# Distribution Network Reconfiguration Using One Rank Cuckoo Search Algorithm

Tung The Tran, Dieu Ngoc Vo and Pandian Vasant

***Abstract—*** *This paper presents the method using Cuckoo Search Algorithm (CSA) for solving the optimal Distribution Network Reconfiguration (DNRC) problem for power loss minimization. The CSA is based on the obligate brood parasitic behaviour of some cuckoo species in combination with the Lévy flight behaviour of some birds and fruit flies. The One Rank Cuckoo Search Algorithm (ORCSA) method is created based on the conventional CSA method so as to improve optimal solution and speed up convergence. In the ORCSA method, new eggs generated via Lévy flights are replaced partially and the newly generated eggs are then evaluated and ranked at once. On the other hand, there is a bound by best solution technique proposed for replacing the invalid dimension in order to improve convergence rate and performance. The proposed method has been applied on IEEE 16-bus, IEEE 33-bus and IEEE 69-bus distribution systems. The results obtained using the ORCSA are compared with those obtained using other modern techniques for performance examination.*

***Keywords— Cuckoo search algorithm, one rank cuckoo search algorithm, distribution network reconfiguration.***

## 1. INTRODUCTION

Distribution systems are planned and designed not only to reduce the investment cost but also the system operational cost. During unexpected forced outages of transformers and feeders, or overloads and maintenance the system need to be reconfigured by the operator controlling the status of the different switches in order to improve the system efficiency, reliability and operational cost for the new operating conditions. Distribution Network Reconfiguration (DNRC) is the procedure of varying the topological structures of distribution feeders by changing the open/closed states of the sectionalizing and tie switches [1]. This important operating practice is typically used to reduce the system real power loss (loss reduction), relieve network overloads (load balancing) and improve system security.

Many researchers studied the DNRC problems using different methods from conventional ones to artificial intelligence-based methods. Several conventional methods have been applied for solving the DNRC problem such as: Merlin and Back [2], Shirmohammadi and Hong [3][1], Castro et al [4], Baran and Wu [5], Liu et al [6], Nahman et al [7], Zhu et al [8], Simulated Annealing (SA) [9], Tabu Search (TS) [10], etc. The conventional methods are all greedy search algorithm. They are easy to be implemented and provide high searching efficiency, but generally cannot converge to the global optimum solution in the large-scale distribution systems. Recently, artificial intelligence search methods have become popular for solving the DNRC problem. They can direct searching processes to the global optimum at the probability of one hundred percent theoretically. However, they all inevitably involve a large number of computation requirements and control parameters. Various artificial intelligence methods have been applied to solve the Problem such as Binary Group Search Optimization (BGSO) [11], Genetic Algorithm (GA) [12], Fireworks Algorithm (FWA) [13], Ant Colony Optimization (ACO) [14], Particle Swarm Optimization (PSO) [15], Harmonic Search Algorithm (HSA) [16], etc.

The cuckoo search algorithm (CSA) 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 [17]. Marichelvam [18] proposed an improved hybrid cuckoo search algorithm for solving the permutation flow shop scheduling problems. In [19], 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 [20].

In this paper, an ORCSA is first proposed for the DNRC problem. The ORCSA is developed by Ahmed et al [21] in 2013 by performing two modifications on the original Cuckoo Search Algorithm including merging exploration phase and exploitation phase and bound by best solution mechanism.

The purpose of this paper is to apply the ORCSA to solve the DNRC problem. The proposed method has been tested on the IEEE 16-bus, IEEE 33-bus, and IEEE 69-bus systems and the obtained results are compared to those from Simulated Annealing, Differential Evolution,

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Fireworks Algorithm, Genetic Algorithms, Refined Genetic Algorithms, Harmony Search Algorithm and Improved Tabu Search.

## 2. PROBLEM FORMULATION

The network reconfiguration problem in a distribution system is to find the best configuration of radial network that gives minimum power loss while satisfying certain operating constraints. The operating constraints are voltage profile of the system, current capacity of the feeder and radial structure of the distribution system.

Mathematically, the problem is formulated as follows: The objective function for the DNRC problem is the minimum power losses:

$$Min\,F(X)=\sum_{i=1}^{Nbr}R_i\times\frac{P_i^2+Q_i^2}{V_i^2} \tag{1}$$

where $X$ is the vector of control variables:

$$X=[SW_1,SW_2,...,SW_{N_{Tie}}] \tag{2}$$

where $R_i$ is resistance of the $i$th branch, $N_{br}$ is the number of the branches, $X$ is the vector of control variables, $SW$ is the tie-switches to maintain the radial topology of the network, $N_{Tie}$ is the number of the tie-switches, and $P_i$, $Q_i$, $V_i$ are real power load, reactive power load and voltage magnitude at bus $i$, respectively.

The problem includes the equality and inequality constraints as follows:

*a) Power flow equations:*

$$\sum_{i=1}^{Nb}P_{gi}=P_L+\sum_{i=1}^{N_b}P_i;\ i=1,...,N_b \tag{3}$$

$$\sum_{i=1}^{Nb}Q_{gi}=Q_L+\sum_{i=1}^{N_b}Q_i;\ i=1,...,N_b \tag{4}$$

where $P_{gi}$, $Q_{gi}$ are real power and reactive power of the generation. $P_L$, $Q_L$ are total real power loss and total reactive power loss.

*b) Bus voltage limits*

$$V_{i,\min}\le V_i\le V_{i,\max};\ i=1,...,N_b \tag{5}$$

where $V_{i,min}$, $V_{i,max}$ are minimum and maximum voltage limits of $i$th bus, respectively.

*c) Feeder capacity limits:*

$$0\le I_i\le I_{i,\max};\ i=1,...,N_{br} \tag{6}$$

where $I_i$ is current in $i$th branch and $I_{i,max}$ is maximum current capacity of $i$th branch.

*d) Radial configuration:*

The system has to remain radially operated after reconfiguration. In other words, no loop is allowed in the reconfigured network. Following condition must be fulfilled in order to have the radial configuration of the distribution network.

$$N_{Tie}=N_{br}-(N_b-N_{ss}) \tag{7}$$

where $N_{br}$ is the number of branches, $N_b$ is the number of buses, and $N_{ss}$ is the number of substations.

*e) Bus isolation*

All buses have to be served after reconfiguration. The node must not be isolated without output supply from any feeder. It means only one switch should be opened in a loop.

## 3. ONE RANK CUCKOO SEARCH ALGORITHM

### *3.1. One Rank Cuckoo Search Algorithm*

The Cuckoo Search Algorithm, a new meta-heuristic algorithm, was inspired from the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of host birds of other species for solving optimization problems. The CSA was first developed by Yang and Deb in 2009. The CSA is summarized in the three main principal rules as follows [22]:

1. A cuckoo bird lays an egg and chooses a nest among the predetermined number of available host nests to dump its egg.
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 the egg laid by a cuckoo is discovered by the host bird with a probability probability $p_a\in$ [0, 1]. For the fraction of eggs, the host bird can either throw them away, or abandon them and build a new nest.

There is one more parameter is introduced in the proposed method in order to decide if the computational process merges exploration phase and exploitation phase together, called one rank ratio – $r_{or}$. The task of selecting the ratio is easy. It is initially set to 1 to allow merging new eggs from exploration phase and exploitation phase together. The ratio is still fixed at 1 until a better nest cannot be found at a current iteration. For the situation, the ratio is reduced as in the following equation:

$$r_{or}^{Iter+1}=r_{or}^{Iter}-0.5/D \tag{8}$$

where *Iter* is the current iteration and D is the number of objective function dimension.

On the other hand, there is a bound by best solution technique proposed for replacing the invalid dimension in order to improve convergence rate and performance.

$$r_{bbb}=1-1/\sqrt{D} \tag{9}$$

### *3.2. ORCSA for the DRN problem*

#### *3.2.1. Initialization*

For implementation of the proposed ORCSA to the problem, control variables is defined below:

$$X=[SW_1,SW_2,...,SW_{N_{Tie}}] \tag{10}$$

Initialize input of $X_{id}$ is then determined:

$$X_{id}=X_{id}^{\min}+rand\times\left(X_{id}^{\max}-X_{id}^{\min}\right) \tag{11}$$

*3.2.2. Generation of New Solution via Lévy Flights*

The new solution is calculated based on the previous best nests via Lévy flights. In the proposed CSA method, the optimal path for the Lévy flights is calculated by Mantegna's algorithm [23]. The new solution by each nest is calculated as follows:

$$X_d^{new} = Xbest_d + \alpha \times rand_3 \times \Delta X_d^{new} \tag{12}$$

where $\alpha > 0$ is the updated step size; $rand_3$ is a normally distributed random number in [0, 1] and the increased value $\Delta X_d^{new}$ is determined as:

$$\Delta X_d^{new} = v \times \frac{\sigma_x(\beta)}{\sigma_y(\beta)} \times (Xbest_d - Gbest) \tag{13}$$

where

$$v = \frac{rand_x}{\left|rand_y\right|^{1/\beta}} \tag{14}$$

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

$$\sigma_x(\beta) = \left[\frac{\Gamma(1+\beta)\times\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\times\beta\times 2^{\left(\frac{\beta-1}{2}\right)}}\right]^{1/\beta} \tag{15}$$

$$\sigma_y(\beta) = 1 \tag{16}$$

where $\beta$ is the distribution factor ($0.3 \le \beta \le 1.99$) and $\Gamma(.)$ is the gamma distribution function.

*3.2.3. Alien Egg Discovery and Randomization*

The action of discovering 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. The new solution due to this action can be found out in the following way:

$$X_d^{dis} = Xbest_d + K \times \Delta X_d^{dis} \tag{17}$$

where $Xbest_d$ is a solution generated via Lévy flights as in Section 3.2.2 and $K$ is the updated coefficient determined based on the probability of a host bird to discover an alien egg in its nest:

$$K = \begin{cases} 1 & \text{if } rand_4 < p_a \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

and the increased value $\Delta X_d^{dis}$ is determined by:

$$\Delta X_d^{dis} = rand_5 \times \left[randp_1(Xbest_d) - randp_2(Xbest_d)\right] \tag{19}$$

where $rand_4$ and $rand_5$ are the distributed random numbers in [0, 1] and $randp1(Xbest_d)$ and $randp2(Xbest_d)$ are the random perturbation for positions of the nests in $Xbest_d$.

*3.2.4. Bound by best solution mechanism*

For the newly obtained solution using Matpower toolbox 4.1, its upper and lower limits should be satisfied. As described in the second modification in Section 3.1, the bound by best solution mechanism is used to handle the inequality constraint.

*3.2.5. Stopping Criteria*

The algorithm is stopped when the number of iterations (*Iter*) reaches the maximum number of iterations ($Iter_{max}$).

The overall procedure of the proposed ORCSA for solving the DNRC problem is addressed as follows:

Step 1: Select parameters for ORCSA including the number of nest *Np*, the maximum number of iteration Itermax. Initialize population of host nests.

Step 2: Run the radial system checking algorithm and the load flow to calculate the power loss.

Step 3: Evaluate Xbest and Gbest based on the value of their fitness function. Set the iteration counter *Iter* = 1 and one rank ratio $r_{or} = 1$.

Step 4: Generate new solutions for abandoned eggs via Lévy flights as in Section 3.2.2

Step 5: Initialize a random number and compare to one rank ratio $r_{or}$. If the random number is less than $r_{or}$, go to Step 6. Otherwise, go to Step 8

Step 6: Discover alien egg and randomize to generate new solution as in Section 3.2.3

Step 7: Perform bound by best solution mechanism to define new solution as in section 3.2.4.

Step 8: Run the radial system checking algorithm and the load flow to calculate the power loss. Evaluate fitness function to get new *Xbest* and *Gbest*.

Step 9: Discover alien egg and randomize to generate new solution as in Section 3.2.3

Step 10: Perform bound by best solution mechanism to define new solution as in Section 3.2.4.

Step 11: Run the radial system checking algorithm and the load flow to calculate the power loss. Evaluate fitness function to get new *Xbest* and *Gbest*.

Step 12: If the current iteration Iter is equal to the maximum number of predetermined iteration. Stop the iterative procedure. Otherwise, set *Iter* = *Iter*+1 and go to Step 13.

Step 13: If the best nest *Gbest* at the current iteration is not better than that of the previous iteration. Obtain the one rank ratio using eq. (8) and back to 5.

## 4. NUMERICAL RESULTS

### *4.1 Selection of Parameters*

The proposed method was tested on 16-bus, 33-bus, and 69-bus radial distribution systems and results have been obtained to evaluate its effectiveness. In all these systems, the substation voltage is considered as 1.0 p.u. and all the tie and sectionalizing switches are considered as candidate switches for reconfiguration problem. The algorithm of this method was programmed by MATLAB R2009b in 2.4 GHz, i3, personal computer.

In the proposed ORCSA method, there are five parameters including three main ones from original Cuckoo Search Algorithm and two others from the two modifications on the original CSA. Two main parameters among the three affect each new solution generated from exploration and exploitation phases are the number of nests $N_p$ and the probability of an alien egg to be discovered $p_a$ whereas the maximum number of iteration Itermax directly influences the final optimal solution. On the other hand, the two other parameters affect merging exploration phase and exploitation phase and satisfying upper and lower limits are respectively one rank ratio $r_{or}$ and bound by best ratio $r_{bbb}$. The bound by best solution allows the proposed ORCSA method to improve convergence rate and performance. Furthermore, the demonstarted ORCSA method outperforms the original CSA method due to those two parameters. Contrary to the three main parameters from original CSA method, they are chosen with ease thanks to the definition shown in equation (8) and (9). The parameters of the ORCSA methods for the test systems are summarized in Table 1 [22].

**Table 1: The parameters of the ORCSA method**

| Test system | Number of nest | Pa | Itermax | Number of variables |
|---|---|---|---|---|
| 16 bus | 20 | 0.26 | 25 | 3 |
| 33 bus | 20 | 0.26 | 30 | 5 |
| 69 bus | 20 | 0.26 | 60 | 5 |

### *4.2 IEEE 16-bus system*

The first example is a three feeder, 16–bus radial distribution system, as shown in figure 1. Data for the system can be found in [24]. The system consists of 13 sectionalizing switches (normally closed) and three tie switches (normally open). The solid line in Figure 1 represents the sectionalizing switches and a dotted line represents the tie switches. The tie switches of the system are 14, 15 and 16

The total active and reactive power loads on the system are 28.7 MW and 16.3 MVAr. The system load is assumed to be constant and base MVA and voltage ratings of the system are selected as 100 MVA and 11 kV. The initial power loss obtained for the original configuration is 514 kW.

For this test case, the optimal power loss after reconfiguration is obtained as 465.3 kW. The results of the proposed algorithm are compared with the algorithms of Simulated Annealing [9] and Differential Evolution [26] and shown in Table 2. From there it is observed that the optimal power loss obtained by the proposed method is less than the other two methods SA [25], DE [24]. Figure 2 shows the voltage profile improvement achieved by ORCS algorithm, the convergence characteristic is shown in Figure 3.

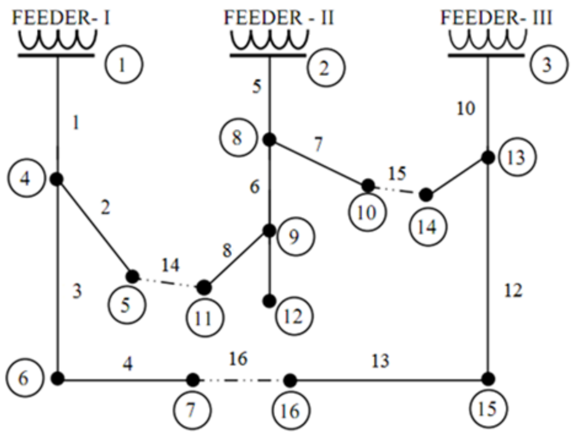


**Fig. 1. IEEE 16 bus test system.**

**Table 2: Comparision of simulation results for IEEE 16 bus test system**

| Method | Tie switches | Power loss (kW) | $V_{min}$ (p.u.) |
|---|---|---|---|
| Initial | 15,16,17 | 514.0293 | 0.9682 |
| ORCSA | 7,8,16 | 465.3 | 0.9721 |
| SA [9] | 7,8,16 | 466.1 | 0.9716 |
| DE [24] | 7,8,16 | 466.1 | 0.9716 |

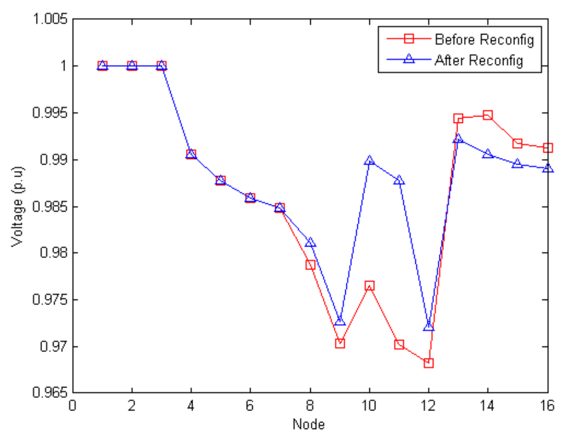


**Fig. 2. Voltage profile improvement of ORCSA for IEEE 16 bus test system.**

### *4.3 IEEE 33-bus test syste*

The 33-bus test system is a 12.66 kV, 33 buses, 5 tie switches and 32 sectionalize switches. The system data is given in [25]. The schematic diagram of the system is shown in Figure 4.

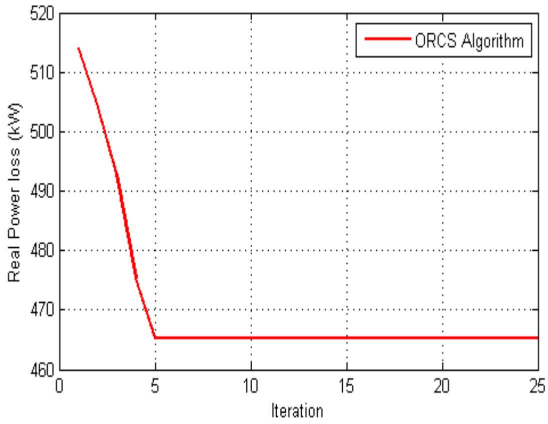


**Fig. 3. Convergence characteristics of ORCSA for IEEE 16 bus test system.**

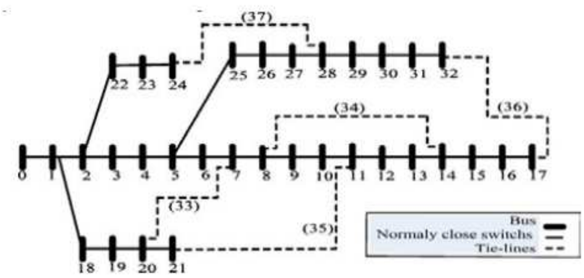


**Fig. 4. IEEE 33 bus test system.**

The simulation results are listed in Table 3. The initial system real power loss was 208.46kW. By applying the ORCSA, the final power loss is 138.92 kW. The results of the proposed algorithm are compared with Fireworks Algorithm [13], Genetic Algorithms [12], Refined Genetic Algorithms [26], Harmony Search Algorithm [16] and Improved Tabu Search [27]. From there, it is observed that the optimal power loss obtained by the proposed method is less than those others. Figure 5 shows the voltage profile improvement achieved by ORCS algorithm, the convergence characteristic is shown in figure 6.

**Table 3: Comparision of simulation results for IEEE 33 bus test system**

| Method | Tie switches | Power loss (kW) | $V_{min}$ (p.u.) |
|---|---|---|---|
| Initial | 33,34,35,36,37 | 208.46 | 0.9108 |
| ORCSA | 7,9,14,32,37 | 138.92 | 0.9423 |
| FWA [13] | 7,9,14,28,32 | 139.98 | 0.9413 |
| GA [12] | 7,9,14,32,37 | 139.55 | 0.9378 |
| RGA [26] | 7,9,14,32,37 | 139.55 | 0.9378 |
| HSA [16] | 7,10,14,28,36 | 146.39 | 0.9336 |
| ITS [27] | 7,9,14,36,37 | 145.11 | 0.9336 |

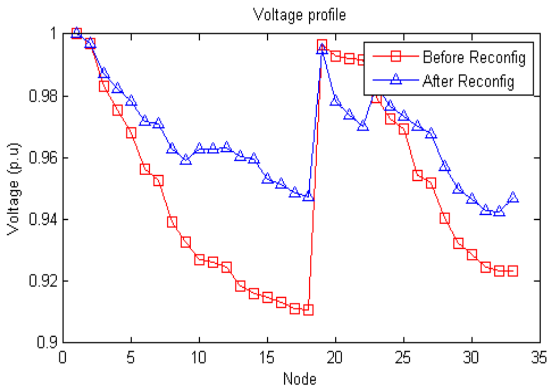


**Fig. 5. Voltage profile improvement of ORCSA for IEEE 33 bus test system.**

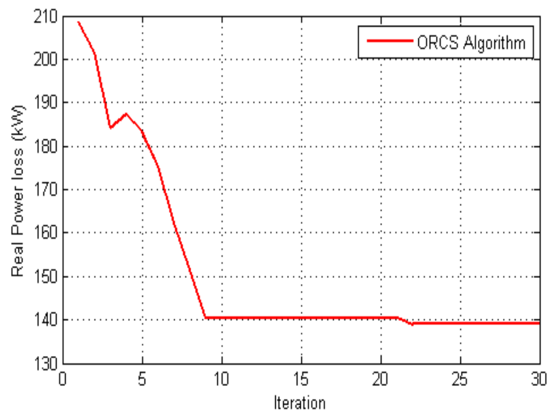


**Fig. 6. Convergence characteristics of ORCSA for IEEE 33 bus test system.**

### *4.4 IEEE 69-bus test system*

This is a 69-bus large-scale radial distribution system with 68 sectionalizing and five tie switches. The system data is given in [28]. The schematic diagram of the system is shown in Figure 7.

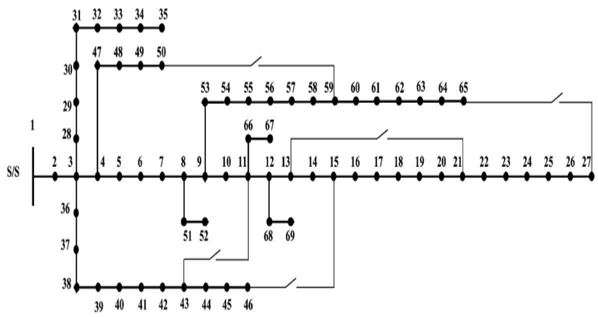


**Fig. 7. IEEE 69 bus test system**

The obtained best results from the proposed ORCSA method are compared with Harmony Search Algorithm [29], Genetic Algorithms [30] and Simulated Annealing [31]. From there, it is observed that the optimal power loss obtained by the proposed method is less than the other two. Figure 8 shows the voltage profile improvement achieved by ORCS algorithm, the convergence characteristic is shown in Figure 9.

**Table 4: Comparision of simulation results for IEEE 69 bus test system**

| Method | Tie switches | Power loss (kW) | $V_{min}$ (p.u.) |
|---|---|---|---|
| Initial | 69,70,71,72,73 | 224.98 | 0.9092 |
| ORCSA | 14,57,61,69,70 | 98.59 | 0.9495 |
| HAS [29] | 13,18,56,61,69 | 99.35 | 0.9428 |
| GA [30] | 12,44, 65,70,72 | 99.62 | 0.9428 |
| SA [31] | 12,44, 65,70,72 | 99.62 | 0.9428 |

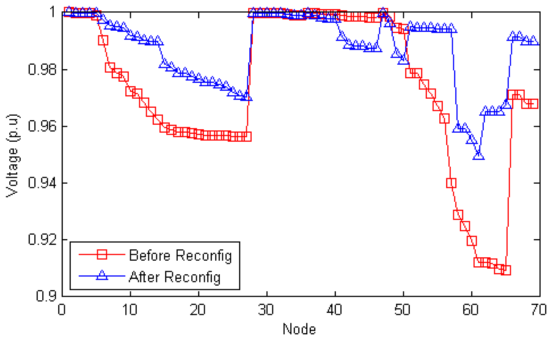


**Fig. 8. Voltage profile improvement of ORCSA for IEEE 69 bus test system.**

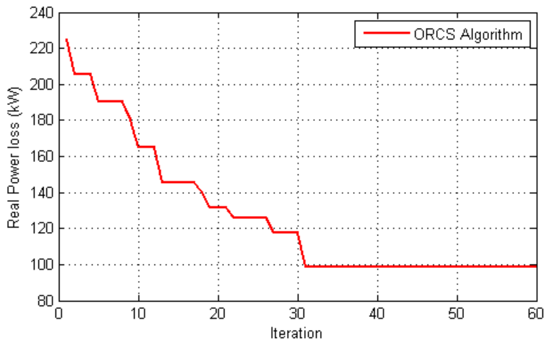


**Fig. 9. Convergence characteristics of ORCSA for IEEE 69 bus test system.**

## 5. CONCLUSION

This paper has proposed the ORCSA method, as a new evolutionary technique, for reconfiguration of distribution systems. The main advantage of solving such problems using ORCSA over the conventional mathematical methods is its simplicity. The results obtained during simulation show that the proposed ORCSA is capable of finding the optimal or near-optimal solution to the three cases studied in this paper. Simulations are carried out with 16, 33 and 69 bus systems then compared with other methods. The results obtained by the proposed method outperform the other methods in terms of solution quality and computation efficiency. Therefore, the proposed ORCSA could be a useful and powerful method for solving the DNRC problem.

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