousi Fard and A. Baziar, "Multi-objective stochastic distribution feeder reconfiguration problem considering hydrogen and thermal energy production by fuel cell power plants", *Energy,* vol. 42, no. 1, pp. 563-573, 2012.

[6] Y. M. Shuaib, M. S. Kalavathi and C. C. Asir Rajan, "Optimal reconfiguration in radial distribution system using gravitational search algorithm", *Elec. Power Compon. Sys.,* vol. 42, no. 7, pp. 703-715, 2014.

[7] D. L. Duan, X. D. Ling, X. Y. Wu, and B. Zhong, "Reconfiguration of distribution network for loss reduction and reliability improvement based on an enhanced genetic algorithm", *Int. J. Electr. Power Energy Syst.,* vol. 64, pp. 88-95, 2015.

[8] H. Shareef, A. A. Ibrahim, N. Salman, A. Mohamed and W. Ling Ai, "Power quality and reliability enhancement in distribution systems via optimum network reconfiguration by using quantum firefly algorithm", *Int J. Electr. Power Energy Syst.,* vol. 58, pp. 160-169, 2014.

[9] A. Kavousi-Fard and T. Niknam "Multi-objective Stochastic distribution feeder reconfiguration from the reliability point of view", *Energy,* vol. 64, pp. 342-354, 2014.

[10] Sh. Saremi, S.A. Mirjalili and A. Lewis, "Grasshopper optimisation algorithm: theory and application", *Advances in Eng. Software,* vol.105, pp. 30-45, 2017.

[11] J. Wu, W. Honglun, N. Li and P. Yao, "Distributed trajectory optimization for multiple solar-powered UAVs target tracking in urban environment by Adaptive Grasshopper Optimisation Algorithm", *Aerosp. Sci. Technol,* vol. 70, 2017.

[12] S. Mirjalili, S.A. Mirjalili, Sh. Saremi, H. Faris and I. Aljarah, "Grasshopper optimization algorithm for multi-objective optimization problems", *Appl Intell,* vol. 48, no. 4, pp. 805-820, 2018.

[13] K. Deb, N. Padhye, "Enhancing performance of particle swarm optimization through an algorithmic link with genetic algorithms", *Comput Optim Appl,* vol. 57, pp. 761-794, 2014.

[14] J. Endrenyi, J. Reliability and J. Wiley, "Modeling in electric power systems", *New York, NY,* 1978.

[15] S. Yin, C. Lu, "Distribution feeder scheduling considering variable load profile and outage costs", *IEEE Trans., Power Syst.,* vol. 24, pp. 652-60, 2009.

[16] SA. Yin, CN. Lu, "Distribution feeder scheduling considering variable load profile and outage costs", *IEEE Trans., Power Syst.,* vol. 24, pp. 652-60, 2009.

[17] I. Waseem, "Impacts of distributed generation on the residential distribution network operation", *in Electrical Engineering, Virginia Polytechnic Institute and State University,* 2008.

[18] D. Q. Hung and N. Mithulananthan, "Loss reduction and load ability enhancement with DG: a dual-index analytical approach", *Appl Energy,* vol. 115, pp. 233-241, 2014.

[19] M. Sedighizadeh, M. Esmaili and M. M. Mahmoodi, "Reconfiguration of distribution systems to improve reliability and reduce power losses using imperialist competitive algorithm", *Iranian J. Electr. & Electron. Eng.,* vol. 13, No. 3, pp. 287-302, 2017.

[20] N. M. G. Kumar, "Reliability improvement of radial distribution system with incorporating protective devices-case study", *Int. J. Eng. Sci. Emerg Technol,* vol. 4, no.2, pp. 60-74, 2013.

[21] P. Carvalho, P. F. Correia and L. Ferreira, "Mitigation of interruption reimbursements by periodic network reconfiguration: risk-based versus expected-value optimization", *IEEE Trans. Power Syst.,* vol. 22, no. 2, pp. 845-50, 2007.

[22] S. Chen, W. Hu and Z. Chen, "Comprehensive cost minimization in distribution networks using segmented-time feeder reconfiguration and reactive power control of distributed generators", *IEEE Trans. Power Syst.,* vol. 31, no. 2, pp. 983-993, 2016.

[23] J. Tian, C. Su, and Z. Chen, "Reactive power capability of the wind turbine with doubly fed induction generator", *in Proc.* 39th IEEE IECON, pp. 5310-5315, 2013.

[24] K. Deb, N. Padhye, "Enhancing performance of particle swarm optimization through an algorithmic link with genetic algorithms", *Comput Optim Appl,* vol. 57, pp. 761-794, 2014.

[25] N. Padhye, P. Bhardawaj and K. Deb, "Improving differential evolution through a unified approach", *J Glob Optim,* vol. 55, pp. 771, 2013.