Indonesian Journal of Electrical Engineering and Computer Science
Vol. 1, No. 3, March 2016, pp. 480 ~ 489
DOI: 10.11591/ijeecs.v1.i3.pp480-489

A Comprehensive Study on Specifying an Intelligent Approach to Solve Network Reconfiguration Problem

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Abstract

This paper presents an approach based on biogeography-based optimization (BBO) algorithm to solve the distribution network reconfiguration (DNR) problem for minimizing active power loss. Also it is demonstrated that with considering the nature of reconfiguration problem, among the intelligent algorithms, BBO approach could result the best performance. One of the remarkable advantages of this study is comparing seven different intelligent algorithms in solving network reconfiguration problem. This comparison, not only includes final fitness in optimization process, but also considers number of function evaluation (NFE). The effectiveness of the BBO method has been tested on two different distribution systems and the obtained simulation results are compared with Genetic algorithm (GA), Particle swarm optimization (PSO), Artificial bee colony (ABC), Gravitational search algorithm (GSA), Technical learning based optimization (TLBO) and Cuckoo algorithm (CA). The comparison results show that BBO approach can be an efficient and promising method for solving DNR problems.

Keywords*: Distribution network reconfiguration, Power loss, Biogeography-Based Optimization (BBO), Number of function evaluation*

1. Introduction

Due to operating at low voltage, distribution system contributes a large amount of power losses. Also by increasing the total network load, the required current will increase. Such scenario will cause some voltage profile reduction and power system losses [1, 2]. Considering the above mentioned problems, implementing radial distribution system reconfiguration, is one of the effective and efficient techniques to distribution network losses reduction, voltage profile improvement, load congestion management and system reliability enhancement. The electrical energy is delivered directly from the intermediate transformer substations to consumers through the distribution networks which are always operate with radial structures. Operating in radial configuration reduces the short-circuit current significantly. The restoration of the network from faults is performed through the cutting/closing manipulations of electrical switch pairs located on the loops, consequently. Therefore, there are many switches on the distribution system. Distribution network reconfiguration (DNR) is the process of altering the topological arrangement of distribution feeders by changing the status (open/closed) of sectionalizing and tie switches with taking consideration on system constraints upon satisfying the distribution network operators' (DNOs) objectives. Many studies have been investigated to solve network reconfiguration problems using different techniques for the last two decades. Extensive research works have been explored in the area of reconfiguration of radial distribution system (RDS). Reference [3] firstly reported a method for distribution system reconfiguration to minimize line losses. The structure of the method was based on formulated the problem as integer mixed non-linear optimization problem and solving it by a discrete branch-and-bound technique. Reference [4] 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. Reference [5] developed a branch exchange method in which 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. Reference [6] introduced genetic algorithm (GA) for reconfiguration of RDS with considering loss minimization. A method based on a shuffled frog leaping algorithm (SFLA) has been studied to minimize the cost of power loss and power of distributed generators [7]. A discrete artificial bee colony (DABC) has proposed to optimize the distribution network [8].

Received October 17, 2015; Revised February 18, 2016; Accepted February 27, 2016

A method based on harmonic search algorithm (HSA) was investigated for DNR problem to minimize power loss [9]. A new method based on adapted ant colony optimization (AACO) is proposed for minimization of real power loss reconfiguration [10]. The proposed algorithms and methods for network reconfiguration problem, generally, can be classified into two following main classes:

- Heuristic algorithms [3-5], such as discrete branch-and-bound technique and switch exchange algorithm.
- Intelligent algorithms [6–10], such as GA, SFLA, DABC, HSA, AACO.

Among these algorithms, heuristic algorithms are all greedy search algorithms. These methods are easy to be implemented and applied on the problems with high searching efficiency, but generally cannot converge to the global optimum solution in the large-scale distribution networks. Intelligent group algorithms can direct searching process to the global optimum at the probability of one hundred percent in theory. But they all inevitably involve a large number of computation requirements and really have various control parameters.

In this paper an approach based on biogeography-based optimization (BBO) algorithm is proposed to solve the distribution network reconfiguration (DNR) problem for minimizing active power losses. The significant advantage of this study is comparing seven different heuristic algorithms in solving network reconfiguration problem. This comparison, not only includes final fitness in optimization process, but also considers number of function evaluation (NFE). The effectiveness of the BBO approach has been carried out on two different distribution networks and the obtained simulation results are compared with Genetic algorithm (GA), Particle swarm optimization (PSO), Artificial bee colony (ABC), Gravitational search algorithm (GSA), Technical learning based optimization (TLBO) and Cuckoo algorithm (CA). By comparing the simulation results, it is demonstrated that BBO approach can be an efficient and promising method for solving DNR problems in comparison with the six other mentioned intelligent algorithms.

The rest of the paper is formed as follow: Section 2 depicts problem formulation. Meanwhile, Section 3 represents the proposed biogeography-based optimization (BBO) for solving network reconfiguration problem. The simulation results are shown and discribed in section 4 and finally conclusion are drawn in section 5.

2. Formulation of the Problem

2.1. Power Flow Method

During network reconfiguration, the power flow analysis should be performed. For each proposed configuration, the power flow analysis should be implemented to evaluate the nodal voltage, power loss of system and current of each branch. In this section, forward/backward sweep technique has been selected in this study due to several advantages e.g. Needing low memory, high computational performance, simple structure, high convergence capability [11].

2.2. Power Flow Formulation

In this study, the objective function is described for real power losses minimization:

$$\text{Objective Function} = \min\left\{P_L\right\}$$

Which the exact real power losses are obtained by the following equation:

$$P_L = \sum_{1}^{N_b}\sum_{1}^{N_b}[a_{ij}(P_iP_j + Q_iQ_j) + b_{ij}(Q_iP_j - Q_jP_i)] \quad (1)$$

Where

$$a_{ij} = \frac{R_{ij}}{V_iV_j}\cos(\delta_i - \delta_j) \text{ and } \qquad b_{ij} = \frac{X_{ij}}{V_iV_j}\sin(\delta_i - \delta_j)$$

$Z_{ij} = R_{ij} + jX_{ij}$ are the components of impedance matrix and Nb is the number of buses [12].

2.3. Power Flow Constraints

The constraints of objective function are as follows:

- The limitation of voltage

$$V_{min} \le V_i \le V_{max} \tag{2}$$

Where V_{min} and V_{max} indicate the minimum and maximum permissible voltage (±5%) and V_i is the voltage at bus i.

- Feeder capability limits:

$$0 \le I_i \le I_{max}; i = 1, 2, ..., N_{br} \tag{3}$$

Where N_{br} is number of distribution system branches. The radial nature of distribution network must be maintained and also all loads must be served.

2.4. Procedures

In this section a four steps algorithm is presented for checking the radial topology of trial solutions. The method steps are as follows:
Step 1: Initialize a connected matrix of the loop distribution network A(a,a) with a is the number of buses of the distribution network. Each entry in matrix A is defined as below:
A(i,j)=1, A(j,i)=1, if node i is connected to node j.
A(i,j)=0, A(j,i)=0, if node i not connected to node j.
Initialize a set of power buses B=[bus_1 , bus_2 ,…, bus_k], with k is the number of buses in the distribution network.
Step 2: Read the trial solution which is a set of tie-switches that need to check and modify A(i,j)=0, A(j,i)=0 if the switch on the branch from node I to node j is a tie-switch.
Step 3: Evaluate all loads as below:
If node n $\notin$ B and A(m,n) = 1, with m = 1, 2, …, length(B) and n = m+1, m+2, …, b then the node n is moved to B, B = B + [node n] and A(m,n)=0, A(n,m)=0.
Step 4: If matrix A is a zero matrix and array B is equal to the number of buses, then the trial solution can be considered as a radial network configuration.

3. Biogeography Theory

3.1. Based Theory

Biogeography Based Optimization (BBO) approach is based on biogeography theory [13]. In the science of biogeography, a habitat is an ecological area that is lived by particular plant or animal species and geographi-cally isolated from other habitats. Each habitat is organized by Habitat Suitability Index (HSI). Geographical areas, which are well suited as residences for biological species are said to have a high HSI. Features that correlate with HIS include rainfall, diversity of vegetation, diversity of topographic features, land area, tempera-ture, etc. If each of the features is assigned a value, HSI is a function of these values. Each of these features that characterize habitability is known as Suitability Index Variables (SIV). SIVs are the independent variables while HSI are the dependent variables. Habitats with high HSI have the large population and have high emigration rate μ, simply by virtue of a large number of species that migrate to other habitats. The immigration rate λ is low for those habitats which are already saturated with species. On the other hand, habitats with low HSI have high immigration rate λ, low emigration rate μ due to sparse population. The value of HIS, for low HSI habitat, may increase with the influx of species from other habitats as suitability of a habitat is the function of its biological diversity. However, if HSI does not increase and remains low, species in that habitat go extinct and this leads to additional immigration. For the sake of simplicity, it is safe to assume a linear relationship between habitats HIS, its immigration and emigration rate.

These rates are same for all the habitats and depend upon the number of species in the habitats.

Figure 1 depicts the relationships between fitness of habitats (species), emigration rate μ and immigration rate λ. E is the possible maximum value of emigration rate and S is the number of species in the habitat, which relates to fitness. S_{max} is the maximum number of species that can be supported by the habitat. S_0 is the equilibrium value.

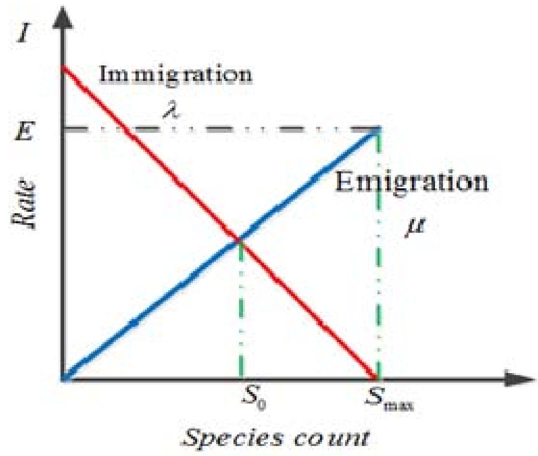

Figure 1. Species model of a single habitat

3.2. Proposed Method Steps

This study proposed an approach based on BBO algorithm which is investigated to determine the network reconfiguration applied to reduce power losses of the distribution system. The proposed algorithm steps are performed as follow:

- Step 1: Enter the branch and load data and also open switches of the system (network reconfiguration initial data) and initial data of power flow.
- Step 2: Initialize population size randomly and species count probability of each habitat.
- Step 3: Evaluate the fitness for each individual in population size.
- Step 4: While The termination criterion is not met do.
- Step 5: Save the best habitats in a temporary array.
- Step 6: For each habitat, map the HSI to number of species S, λ and μ.
- Step 7: Probabilistically choose the immigration island based on the immigration rate μ.
- Step 8: Migrate randomly selected SIVs based on the selected island in Step 7.
- Step 9: Mutate the worst half of the population as permutation algorithm.
- Step 10: Evaluate the fitness for each individual in population size.
- Step 11: Sort the population from best to worst.
- Step 12: Replace worst with best habitat from temporary array.
- Step 13: Go to step 3 for the next iteration.
- Step 14: end while

The following BBO parameters have been used, population size = 15 for IEEE-33 bus test system and population size = 40 for IEEE-69 bus test system, Habitat Modification Probability = 1, per gene immigration Probability bounds = [0, 1], elitism parameter = 4, step size related to numerical integration of probabilities = 1, maximum λ and μ rates for each island = 1 and Probability of mutation = 0.05.

To demonstrate the performance and effectiveness of the proposed BBO method, it is applied to two standard IEEE 33, 69 bus test systems. The obtained results of BBO method implementation are compared with some of well-known intelligent algorithms including Genetic algorithm (GA), PSO, ABC, GSA, TLBO and Cuckoo algorithm (CA). All the seven mentioned algorithms are implemented on distribution systems. Simulations were developed by MATLAB R2015a in 2 GHz, i3, personal computer.

4. Simulation Results and Discussion

4.1. IEEE-33 Bus Test System

The IEEE 33-bus distribution system, includes 37 branches, 32 sectionalizing switches and 5 tie switches. The line and load data of this system are presented in [14]. The diagram of this network is shown in Figure 2. The total active and reactive power of loads in this network are 3.715MW and 2.3 MVAr, respectively, also real and reactive power losses for the initial case evaluated from load flow are 210.679 kW and 143.14 kVAr, respectively. The simulation results of network reconfiguration for the 33-bus system obtained by seven different intelligent algorithms with population size=15 and 100 iterations, are shown in Table 1. It should be noticed that, this work emphasizes on selecting best method for solving network reconfiguration problem and the comparison between methods is based on both minimum number of function evaluations and final fitness, therefore the least possible value of population size that could be converged to the final answer is chosen. Figure 3, 4 show the comparison of final fitness convergence of BBO approach with six other different methods. The optimal configuration of IEEE-33 bus system is 7–9–14–32–37 which is only obtained by proposed BBO approach and Cuckoo algorithm (CA) with 15 populations. Also the minimum power loss is obtained by performing BBO and cuckoo methods.

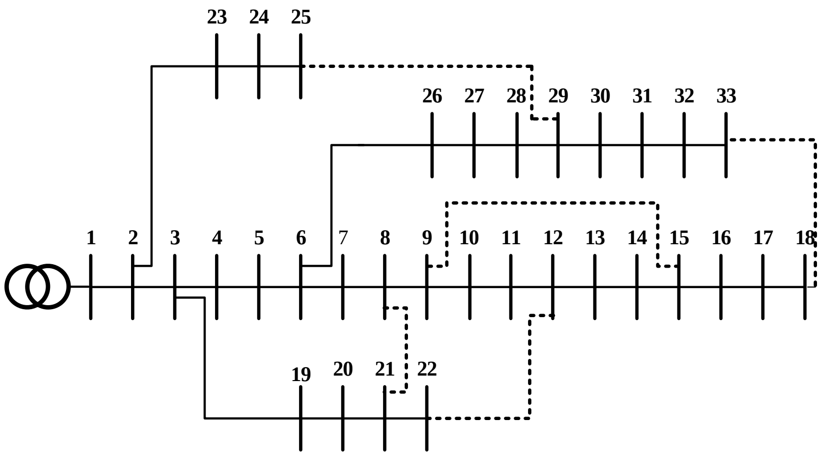

Figure 2. Single line diagram of 33-bus distribution test system

Figure 5 illustrates the comparison between the number of function evaluations (NFEs) of seven different algorithms. These NFEs are obtained from 100 iterations for solving network reconfiguration problem for IEEE-33 Bus and 150 iterations for IEEE-69 Bus distribution systems. As shown in Figure 5, the number of function evaluation for CA is much greater than BBO and the other intelligent methods, therefore it can be concluded that for this specific problem i.e. DNR, BBO approach is better than the other six intelligent methods.

Table 1. 33-Bus System Results on the Different Methods

Method	Open switches	Ploss (kW)
Initial	33,34,35,36,37	210.84
BBO	7,9,14,32,37	139.55
Cuckoo	7,9,14,32,37	139.55
TLBO	8,9,28,32,33	147.91
PSO	7,11,14,28,36	143.15
GA	9,33,34,35,36	151.76
GSA	7,11,28,34,36	144.28
ABC	7,11,12,28,32	150.29

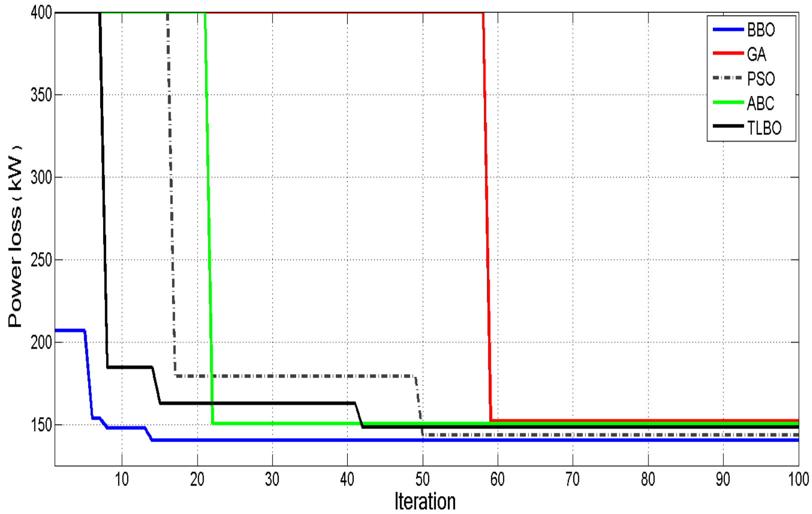

Figure 3. Comparison of 33-bus system indices for BBO, GA, PSO, ABC and TLBO in power loss

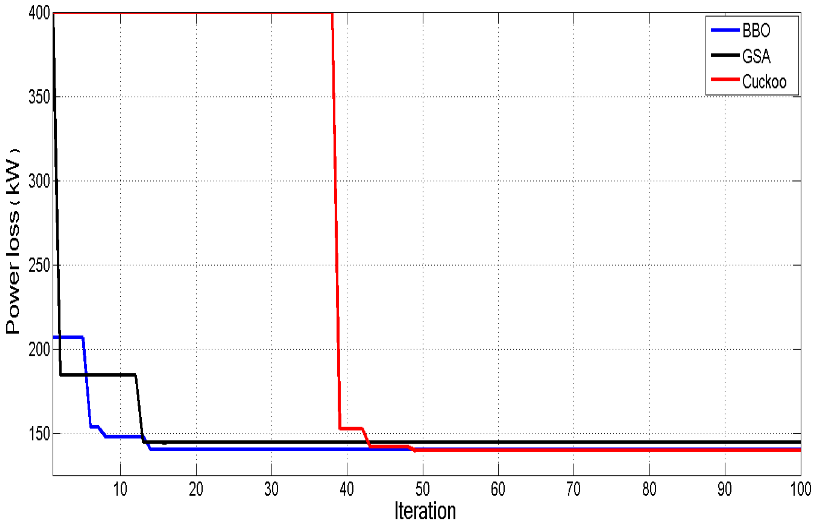

Figure 4. Comparison of 33-node system indices for BBO, GSA and Cuckoo in power loss

The power loss of the optimum configuration in comparison with power loss of initial configuration is reduced from 210.679 kW to 139.55 kW. Another advantage of DNR is improving voltage profile. Figure 6 represents the voltage profile of the distribution system before and after network reconfiguration.

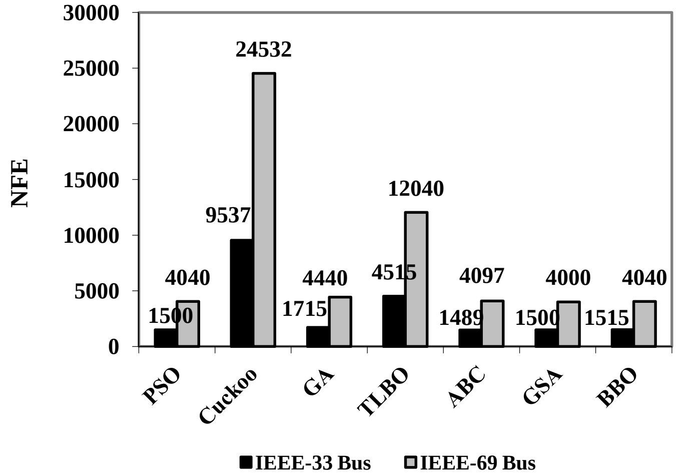

Figure 5. Comparison of number of function evaluation (NFE) for solving network reconfiguration problem between PSO, Cuckoo, GA, TLBO, ABC, GSA and BBO methods for IEEE-33, 69 systems

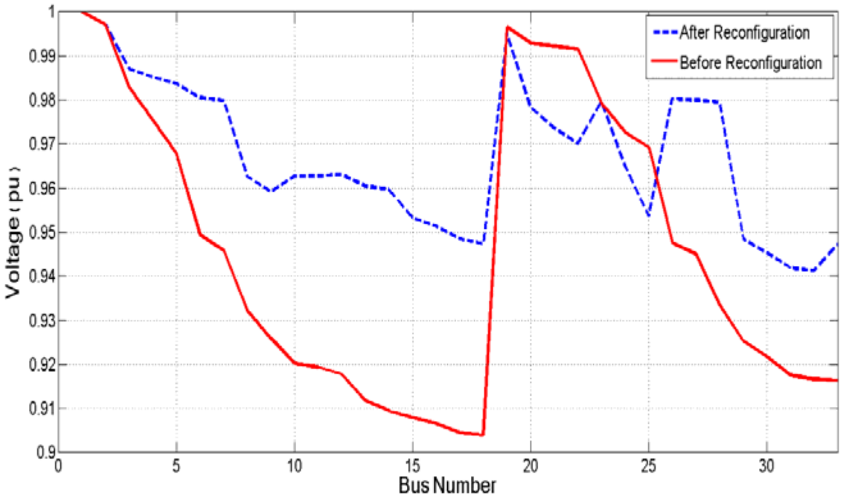

Figure 6. Voltage profile for the 33-Bus system before and after reconfiguration

It should be noted that greater NFE cause more time consuming and slow performance during optimization process. For example cpu time consumed during IEEE-33 bus network reconfiguration, was 6.05s for BBO approach and 17.12s for CA.

4.2. IEEE-69 Bus Test System

The 69-Bus distribution system, includes 69 nodes and 73 branches. There are 68 sectionalizing switches and 5 tie switches and the total loads are 3.802MW and 3.696 MVAr [15]. The diagram of the system is depicted in Figure 7. The open switches are 69, 70, 71, 72, 73. After performing the proposed reconfiguration based on BBO, switches 20, 58, 61, 69, 71 are opened and the network losses are reduced from 224.95 kW to 115.88 kW. These network configuration and power loss reduction are only obtained by using cuckoo approach but with greater NFE. The simulation results of network reconfiguration for the 69-bus system obtained by seven different intelligent algorithms with population size=40 and 150 iterations, are shown in Table 2.

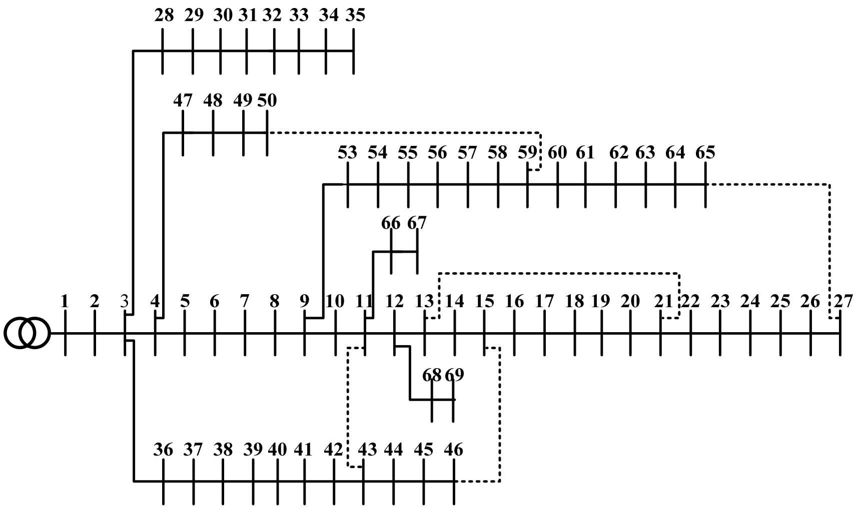

Figure 7. Single line diagram of 69-bus distribution test system

Figure 8, 9 show the comparison between final fitness convergences of BBO approach with six other different methods. The optimal configuration of IEEE-69 bus system only obtained by proposed BBO approach and Cuckoo algorithm (CA). But as shown in Figure 5, the number of function evaluation for CA is much greater than BBO method therefore it can be concluded that for this specific problem (DNR), BBO approach is better than the other six intelligent methods.

Table 2. 69-Bus System Results on the Different Methods

Method	Open switches	P_{loss} (kW)
Initial	69,70,71,72,73	224.95
BBO	20,58,61,69,71	115.88
Cuckoo	20,58,61,69,71	115.88
TLBO	20,45,58,64,69	127.23
PSO	20,42,45,57,64	128.89
GA	13,26,42,57,71	133.69
GSA	14,22,57,69,71	135.01
ABC	20,22,42,45,57	138.54

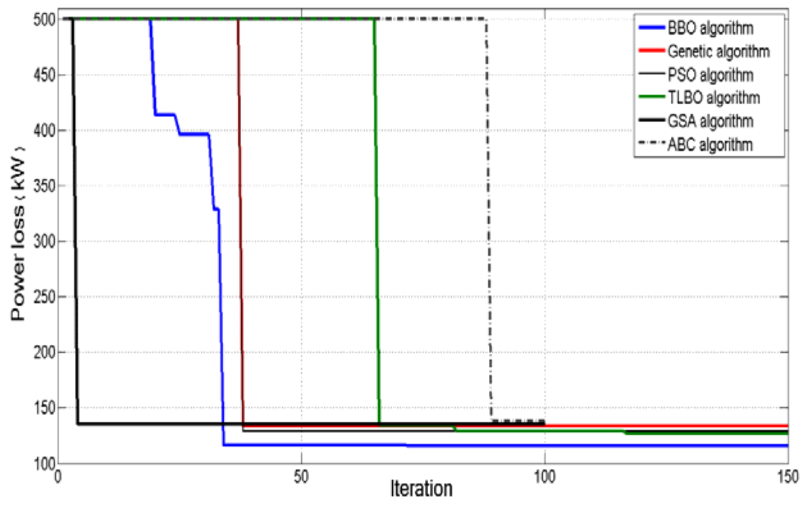

Figure 8. Comparison of 69-bus system indices for BBO, GA, PSO, ABC and TLBO in power loss

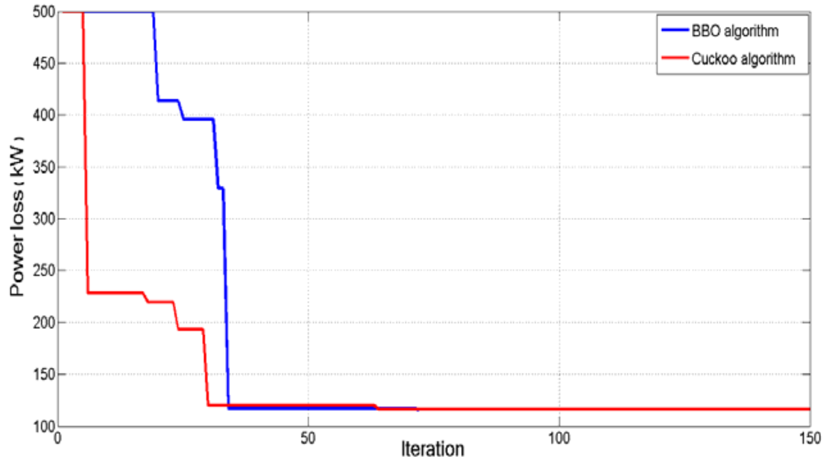

Figure 9. Comparison of 69-Bus system indices for BBO and Cuckoo in power loss

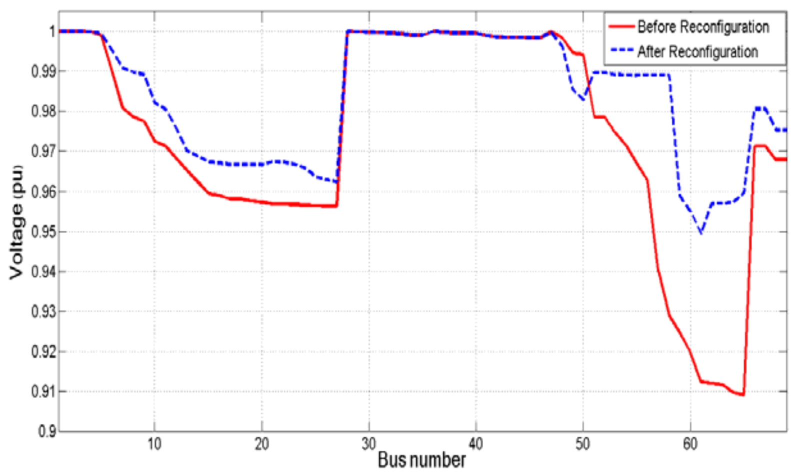

Figure 10. Voltage profile for the 69-Bus system before and after reconfiguration

Figure 10 shows the voltage profile of the IEEE-69 bus distribution system before and after network reconfiguration. As it can be seen in Figures 6, 10 network reconfiguration not only improves voltage profile, but also reduces the deviation of voltages. These affects increase the distribution system power quality.

5. Conclusion

This paper proposes an approach based on biogeography-based optimization (BBO) algorithm to solve the distribution network reconfiguration (DNR) problem for reducing active power losses. Voltage profile improvement after network reconfiguration is also illustrated in this study. The main advantage of this study is comparing seven different intelligence algorithms in solving network reconfiguration problem. This comparison includes final fitness in optimization process and number of function evaluation (NFE). The effectiveness of the BBO approach has been tested on two different distribution networks and the obtained simulation results are compared with Genetic algorithm (GA), PSO, ABC, GSA, TLBO and Cuckoo algorithm (CA). Comparing the simulation results verifies that BBO approach can be an efficient and promising method for solving DNR problems in comparison with the six other mentioned intelligent algorithms.

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