Distribution network reconfiguration for power loss minimization and voltage profile improvement using cuckoo search algorithm

CrossMark

Thuan Thanh Nguyen [a,b,*], Anh Viet Truong [a]

[a] Faculty of Electrical and Electronics Engineering, HCMC University of Technology and Education, 1 Vo Van Ngan Str., Thu Duc Dist., Ho Chi Minh City, Viet Nam
[b] Dong An Polytechnic, 30/4 Str., Di An Dist., Binh Duong Province, Viet Nam

A B S T R A C T

This paper proposes a reconfiguration methodology based on a cuckoo search algorithm (CSA) for minimizing active power loss and the maximizing voltage magnitude. The CSA method is a new meta-heuristic algorithm inspired from the obligate brood parasitism of some cuckoo species which lay their eggs in the nests of other host birds of other species for solving optimization problems. Compared to other methods, CSA method has fewer control parameters and is more effective in optimization problems. The effectiveness of the proposed CSA has been tested on three different distribution network systems and the obtained test results have been compared to those from other methods in the literature. The simulation results show that the proposed CSA can be an efficient and promising method for distribution network reconfiguration problems.

© 2014 Elsevier Ltd. All rights reserved.

Introduction

The distribution network transfers the electrical energy directly from the intermediate transformer substations to consumers. While the transmission networks are often operated with loops or radial structures, the distribution networks are always operated radially. By operating radial configuration, it significantly reduces the short-circuit current. The restoration of the network from faults is implemented through the closing/cutting manipulations of electrical switch pairs located on the loops, consequently. Therefore, there are many switches on the distribution network. Distribution network reconfiguration (DNR) is the process of varying the topological arrangement of distribution feeders by changing the open/closed status of sectionalizing and tie switches while respecting system constraints upon satisfying the operator's objectives.

Many researches have been carried out to solve distribution network reconfiguration problems using different methods for the last two decades. Merlin and Back [1] were the first to report a method for distribution network reconfiguration to minimize feeder loss. They formulated the problem as a mixed integer non-linear optimization problem and solved it through a discrete branch-and-bound technique. Civanlar et al. [2] proposed a switch

exchange method from which a simple formula for the estimation of the loss reduction by a particular switching option is developed. In [3], a binary group search optimization (BGSO) has been presented to handle the reconfiguration problem with power losses indices as an objective function. Duan et al. [4] have solved the reconfiguration problem for both the indices of power loss reduction and reliability improvement by using an enhanced genetic algorithm (EGA). In this work, GA has been improved on crossover and mutation operations to determine the switch operation schemes. In [5,6], a fireworks Algorithm (FWA) has been employed to minimize power loss and improve voltage profile and to optimize the distribution network configuration considering distributed generation. In [7], a method based on a shuffled frog leaping algorithm (SFLA) has been proposed to minimize the cost of power loss and power of distributed generators. A discrete artificial bee colony (DABC) has presented in [8] to optimize the distribution network. In [9], a method based on harmonic search algorithm (HSA) was developed for DNR problem to minimize power loss. In [10], a particle swarm optimization (PSO) was applied successfully to handle the reconfiguration problem with multi-objective functions. In [11], a new method was proposed for minimization of real power loss reconfiguration using adapted ant colony optimization. Sedighizadeh et al. [12] have proposed Hybrid Big Bang-Big Crunch algorithm (HBB-BC) to optimize the distribution network with objective functions of power losses, voltage stability, DG cost and greenhouse gas emissions.

Algorithms proposed for network reconfiguration problem, generally, can be classified into two following main classes: (1)

* Corresponding author at: Faculty of Electrical and Electronics Engineering, HCMC University of Technology and Education, 1 Vo Van Ngan Str., Thu Duc Dist., Ho Chi Minh City, Viet Nam. Tel.: +84 0916664414.

E-mail address: thuan.dap@gmail.com (T.T. Nguyen).

Nomenclature

ΔP_{loss}^{R}	total power loss of the system after reconfiguration
ΔP_{loss}^{R}	total power loss of the system after reconfiguration
ΔP_{loss}^{0}	total power loss of the system before reconfiguration
N_{br}	total number of branches
N_{bus}	total number of buses
N_{ss}	the number of substations
P_i	real power load at bus i

Q_i	reactive power load at bus i
V_i	voltage magnitude at bus i
V_{min}	minimum acceptable bus voltage
V_{max}	maximum acceptable bus voltage
I_i	current at branch i
$I_{max,i}$	upper limit of line current as defined by the manufacturer

---

heuristic algorithms [1,2], such as discrete branch-and-bound technique and switch exchange algorithm and (2) intelligent algorithms [3–12], such as BGSO, EGA, FWA, SFLA, DABC, HSA and PSO. Among these algorithms, heuristic algorithms are all greedy search algorithm. They are easy to be implemented and with high searching efficiency, but generally cannot converge to the global optimum solution in the large-scale distribution systems. Intelligent 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 a lot of control parameters.

The cuckoo search algorithm developed by Yang and Deb is a new meta-heuristic algorithm for solving optimization problems inspired from the obligate brood parasitism of some cuckoo species which lay their eggs in the nests of other host birds of other species. This is a more efficient algorithm compared with GA and PSO [13]. Marichelvam [14] proposed an improved hybrid cuckoo search algorithm for solving the permutation flow shop scheduling problems. In [15], a hybrid cuckoo search algorithm integrated with fuzzy system was proposed for solving multi-objective unit commitment problem. CSA was also implemented to solve the structural optimization tasks [16]. In this work, CSA has been tested on many design problems and obtained better solution than several methods in the literature such as adaptive response surface method (ARSM), improved ARSM and PSO. Recently, CSA has been further improved to minimize the completion time of the last job to leave the production system for the hybrid flow shop (HFS) scheduling problems [17]. In addition, CSA has been also proposed to track Maximum Power Point in the Photovoltaic (PV) system [18]. In this work, the tests have carried out for PV system when irradiance and temperature change gradually and rapidly. The tested results have been demonstrated that CSA outperforms both Perturbed and Observed (P&O) and PSO. Yang and Deb [19] have analyzed the CSA and found out why CSA is efficient. Recently studies have demonstrated that CSA is an efficient method for solving optimal problems.

In this paper, the CSA is proposed for solving distribution network reconfiguration problem considering power losses in transmission systems and voltage profile improvement. The effectiveness of the proposed CSA has been tested on different distribution network systems and the obtained results have been compared to those from other methods available in the literature such as existing FWA in [5,6], GA, ITS, RGA and HSA in [9,20] and a novel improved adaptive imperialist competitive algorithm (IAICA) in [21].

Problem formulation

Objective functions

The reconfiguration is defined as the process of changing the topology of system for a certain objective. The DNR is accomplished by changing open/close state of switches. In this study, the objective is to minimize total system active power loss and voltage deviation. The objective function can be described as follows [5]:

$$minimize\ F = \Delta P_{loss}^{R} + V_D \tag{1}$$

The net power loss reduced (ΔP_{loss}^{R}) is taken as the ratio of total power loss before and after the reconfiguration of the system:

$$\Delta P_{loss}^{R} = \frac{P_{loss}^{rec.}}{P_{loss}^{0}} \tag{2}$$

The total power loss of the system is determined by the summation of losses in all line sections:

$$P_{loss} = \sum_{i=1}^{Nbr} R_i \times \left(\frac{P_i^2 + Q_i^2}{V_i^2} \right) \tag{3}$$

The voltage deviation index (ΔV_D) can be defined as follows:

$$\Delta V_D = \max \left(\frac{V_1 - V_i}{V_1} \right) \forall i = 1, 2, \ldots, N_{bus} \tag{4}$$

The reconfigured process will try to minimize the ΔV_D closer to zero and thereby improves voltage stability and network performance.

Constraints

During network reconfiguration, the power flow analysis should be derived. For each proposed configuration, the power flow analysis should be carried out to compute the nodal voltage, power loss of system and current of each branch. The constraints of objective function are as follows:

(1) For the proposed configuration, the computed voltages and currents should be in their premising range.

$$V_{min} \leq V_i \leq V_{max}; \quad i = 1, 2, \ldots, N_{bus} \tag{5}$$
$$0 \leq I_i \leq I_{max,i}; \quad i = 1, 2, \ldots, N_{br} \tag{6}$$

(2) The radial nature of distribution network must be maintained and all loads must be served.

Checking radial topology

In this section a new algorithm is proposed for checking the radial topology of trial solutions. The flow chart of the algorithm is shown in Fig. 1.

Step 1: Initialize a connected matrix of the loop distribution network $A(b,b)$ with b is the number of buses of the network system. Each entry in matrix A is defined as follows:

$A(i,j) = 1$ and $A(j,i) = 1$ if node i is connected to node j.
$A(i,j) = 0$ and $A(j,i) = 0$ if node i is not connected to node j.
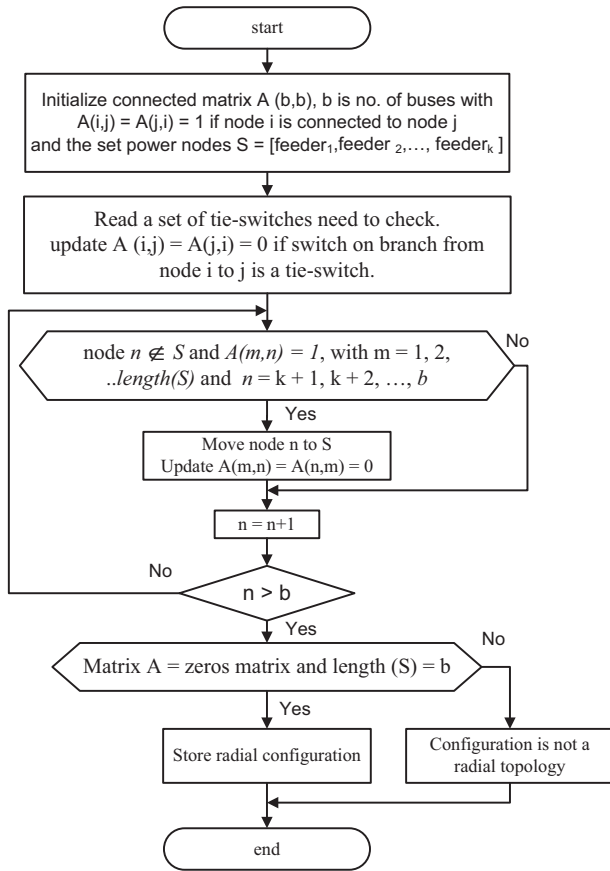
Fig. 1. Flow chart for checking radial topology.

Initialize a set of power buses $S = [feeder_1, feeder_2, \ldots, feeder_k]$, with k is the number of feeders in the network system.

Step 2: Read the trial solution. This is a set of tie-switches, which need to check and modify $A(i,j) = 0$ and $A(j,i) = 0$ if the switch on the branch from node i to node j is a tie-switch.

Step 3: Evaluate all load nodes as follows:

If node $n \notin S$ and $A(m,n) = 1$, with $m = 1, 2,\ldots,length(S)$ and $n = k + 1, k + 2,\ldots,b$ then the node n is moved to S, $S = S + [node\ n]$ and $A(m,n) = 0$, $A(n,m) = 0$.

Step 4: If matrix A is a zero matrix and length of array S is equal to the number of buses then the trial solution is a radial network configuration.

Cuckoo search algorithm for distribution system reconfiguration

Cuckoo search algorithm

The cuckoo search algorithm (CSA) is a recently developed optimization algorithm by Yang and Deb [13]. In comparison with other meta-heuristic search algorithms, the CSA is an efficient population-based heuristic evolutionary algorithm for solving optimization problems with the advantages of simple implementation procedure and few control parameters. This algorithm is based on the obligate brood parasitic behavior of some cuckoo species combined with the Lévy flight behavior of some birds and fruit

flies. As stated by authors [22], there are mainly three principal rules during the search process as follows:

1. Each cuckoo lays one egg (a design solution) at a time and dumps its egg in a randomly chosen nest among the fixed number of available host nests.
2. The best nests with high quality of egg (better solution) will be carried over to the next generation.
3. The number of available host nests is fixed, and a host bird can discover an alien egg with a probability $P_a \in [0, 1]$. In this case, it can either throw the egg away or abandon the nest so as to build a completely new nest in a new location.

Implementation of CSA for DNR

Based on the three rules in Section 'Cuckoo search algorithm', the CSA method is implemented for DNR as follows.

Initialization

To maintain the radial topology of the network in DNR process, the number of open branches should always be equal to the number of tie-switches (N_{ts}) and could be obtained through Eq. (7)

$$N_{ts} = N_{br} - (N_{bus} - N_{ss}) \tag{7}$$

Therefore, the number of switches which must be open after reconfiguration is specific and must be used as a variable in algorithm. These switches are called tie-switches (SW). Therefore, every member of the initial population is a radial structure of the network. In DNR process using CSA, each radial structure of the network is considered as a host nest. A population of N host nests is represented by $X_i = \left[X_1^i, \ldots, X_{d-1}^i, X_d^i\right]$ with $i = 1, 2,\ldots,N$. In which each X_i represents a solution vector of variables given by:

$$X_i = \left[SW_1^i, SW_2^i, \ldots, SW_d^i\right], \quad with\ d = 1, 2, \ldots N_{ts} \tag{8}$$

where SW_d^i ($d = 1, 2,\ldots,N_{ts}$) are the tie-switches of corresponding to nest d to maintain the radial topology of the network.

In the CSA, each egg can be regarded as a solution which is randomly generated in the initialization. Therefore, each nest i of the population is randomly initialized as follows:

$$X_i = round\left[SW_{min,d}^i + rand \times \left(SW_{max,d}^i - SW_{min,d}^i\right)\right] \tag{9}$$

Based on the initialized population of the nests, the radial topology checking algorithm is run to check the nests and the load flow is run and the fitness of each nest is calculated by the objective function Eq. (1).

The initialized population of the host nests is set to the best value of each nest $Xbest_i$ ($i = 1,\ldots,N$) and the nest corresponding to the best fitness function is set to the best nest $Gbest$ among all nests in the population.

Generation of new solution via Lévy flights

All the nests except for the best one are replaced based on the quality of new cuckoo eggs which are produced by Lévy flights from their position as follows:

$$X_i^{new} = round\left[Xbest_i + \alpha \times rand \times \Delta X_i^{new}\right] \tag{10}$$

where $\alpha > 0$ is the step size parameter; rand is a normally distributed random number in [0,1] and the increased value ΔX_i^{new} is determined by:

$$\Delta X_i^{new} = \frac{rand_x}{|rand_y|^{1/\beta}} \times \frac{\sigma_x(\beta)}{\sigma_y(\beta)} \times (Xbest_i - Gbest_i) \tag{11}$$

where $rand_x$ and $rand_y$ are two normally distributed stochastic variables with standard deviation $\sigma_x(\beta)$ and $\sigma_y(\beta)$ given by:

$$\sigma_x(\beta) = \left[\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right]^{1/\beta} \qquad (12)$$

$$\sigma_y(\beta) = 1 \qquad (13)$$

where β is the distribution factor ($0.3 \leqslant \beta \leqslant 1.99$) and Γ is the gamma distribution function. The radial topology checking algorithm is run to check the nests and the fitness value is calculated using Eq. (1) and the nest corresponding to the best fitness function is set to the best nest *Gbest*.

Alien eggs discovery

The action of discovery of an alien egg in a nest of a host bird with the probability of P_a also creates a new solution for the problem similar to the Lévy flights. Existing eggs will be replaced with a good quality of new generated ones from their current positions through random walks with step size as follow:

$$X_i^{new} = round\left[Xbest_i + K \times \Delta X_i^{new}\right] \qquad (14)$$

where K is the updated coefficient determined based on the probability of a host bird to discover an alien egg in its nest:

$$K = \begin{cases} 1 & if \quad rand < P_a \\ 0 & otherwise \end{cases} \qquad (15)$$

And the increased value ΔX_i^{new} is determined by:

$$\Delta X_i^{new} = rand \times [randp_1(Xbest_i) - randp_2(Xbest_i)] \qquad (16)$$
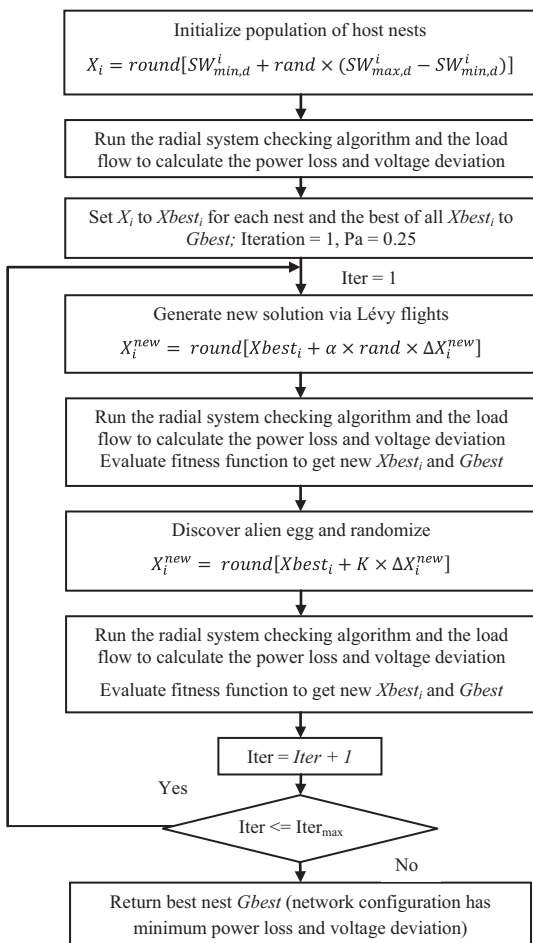

Fig. 2. Flowchart of proposed algorithm based on CSA.

where *rand* is the distributed random numbers in $[0, 1]$ and $randp_1$ $(Xbest_i)$, $randp_2(Xbest_i)$ are the random perturbation for positions of the nests in $Xbest_i$. For the newly obtained solution, the radial topology checking algorithm is run to check the nests and the value of the fitness function is calculated using Eq. (1) and the nest corresponding to the best fitness function is set to the best nest *Gbest*.

Termination criterion

The generating new cuckoos and discovering alien eggs steps are alternatively performed until the number of iterations (Iter) reaches the maximum number of iterations (Iter$_{max}$). The flowchart of the proposed CSA for DNR problem is given in Fig. 2.

Numerical results

To demonstrate the performance and effectiveness of the proposed method using CSA from small-scale to large-scale distribution networks, it is applied to three standard IEEE test systems consisting of 33-node, 69-node and 119-node and compared the results with those of PSO as well as Continuous Genetic Algorithm (CGA). In CGA, arithmetic crossover, Gaussian mutation and roulette wheel selection are used as described in [23]. The CSA based methodology was developed by MATLAB R2014a in 2 GHz, i3, personal computer. The threshold value of power flow analysis is 0.005. Moreover, the upper and lower voltage ranges are set as V_{min} = 0.9 p.u. and V_{max} = 1 p.u. Summary of total features of three algorithms that are applied for reconfiguration are shown in Table 1 for the 33-node, 69-node and 119-node system. Values of these parameters can be different in each optimal problem. In this case, the optimal values of control parameters of the algorithms have been obtained by numerous trial simulations. In addition, to analyze the performance of CSA in DNR problem, the value of discovering probability P_a will be adjusted in the range from 0.1 to 0.9 with a step 0.1 with the same initial population set.

33-Node system

The 33-node distribution system, which is a small-scale system, includes 37 branches, 32 sectionalizing switches and 5 tie switches. The line, load data of this system are taken from [24]. Fig. 3 shows the diagram of this network. The total real and reactive power loads of the system are 3.72 MW and 2.3 MVAr, respectively. The total real and reactive power losses for the initial case calculated from power flow are 203.679 kW and 135.14 kVAr, respectively. The minimum voltage magnitude of the system is 0.91 occurs at bus no. 18.

The parameters and simulation results for the 33-node system are shown in Table 2. The optimal configuration of this system obtained by the proposed method is 7–9–14–32–37. The power loss of the optimum configuration in comparison with power loss of initial configuration is reduced from 203.679 kW to 138.9094 kW. Also the minimum voltage magnitude has been improved from 0.91081 to 0.9423 p.u. after reconfiguration by CSA. These results are identical to the results obtained by the methods proposed in Refs. [20,21] and are better than the results obtained by the FWA method proposed in Ref. [5]. The minimum power loss obtained by FWA is 139.98 kW which is 1.11 kW higher than the optimum solution obtained from CSA. Also the minimum bus voltage is 0.9413 which is 0.001 p.u. lower than the proposed method. The voltage profiles of the system for initial case and optimum case are compared and shown in Fig. 4. From the figure, it is observed that the voltage profile at all buses has been improved significantly after reconfiguration.

When adjusting the value of the probability P_a, the simulation results of DNR in case 33-node system are tabulated in Table 3.

Table 1
Summary of total features of applied algorithm for three distribution network systems.

Algorithm	33-Node and 69-node systems	119-Node system
PSO	Swarm size = 30, weighting factors C_1 = 2, C_2 = 1.5, maximum number of iterations N_{max} = 100, number of variables = 5	Swarm size = 30, weighting factors C_1 = 2, C_2 = 1.5, maximum number of iterations N_{max} = 500, number of variables = 15
CGA	Number of initial chromosome = 30, mutation rate = 0.2, fraction of population kept = 0.5, number of variables = 5	Number of initial chromosome = 30, mutation rate = 0.2, fraction of population kept = 0.5, number of variables = 15
CSA	Number of nests N_p = 30, maximum number of iterations N_{max} = 100, probability of an alien egg to be discovered P_a = 0.26, number of variables = 5	Number of nests N_p = 30, maximum number of iterations N_{max} = 500, probability of an alien egg to be discovered P_a = 0.25, number of variables = 15
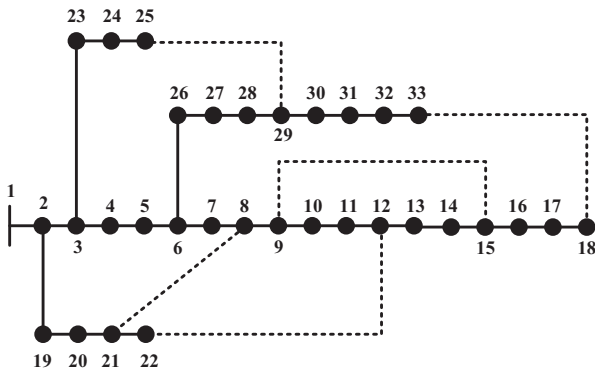
Fig. 3. IEEE 33-bus test system.

The proposed CSA method can obtain optimal solution for the values of P_a from 0.1 to 0.9. The convergence behaviors are presented Fig. 5. It can be seen from Fig. 5 that in P_a = 0.2 case, CSA tends to find the global optimum faster than other cases.

In order to illustrate the efficiency of CSA, the CGA and PSO have been implemented and applied to system. All of them have used the same initial population set. The convergence characteristics of algorithms for the best solution are shown in Fig. 6. As illustrated in this figure, the fitness function settles at the minimum after 24 iterations with the CSA, while with the GA and PSO algorithm settles at the minimum after 37 and 94 generations, respectively. The power loss characters and deviation index (ΔV_D) characters are shown in Figs. 7 and 8. According to these figures, the membership functions for real power loss reduction and voltage deviation index also tend to find the optimal values. Although sometimes they are not the optimal value in each iteration, because it depends on the fitness function. This illustration for this point can be seen from Fig. 7 that for the CSA, the power loss at the second iteration is about 143.7 kW but it increases to 145.6 kW at the third iteration and similarly in Fig. 8 at the first and the second iteration, the voltage deviation index are 0.069 and 0.077, respectively.
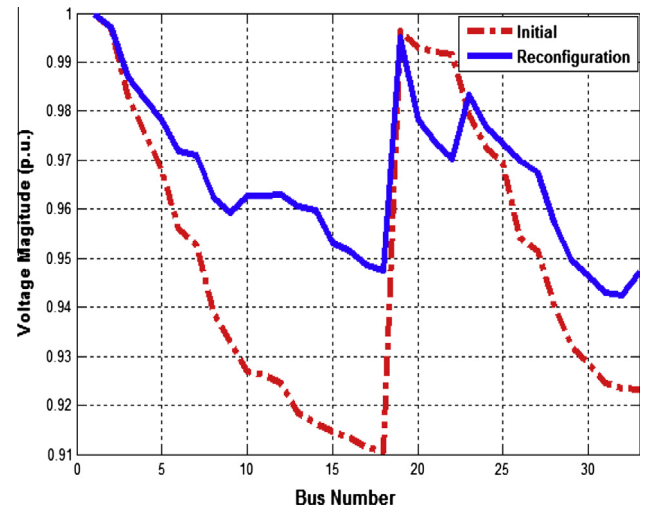

Fig. 4. Voltage profile for the 33-node system before and after reconfiguration.

Table 3
Results by CSA for 33-node, 69-node and 119-node system with different values of P_a.

P_a	33-Node system		69-Node system		119-Node system	
	Fitness	Iterations	Fitness	Iterations	Fitness	Iterations
0.1	0.73965	33	0.48879	69	0.72894	431
0.2	0.73965	26	0.48879	53	0.72894	364
0.3	0.73965	41	0.48879	83	0.72894	390
0.4	0.73965	34	0.48879	72	0.72894	437
0.5	0.73965	48	0.48879	55	0.72894	393
0.6	0.73965	45	0.48879	74	0.72894	387
0.7	0.73965	51	0.48879	79	0.72894	412
0.8	0.73965	36	0.48879	93	0.72894	484
0.9	0.73965	79	0.48879	81	0.72894	406

69-Node system

The 69-node distribution system, which is a medium-scale system, includes 69 nodes, 73 branches. There are 68 sectionalizing
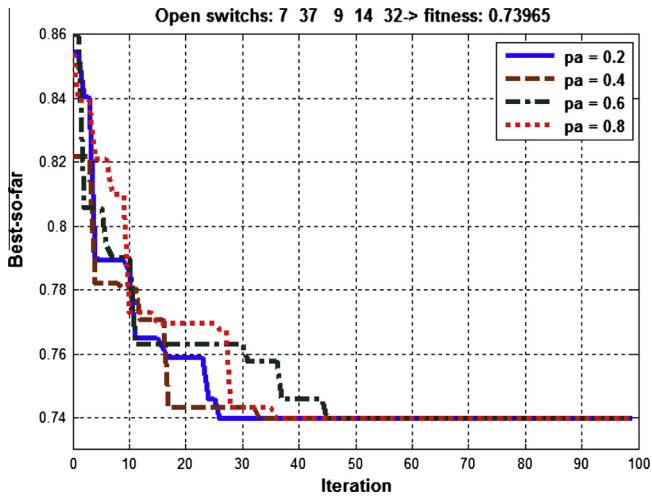
Table 2
33-Node system results on the different methods.

Methods	Open switches	Fitness	ΔP (kW)	ΔV_D	V_{min} (p.u.)
Initial	33, 34, 35, 36, 37	1.1116	203.679	0.0891	0.91081
Proposed CSA	7, 9, 14, 32, 37	0.73948	138.87	0.0576	0.94235
PSO	7, 9, 14, 32, 37	0.73948	138.87	0.0576	0.94235
CGA	7, 9, 14, 32, 37	0.73948	138.87	0.0576	0.94235
FWA [5]	7, 9, 14, 28, 32	0.74	139.98	0.0587	0.9413
GA [20]	7, 9, 14, 32, 37	0.7473	139.55	0.0622	0.9378
RGA [20]	7, 9, 14, 32, 37	0.7473	139.55	0.0622	0.9378
ITS [20]	7, 9, 14, 36, 37	0.7788	145.11	0.0664	0.9336
HSA [20]	7, 10, 14, 28, 36	0.7851	146.39	0.0664	0.9336
IAICA [21]	7, 9, 14, 32, 37	0.7472	139.51	0.0622	0.9378

Fig. 5. Effect of adjusting discovered probability on the 33-node system.
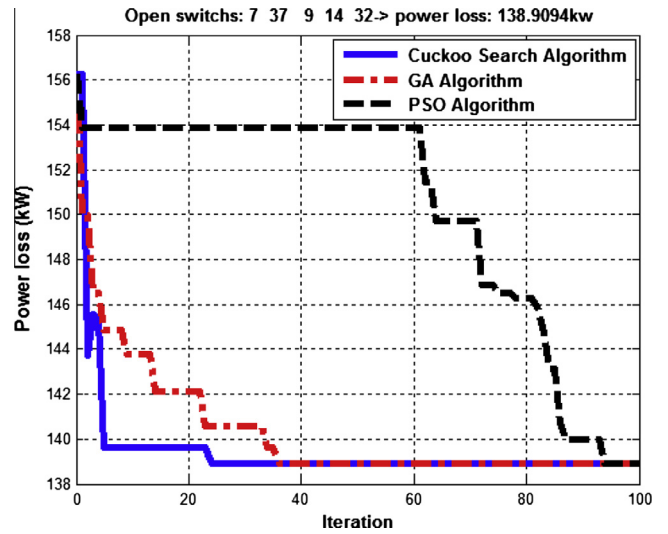

Fig. 7. Comparison of 33-node system indices for CSA, CGA and PSO in power loss.
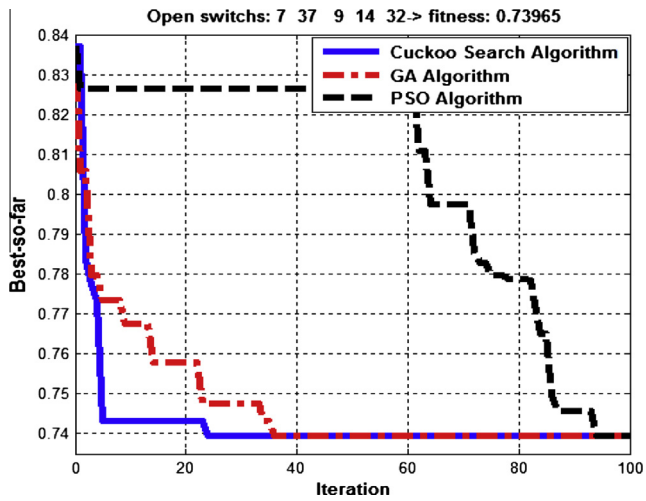

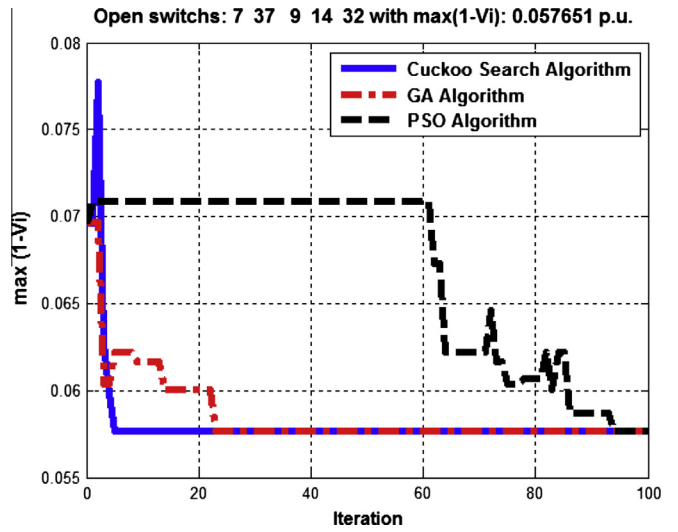**Fig. 6.** Comparison of 33-node system indices for CSA, CGA and PSO.

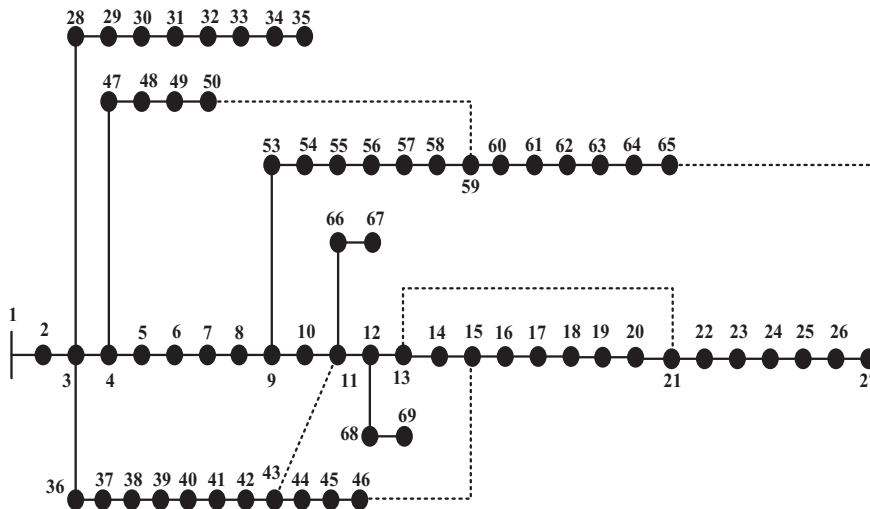**Fig. 8.** Comparison of 33-node system indices for CSA, CGA and PSO in deviation index.
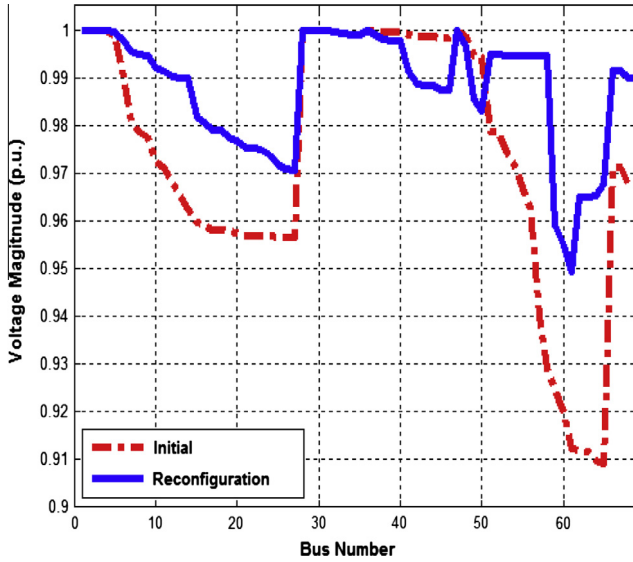

Fig. 9. IEEE 69-bus test system.

Fig. 10. Voltage profile for the 69-node system before and after reconfiguration.

Table 4
Comparison of simulation results for 69-node network.

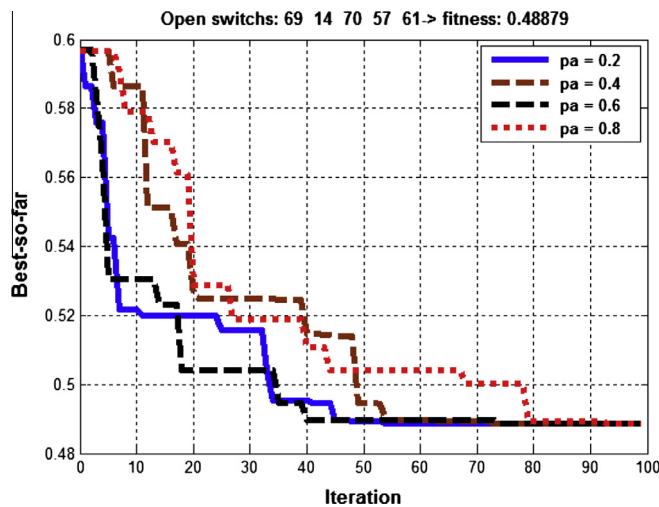| Method	Open switches	Fitness	ΔP (kW)	ΔV_D	V_{min} (p.u.)
Initial	69, 70, 71, 72, 73	1.0908	224.95	0.0908	0.9092
CSA	14, 57, 61, 69, 70	0.48879	98.5680	0.0505	0.9495
PSO	14, 57, 61, 69, 70	0.48879	98.568	0.0505	0.9495
CGA	14, 57, 61, 69, 70	0.48879	98.568	0.0505	0.9495
FWA [6]	14, 56, 61, 69, 70	0.48879	98.59	0.0505	0.9495
HSA [9]	13, 18, 56, 61, 69	0.49875	99.35	0.0572	0.9428
IAICA [21]	14, 57, 61, 69, 70	0.48879	98.5707	0.0505	0.9495

Fig. 11. Effect of adjusting discovered probability on the 69-node system.

switches and 5 tie switches and total loads are 3.802 MW and 3.696 MVAr [25]. The schematic diagram of the test system is shown in Fig. 9. In a normal operation, switches {69, 70, 71, 72, 73} are opened. After performing the proposed reconfiguration problem based on CSA, switches {14, 57, 61, 69, 70} are opened and the network losses are reduced from 224.95 kW to 98.568 kW. Fig. 10 shows the voltage profile improvement
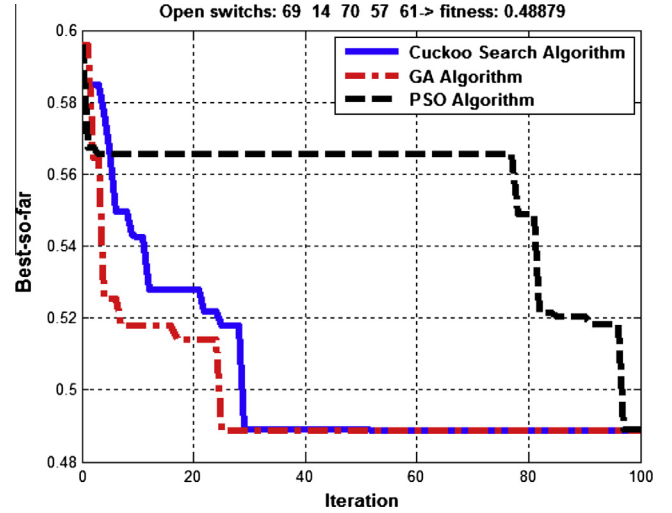

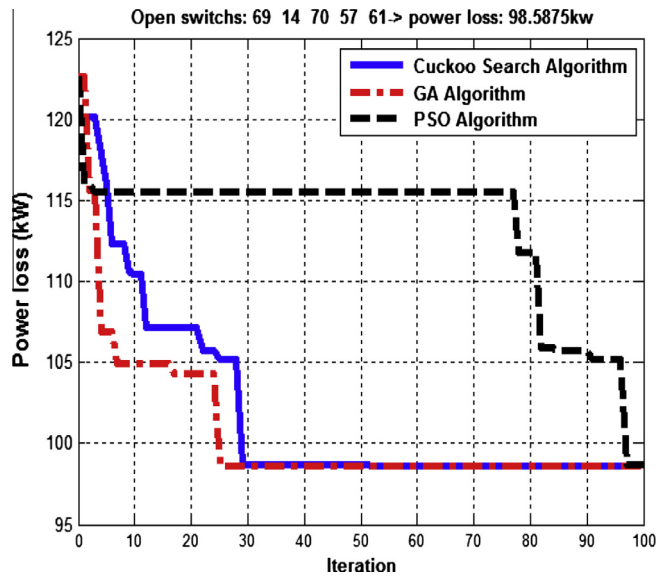**Fig. 12.** Comparison of 69-node system indices for CSA, CGA and PSO.

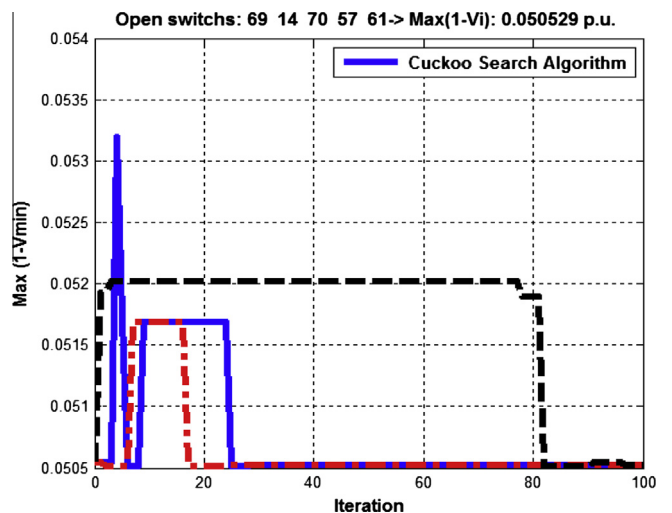**Fig. 13.** Comparison of 69-node system indices for CSA, CGA and PSO in power loss.

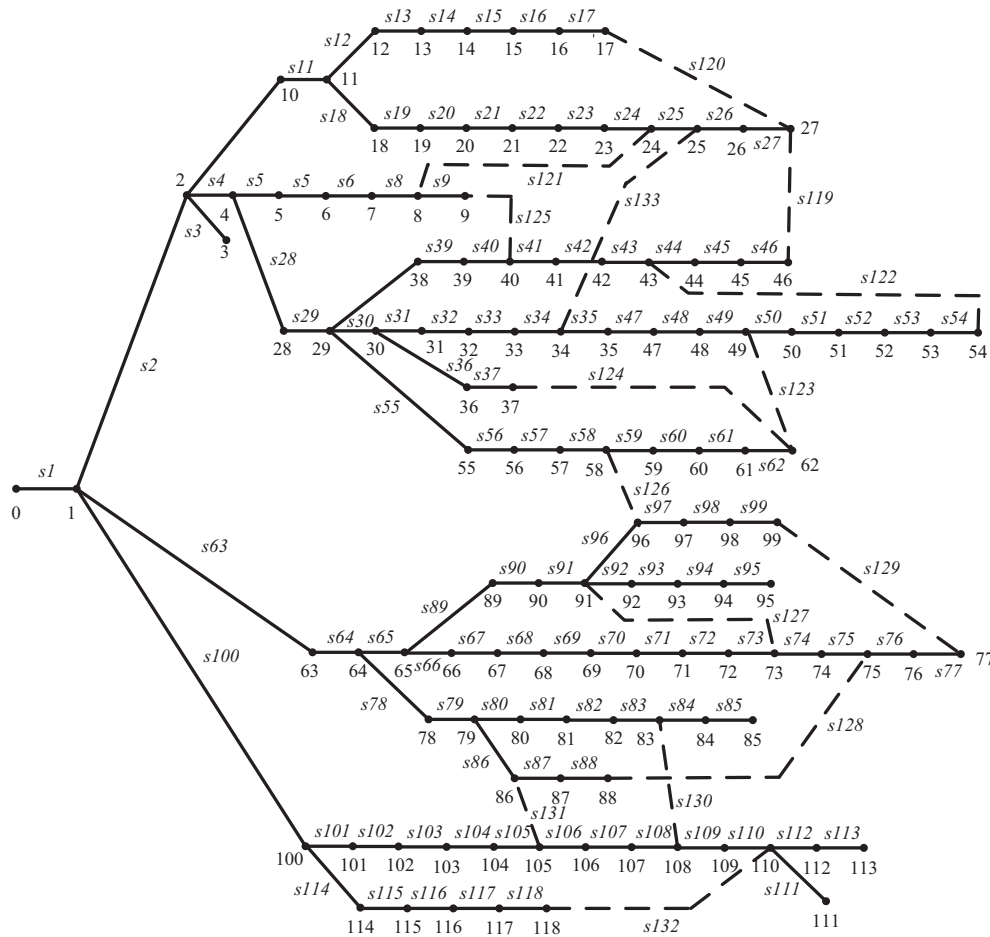**Fig. 14.** Comparison of 69-node system indices for CSA, CGA and PSO in deviation index.

Fig. 15. 119-bus test system.

achieved by the proposed CSA algorithm. As shown, most of the bus voltages have been improved after reconfiguration. The minimum bus voltage before reconfiguration was equal to 0.9092 p.u. and after reconfiguration; it is raised to 0.9495 p.u.

Reconfiguration results are given in Table 4 while a comparison is made with previous study. It can be observed that using the proposed CSA algorithm, the final power loss after reconfiguration is 98.568 kW and the minimum bus voltage is 0.9495 p.u. These results are identical to the results obtained by the methods proposed in Ref. [21] and are better than the results obtained by the method proposed in Refs. [6,9]. In Ref. [6], the optimum configuration is obtained by opening the switches {14, 56, 61, 69, 70}, which causes a power loss of 98.59 kW which is 0.022 kW higher than the optimum solution obtained from CSA. The minimum power loss so far reported in literature is 99.35 kW Ref. [9] which is 0.79 kW higher than the optimum solution obtained from CSA. Also the minimum bus voltage is 0.9428 which is 0.0067 p.u. lower than the proposed method.

In the 69-node network system, the proposed CSA method can obtain optimal solution for the values of P_a from 0.1 to 0.9 when adjusting the value of the probability P_a in Table 3. The convergence behaviors are presented Fig. 11. Similarly to the 33-node system in P_a = 0.2 case, CSA tends to find the global optimum faster than other cases.

The performance of CSA on 69-node system is also compared with the results of the other methods similar to 33-node system. From Fig. 12, it is clear that the CSA has outperformed PSO with the fitness function settles at the minimum after 29 iterations with
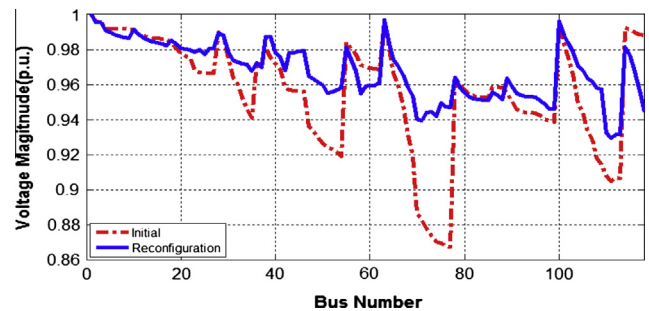

Fig. 16. Voltage profile for the 119-node system before and after reconfiguration.

the CSA, while with the CGA and PSO algorithm settles at the minimum after 25 and 97 generations, respectively. The power loss characters and deviation index (ΔV_D) characters of the 69-node system are shown in Figs. 13 and 14. Similarly to 33-node system, the membership functions for real power loss reduction and voltage deviation index also tend to find the optimal values.

119-Node system

To demonstrate the applicability of the proposed method using CSA in large-scale distribution networks, it is tested on 119-node system. This is the large-scale distribution system with 118 sectionalizing switches, 119 nodes and 15 tie switches as

Table 5
Comparison of simulation results for 119-node network.

Methods	Open switches	Fitness	ΔP (kW)	ΔV_D	V_{min} (p.u.)
Initial	119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133	1.1322	1,298.09	0.1322	0.8678
Proposed CSA	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	0.72894	855.0402	0.070247	0.9298
PSO	9, 23, 35, 43, 52, 60, 71, 74, 82, 96, 99, 110, 120, 122, 131	0.76178	897.192	0.07062	0.9294
CGA	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	0.72894	855.0402	0.070247	0.9298
FWA [5]	24, 26, 35, 40, 43, 51, 59, 72, 75, 96, 98, 110, 122, 130, 131	0.7275	854.06	0.0677	0.9323
HSA [20]	23, 27, 33, 43, 53, 62, 72, 75, 123, 125, 126, 129, 130, 131, 132	0.7275	854.21	0.0677	0.9323
MTS [27]	24, 27, 34, 40, 43, 52, 59, 72, 75, 96, 98, 110, 123, 130, 131	0.7369	865.865	0.0679	0.9321

shown in Fig. 15. The total power loads are 22,709.7 kW and 17,041.1 kVAr [26]. The initial system real loss was 1298.09 kW and minimum bus voltage was 0.8678 p.u.. By applying the proposed CSA, the power losses were reduced from 1,298.09 kW to 855.0402 kW and minimum bus voltage was increased from 0.8678 p.u. to 0.9298 p.u. after reconfiguration. Also, it is shown from Fig. 16
that the voltage profile has been improved by the proposed CSA.

The reconfiguration results are given in Table 5. It is clear that the optimization network structure of CSA is the same with that of CGA and it is different with that of PSO algorithm. CSA gets better optimization results both in power loss reduction and nodal voltage profile than that of PSO algorithm. The total power loss obtained by PSO is 897.192 kW which is 42.1518 kW higher than the proposed method and the minimum bus voltage is 0.9294 p.u. which is 0.0004 p.u. lower than CSA. The results are identical to results obtained by the method proposed in Refs. [5,20] and are better than the results obtained by the MTS methods proposed in Ref. [27]. The minimum bus voltage obtained by MTS is 0.9321 p.u. which is 0.0023 p.u. higher than CSA. However, the
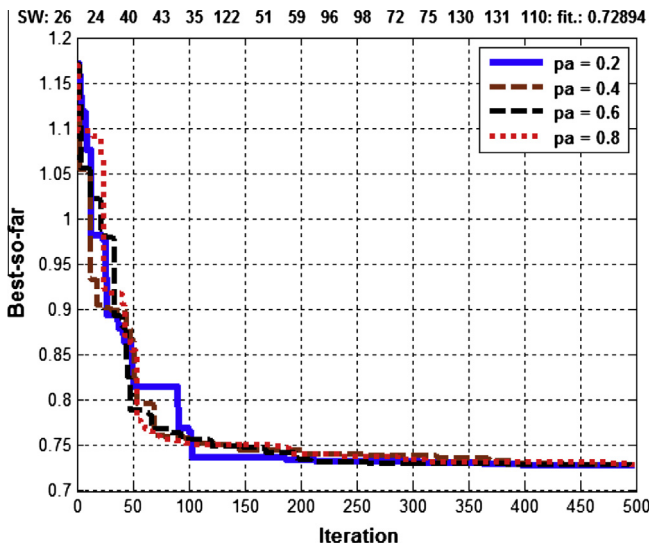

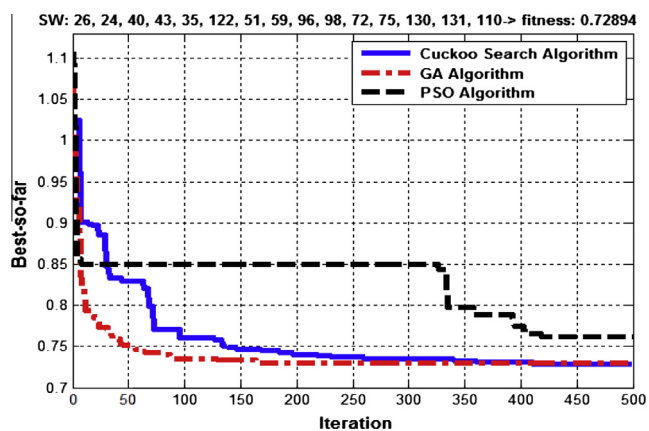**Fig. 17.** Effect of adjusting discovered probability on the 119-node system.

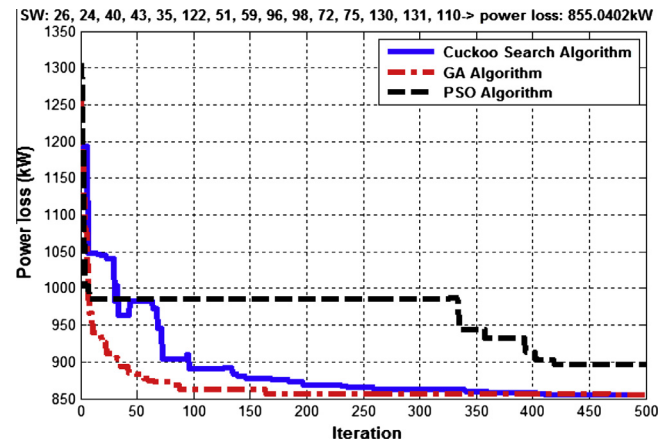**Fig. 19.** Comparison of 119-node system indices for CSA, CGA and PSO in power loss.

Fig. 18. Comparison of 119-node system indices for CSA, CGA and PSO.
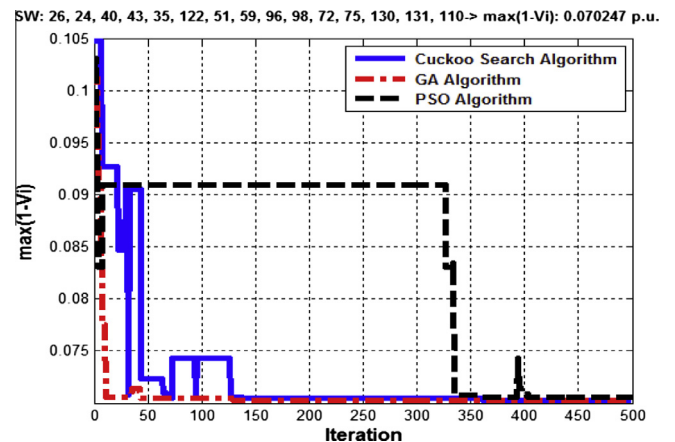

Fig. 20. Comparison of 119-node system indices for CSA, CGA and PSO in deviation index.

minimum power loss obtained by MTS is 865.865 kW which is 10.8248 kW higher than the optimum solution obtained from CSA.

When adjusting the value of the probability P_a, the simulation results of DNR in case 119-node system are tabulated in Table 3. The proposed CSA method can obtain optimal solution for the values of P_a from 0.1 to 0.9. The convergence behaviors are presented Fig. 17. It can be seen that CSA will be better convergence with the value of probability P_a between 0.2 and 0.6.

The convergence results of system indices for CSA, CGA and PSO are shown in Fig. 18. It can be seen from the Fig. 18 that the CSA and CGA reach the minimum fitness after 413 and 167 iterations, respectively while PSO do not find out the global optimization fitness value. Additionally, although all of them used the same initial population set, the CSA found the best solution at first iteration with fitness value is 1.024 while CGA and PSO is 1.108 because every each iteration, the CSA generate two solution sets via Lévy flights and Discover alien egg. The power loss characters and deviation index (ΔV_D) characters of the 119-node system are shown in Figs. 19 and 20. It can be seen from these figures that both membership objectives also tend to find the optimal values.

Conclusion

In this paper, the CSA method has been successfully applied for distribution network reconfiguration problem. The objective is to minimize the active power loss and voltage profile enhancement of power distribution systems. The radial topology of the network is maintained by the new algorithm based on the movement of each load node to the set of power nodes when it is connected to a node in the set of power nodes. The effectiveness of proposed method is demonstrated on 33-node, 69-node, and 119-node distribution networks. The numerical results verify that the proposed algorithm is capable of finding optimal solution and found to be better than the PSO and some other compared methods in literature. In addition, it has been shown that the potential of using the CSA in distribution network reconfiguration because it needs a few parameters to be tuned, the global solution obtained by using Lévy flight is not sensitive to the parameters used. The simulated results on the medium and large-scale systems like 69-node and 119-node distribution systems have shown that the applicability of CSA is more noticeable. Thus, the proposed method can be applied to any large-scale practical radial distribution networks.

References

[1] Merlin A, Back H. Search for a minimal loss operating spanning tree configuration in an urban power distribution system. In: Proceeding in 5th power system computation conf (PSCC). Cambridge (UK); 1975. p. 1–18.

[2] Civanlar S, Grainger JJ, Le SSH. Distribution feeder reconfiguration for loss reduction. IEEE Trans, Power Deliv 1988;3:1217–23.

[3] Teimourzadeh Saeed, Zare Kazem. Application of binary group search optimization to distribution network reconfiguration. Electr Power Syst Res 2014;62:461–8.

[4] Duan Dong-Li, Ling Xiao-Dong, Wu Xiao-Yue, Zhong Bin. Reconfiguration of distribution network for loss reduction and reliability improvement based on enhanced genetic algorithm. Electr Power Syst Res 2015;64:88–95.

[5] Mohamed Imran A, Kowsalya M. A new power system reconfiguration scheme for power loss minimization and voltage profile enhancement using Fireworks Algorithm. Electr Power Syst Res 2014;62:312–22.

[6] Mohamed Imran A, Kowsalya M, Kothari DP. A Novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution network. Electr Power Energy Syst 2014;63:461–72.

[7] Arandian Behdad, Hooshmand Rahmat-Allah, Gholipour Eskandar. Decreasing activity cost of a distribution system company by reconfiguration and power generation control of DGs based on shuffled frog leaping algorithm. Electr Power Energy Syst 2014;61:48–55.

[8] Aman MM, Jamson GB, Bakar AHA, Mokhlis H. Optimum network reconfiguration based on maximization of system load ability using continuation power flow theorem. Electr Power Energy Syst 2014;54:123–33.

[9] Srinivasa Rao R, Ravindra K, Satisk K, Narasimham SVL. Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation. IEEE Trans Power Syst 2013;28(1):317–25.

[10] Andervazh MR, Olamaei J, Haghifam MR. Adaptive multi-objective distribution network reconfiguration using multi-objective discrete particles swarm optimisation algorithm and graph theory. IET Gener Transm Distrib 2013;7(12):1367–82.

[11] Swarnkar Anil, Gupta Nikhil, Niazi KR. Adapted ant colony optimization for efficient reconfiguration of balanced and unbalanced distribution systems for loss minimization. Swarm Evol Comput 2011;1:129–37.

[12] Sedighizadeh Mostafa, Esmaili Masoud, Esmaeili Mobin. Application of the hybrid Big Bang-Big Crunch algorithm to optimal reconfiguration and distributed generation power allocation in distribution systems. Energy 2014:1–11.

[13] Yang X-S, Deb S. Cuckoo search via Lévy flights. In: Proc world congress on nature & biologically inspired computing (NaBIC 2009). India; 2009. p. 210–14.

[14] Marichelvam MK. An improved hybrid Cuckoo Search (IHCS) metaheuristics algorithm for permutation flow shop scheduling problems. Int J Bio-Inspired Comput 2012;4:200–5.

[15] Chandrasekaran K, Simon SP. Multi-objective scheduling problem: hybrid approach using fuzzy assisted cuckoo search algorithm. Swarm Evol Comput 2012;5:1–16.

[16] Gandomi A, Yang XS, Alavi A. Cuckoo search algorithm: a metaheuristic approach to solve structural optimization problems. Eng Comput 2013;29(1):17–35.

[17] Marichelvam MK, Prabaharanb T, Yang XS. Improved cuckoo search algorithm for hybrid flow shop scheduling problems to minimize makespan. Appl Soft Comput 2014;19:93–101.

[18] Jubaer Ahmed, Zainal Salam. A maximum power point tracking (MPPT) for PV system using Cuckoo search with partial shading capability. Appl Energy 2014;119:118–30.

[19] Yang Xin-She, Deb Suash. Cuckoo search: recent advances and applications. Neural Comput Appl 2014;24(1):169–74.

[20] Srinivasa Rao Rayapudi, Venkata Lakshmi, Narasimham Sadhu, Ramalinga Raju Manyala, Srinivasa Rao A. Optimal network reconfiguration of large-scale distribution system using harmony search algorithm. IEEE Trans Power Syst 2011;26(3):1080–8.

[21] Mirhoseini Seyed Hasan, Hosseini Seyed Mehdi, Ghanbari Mehdi, Ahmadi Mehrdad. A new improved adaptive imperialist competitive algorithm to solve the reconfiguration problem of distribution systems for loss reduction and voltage profile improvement. Electr Power Energy Syst 2014;55:128–43.

[22] Nguyen Thang Trung, Vo Dieu Ngoc, Truong Anh Viet. Cuckoo search algorithm for short-term hydrothermal scheduling. Appl Energy 2014;132:276–87.

[23] Haupt RL, Haupt E. Practical genetic algorithms. 2nd ed. John Wiley & Sons; 2004.

[24] Baran ME, Wu FF. Network reconfiguration in distribution systems for loss reduction and load balancing. IEEE Trans Power Deliv 1989;4(2):1401–9.

[25] Chiang HD, Jean-Jumeau R. Optimal network reconfigurations in distribution systems: Part II. IEEE Trans Power Deliv 1990;5(July 3):1568–74.

[26] Zhang Dong, Fu Zhengcai, Zhang Liuchun. An improved TS algorithm for loss-minimum reconfiguration in large-scale distribution systems. Electr Power Syst Res 2007;77:685–94.

[27] Abdelaziz AY, Mohamed FM, Mekhamer SF, Badr MAL. Distribution system reconfiguration using a modified Tabu Search algorithm. Electr Power Syst Res 2010;80:943–53.