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Distribution Networks Reconfiguration for Power Loss Reduction and Voltage Profile Improvement Using Hybrid TLBO-BH Algorithm

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Abstract
In this paper, a new method based on the combination of the Teaching-learning-based-optimization (TLBO) and Black-hole (BH) algorithm has been proposed for the reconfiguration of distribution networks in order to reduce active power losses and improve voltage profile in the presence of distributed generation sources. The proposed method is applied to the IEEE 33-bus radial distribution system. The results show that the proposed method can be a very promising potential method for solving the reconfiguration problem in distribution systems and has a significant effect on loss reduction and voltage profile improvement.

KEYWORDS: Black-Hole Algorithm, Distribution Networks, Power Loss Reduction, Reconfiguration, Teaching-Learning-Based Optimization, Voltage Profile Improvement

I. Introduction

The distribution system is the final step in the transmission of power to individual consumers. To continuous and reliable power supply to consumers, distribution networks sometimes have a ring topology, however, due to the problem of using ring topology, these networks used radially [1]. Distribution networks reconfiguration is the process of opening a number of switches and closing the same number of switches to minimize losses while maintaining the radial topology and constraints of the distribution system. Although loss reduction is the main goal in distribution network reconfiguration, it used for other purposes such as improving voltage profiles, increasing voltage stability, improving reliability, feeders load balancing, reducing network operating costs, and so on [2].

Recently, various methods have been proposed for distribution systems reconfiguration. Reference [3] has been proposed a bio-inspired meta-heuristic Artificial Immune System to minimize energy losses. This method can handle this combinatorial mixed integer problem of nonlinear programming. Radiality and connectivity constraints are considered as well as different load levels for planning the system operation. For this purpose, in this study, an improved algorithm is proposed to better accommodate the features of the problem and to improve the search process. Reference [4] is presented the Binary Group Search Optimization algorithm (BGSO) with fundamental modifications to be fit for reconfiguration and all binary form problems. All formulation of conventional GSO has been modified for accessing a novel powerful binary searching algorithm. Moreover, the forward–backward sweep, load flow is used due to its accuracy. Reference [5] is proposed a Meta-heuristics Fireworks Algorithm (FWA) to optimize the radial distribution network while satisfying the operating constraints. The radial nature of the system is maintained by generating proper parent node–child node path of the network during power flow. This method was tested on 33-bus and 19-bus IEEE systems and the simulation results were compared with other methods and it was proved that this method performs better than other methods based on the quality of solutions. Reference [6] is presented an Interval Multi-objective Evolutionary Algorithm for Distribution Feeder Reconfiguration. This method uses interval analysis to perform configuration assessment by considering the uncertainties in the power demanded by customers. The simulations have been performed on a 70-bus system in three case studies and show that this method is able to determine robust configurations that can maintain the stable performance of such system working under significant load variations. Thus, the effectiveness of the proposed method is demonstrated. Moreover, this method achieves stable configurations that remained feasible over long periods of time without requiring further reconfigurations. These results indicate the need to include load uncertainties when analyzing under realistic conditions. A feeder reconfiguration problem in the presence of distributed generators has been presented in [7] to minimize the system power loss while satisfying operating constraints using Hyper Cube-Ant Colony Optimization (HC-ACO) algorithm. In this study, loss sensitivity analysis was used to identify the optimal location for the installation of DG units. The simulations have been performed on a 33- bus radial distribution system at four different cases to confirm the efficiency of the proposed method compared to other methods in the articles. The results of this method were very fast and effective. In [8] the Cuckoo Search Algorithm (CSA) has solved the distribution system reconfiguration with the goal of reducing losses and improving the voltage profile. In [9] A Modified Bacterial Foraging Optimization Algorithm (MBFOA) is presented and the problem of distribution network reconfiguration is studied to minimize power loss. In reference [10] with the help of multi-objective distribution network reconfiguration, a method for optimizing unbalanced distribution network to maintain voltage stability using the Firefly algorithm is proposed. The objectives that should be minimized are the total network power losses, the deviation of bus voltage and load equalizing in the feeders. Each goal is moved into the fuzzy domain utilizing its membership function and fuzzy field independently. The proposed method for network reconfiguration has been implemented in 25-node and 19-node UDNs. The results obtained by the suggested method of these two unbalanced networks have been compared with that of obtained by Genetic algorithm (GA), ABC algorithm, PSO algorithm and GA-PSO algorithm using the same objective function. A Combined method with existing methods is also presented. In [11] using Ant Colony Optimization (ACO) technique, a novel method is proposed for simultaneous dynamic scheduling for distribution network reconfiguration in the presence of DG units with uncertain and variant generations over time. This method is applicable to both smart and classic distribution systems. For the second case, state estimation method should be used to estimate the loads at different buses using a limited number of measurements. The objective of this method is to minimize the total operational cost of the grid, the cost of power purchase from the sub transmission substation, cost of customer interruption penalties, Transformers Loss of Life expenses, and the switching costs. In [12] a dynamic reconfiguration method for a three-phase unbalanced distribution network is presented. The topology is optimized for the predicted time periods and is adaptive to the time-varying load demand and DG output while minimizing the daily power loss costs. To improve the calculation efficiency, several linearization methods have been proposed to formulate the dynamic reconfiguration as a mixed-integer linear programming problem. The effectiveness of the proposed method has been verified by the test results obtained on a modified IEEE 33 node test feeder. A new algorithm to solve the problem of distribution networks reconfiguration using Improved Selective Binary Particle Swarm Optimization (IS-BPSO) has been proposed in [13]. The proposed method demonstrates a new sigmoid function that can improve the control in the rate of change of the particles and improve the convergence of the results. The proposed algorithm is used to reduce power losses in distribution networks, this method is used on two test systems of 33 and 94 bus distributions. The simulation results show that the proposed method is very efficient and guarantees the achievement of the global optimum. Reference [14] deals with the simultaneous distributed generation (DG) planning and distribution network reconfiguration issue. The problem is formulized as an optimization model which includes three types of variables such as DGs location as the integer variables, DGs operating point as the continuous ones and switches open or close state as the binary variables. A 3D-GSO method has also been introduced to cope with this issue. The proposed method is a general optimization scheme applicable to all types of optimization problems which deal with an integer, continuous, and binary variables at the same time. Five different scenarios at three load levels are also considered to cover all possible conditions. The proposed method is validated through comprehensive simulation studies on 33-bus and 69-bus test systems.

In this paper, a new method based on the combination of the Teaching-learning-based-optimization (TLBO) and Black-hole (BH) algorithm has been proposed to reconfiguration of distribution networks in order to minimize active power losses and improve voltage profiles in the presence of distributed generation sources. The proposed model is simulated using 33 IEEE radial bus networks and the results show the efficiency of the proposed method.

II. Problem Formulation

As already mentioned, the distribution network reconfiguration problem is actually an optimization problem and, like any other optimization problem, has objective functions and constraints, which are as follows:

A. Minimizing the Active Power Losses

Minimizing the active power losses can be an objective function for the optimization problem. This index is *considered* as follows [15]:

$$P_{loss} = \sum_{i=1}^{Nb} g_m[(V_m^s)^2 + (V_m^r)^2 - 2V_m^s V_m^r \cos\theta_m] \quad (1)$$

Where V_m^s and V_m^r are the values of the voltage amplitude at the two ends of sending and receiving line m, respectively. g_m is conductivity of line m, θ_m is the phase difference between the two ends voltages of line m, and Nb is the number of lines.

B. Voltage Profile Improvement

Voltage is one of the most important indicators of power quality, which its profile improvement can be considered as one of the objective functions in the optimization problem. This objective function can be expressed mathematically as the following equations [15]:

$$VDI = \sqrt{\frac{1}{N_{bus}} \times \sum_{i=1}^{N_{bus}} (v_i - v_p)^2} \quad (2)$$

$$v_p = \frac{1}{N_{bus}} \times \sum_{i=1}^{n_{bus}} v_i \quad (3)$$

Where VDI is the voltage deviation index, v_I is the voltage of ith bus, v_p is the average bus voltage and N_{bus} is the bus number.

C. Bus Voltage Constraint

The voltage fluctuations in distribution systems are very limited and the standards usually allow only minor changes around the nominal value. Therefore, the voltage of the buses should always be within a permissible range, which is expressed according to (4):

$$v_i^{min} \leq v_i \leq v_i^{max} \qquad i = 1, 2, \dots, N_{bus} \quad (4)$$

Where v_I is the voltage of ith bus, v_i^{min} and v_i^{max} are the minimum and maximum permissible voltages of ith bus, respectively and N_{bus} is the number of buses.

D. Line Current Constraint

To prevent overload of the lines, the current of each branch must be kept below or equal to its maximum capacity. This is expressed by the following relation:

$$|I_i| \leq |I_i^{max}| \qquad i = 1, 2, \dots, N_{Line} \quad (5)$$

Where $|I_i|$ is the absolute value of current in ith line, $|I_i^{max}|$ are the maximum permissible current of ith line and N_{Line} is the number of lines.

E. Radial Configuration of the System and Isolation Constraints

The most severe constraint in the problem of distribution network reconfiguration is that distribution system configuration must be radial and all buses must be contained. In this paper, the system configuration is verified using the method proposed in [16].

III. Basis of The Methods

A. Teaching-Learning-Based Optimization

The Teaching-Learning-Based Optimization (TLBO) is an optimization algorithm that introduced in 2012 by Rao et al. [17]. This algorithm is based on concept of teaching and learning process in a classroom. In this algorithm, the population is considered as students of a class and the best member is selected as a teacher. The teacher tries to increase their knowledge by educating the students. Students also learn through communication with each other and increase their level of knowledge. This algorithm has two phases, which include the teacher phase and the learner phase.

1) Teacher phase: In this phase, the teacher increases learner's knowledge by teaching them. The relationships of this step are as follows:

$$X_{\text{new},i} = X_{\text{old},i} + r\left(X_i^{\text{best}} - T_F M_i\right) \quad (6)$$

$$T_F = round[1 + r] \quad (7)$$

Where r is a random number between [0, 1], T_F is teaching factor and its value can be either 1 or 2 and it is obtained randomly by (7), X_i^{best} is the best member of the population at iteration i that it is considered as a teacher, M_i is the class average at iteration i, $X_{\text{old},i}$ is a member that needs training and $X_{\text{new},i}$ is a trained member.

2) Learner phase: In this phase, each learner randomly exchanges information with another learner and thus increases their knowledge. For the ith member, a member is randomly selected from the population (jth member). Then, if $f(X_i) < f(X_j)$, member i is trained according to (8), otherwise it is trained according to (9). This step is done for all members of the population.

$$\mathrm{X}_{\text{new,i}} = \mathrm{X}_{\text{old,i}} + \mathrm{r}\left(\mathrm{X_i} - \mathrm{X_j}\right) \quad (8)$$

$$\mathrm{X}_{\text{new,i}} = \mathrm{X}_{\text{old,i}} + \mathrm{r}\left(\mathrm{X}_j - \mathrm{X}_i\right) \quad (9)$$

Where r is a random number between [0, 1], $X_{\text{old},i}$ is a member that needs training and $X_{\text{new},i}$ is a trained member. If $X_{\text{new},i}$ is better than $X_{\text{old},i}$, it will replace $X_{\text{old},i}$.

B. Black Hole Optimization Algorithm

The Black Hole (BH) Algorithm is a population-based method that is based on concept of the mechanism of black hole phenomenon. The BH algorithm directs the generated population towards the optimal response [18]. The process of the black hole algorithm in this paper is as follows:

1) A random initial population (stars) is generated.

2) The fitness value of each star is evaluated and the best candidate in the population, which has the best fitness value, is selected as the black hole (X_{BH}).

3) The new position of each star is determined according to the previous star and the position of the black hole as follows.

$$X_i(t+1) = X_i(t) + rand \times \left(X_{BH} - X_i(t)\right) \qquad i = 1,2, \dots, N \quad (10)$$

Where $X_i(t)$ and $X_i(t+1)$ are the locations of the ith star at iterations t and $t+1$, respectively. X_{BH} is the location of the black hole in the search space. N is the number of stars (solutions).

4) While moving towards the black hole, a star may reach a location with lower cost than the black hole. Therefore, their location is exchanged and that star is considered as a black hole in the next round and all the stars move towards it.

5) The distance of each star from the black hole is calculated. If its distance is less than the radius of the event horizon, that star is removed and a star is randomly placed in the search space instead. The radius of the event horizon in the black hole algorithm is calculated using the following equation:

$$R = \frac{f_{BH}}{\sum_{i=1}^{N} f_i} \quad (11)$$

Where f_{BH} is the fitness value of the black hole and f_i is the fitness value of the star i.

6) In this paper, the criterion of maximum number of iterations is considered as the criterion of stopping.

C. Hybrid TLBO-BH Algorithm

In this paper, the two mentioned algorithms are used in two separate steps to find the appropriate answer. Since the BH algorithm is more accurate than the TLBO algorithm and the TLBO algorithm is faster than the BH algorithm, the search space is first reduced using the TLBO and then the BH algorithm is used to obtain a more accurate answer. In fact, first the TLBO algorithm is executed and completed, then the answers obtained by the TLBO algorithm are used as the inputs of the BH algorithm.

The implementation process of TLBO algorithm is as follows:

First, the input data (e.g., load data, line data, DGs data, etc.) is imported. Then the initial population is generated. In the next step, based on the network configuration, power flow is performed and the corresponding objective function is calculated. The population is then updated and again based on the network configuration, power flow is carried out and the corresponding objective function is evaluated. In this step, if the convergence criterion is satisfied, the configuration with the minimum objective function is selected as the final solution, otherwise the population is updated and the process continues until the convergence criterion is met.

IV. Simulation and Results

To illustrate the performance of the proposed method, it is tested on a standard 33-bus radial distribution system according to "Fig. 1". The data of this 33-bus network is available in reference [19]. This network has a nominal voltage of 12.66 kV and the active and reactive loads installed in this network is equal to 3715 kW and 2300 kVar, respectively. The total active power loss is equal to 202.6 kW. The system has 37 branches, 32 sectionalizing switches and 5 tie switches. The switches 37, 36, 35, 34 and are open before the reconfiguration of the system.

In this paper numerical results are calculated in four different cases. The first case is related to normal network conditions, the second case is when network reconfiguration is applied separately, in the third case, DG placement and sizing is considered separately, and in the fourth case, DG placement and sizing and network reconfiguration are considered simultaneously.

A. Case I (Normal Network Conditions)

Table I, shows the results of applying the proposed method in all cases. As mentioned before, in the first case, network reconfiguration and DG placement are not considered. In this case, the network is in the normal condition and the switches 37, 36, 35, 34 and 33 are open. The network loss in this case is 202.6 kW.

B. Case II (Network Reconfiguration Using TLBO-BA Algorithm)

According to Table I, it can be seen that after network reconfiguration, the opened switches are 37, 32, 14, 9 and 7 and the active power losses reduced from 202.6 kW to 124.8 kW (38.4% reduction) which indicates the effective and useful role of reconfiguration. The convergence curve of the hybrid TLBO-BH algorithm for this case can be seen in "Fig. 2". It can be seen that the hybrid TLBO-BH algorithm converges to the optimal global solution after 10 iterations. "Fig. 3" shows the results of applying the proposed method in this case on network voltage profile. As shown in "Fig. 3", the network voltage profile has significantly improved after reconfiguration. For instance, in bus 18, the voltage was 0.913 P.U. before the reconfiguration, while after reconfiguration it reaches 0.947 P.U. That is nearly 3.7% increase in bus voltage 18.

C. Case III (Optimal DG Placement and Sizing Using hybrid TLBO-BA Algorithm)

In this case, optimal placement and sizing of DG is determined using hybrid TLBO-BA algorithm. It can be seen from the simulation that bus No. 6 is the optimal location for DG placement and its optimal capacity is 2575 kW. According to Table I, after optimal DG placement and sizing, the opened switches are 11, 14, 17, 33 and 37 and the active power losses reduced from 202.6 kW to 103.97 kW. The convergence curve of the TLBO-BH algorithm and voltage profile for case III can be seen in "Fig. 4" and "Fig.5" respectively. According to "Fig. 4", after 8 iterations, the hybrid TLBO-BH algorithm finds the best global solution. Comparing the results obtained in "Fig. 5", it is clear that the system voltage profile in the presence of DG has been effectively improved.

D. Case IV (Network Reconfiguration and DG Placement and Sizing Using hybrid TLBO-BA Algorithm)

In case IV, network reconfiguration and optimal DG placement and sizing are considered simultaneously. According to Table I, in this case the opened switches are 9, 14, 16, 25 and 32 and the active power losses reduced to 79.67 kW which shows a 61% decrease compared to the first case. In this case, the bus No. 29 is the optimal location for DG placement and its optimal capacity is 1925 kW.

Figure 6 shows the convergence curve of the hybrid TLBO-BH algorithm for case IV. It can be seen that the hybrid TLBO-BH algorithm converges to the optimal global solution after 11 iterations. The result of applying the proposed method in this case on network voltage profile is shown in "Fig. 7". According to "Fig. 7", significant improvement of the network voltage profile is clearly visible after network reconfiguration and DG placement simultaneously. For instance, the voltage of bus 18 reaches from 0.913 P.U. to 0.967 P.U., which means an increase of nearly 5.91% in bus 18 voltage.

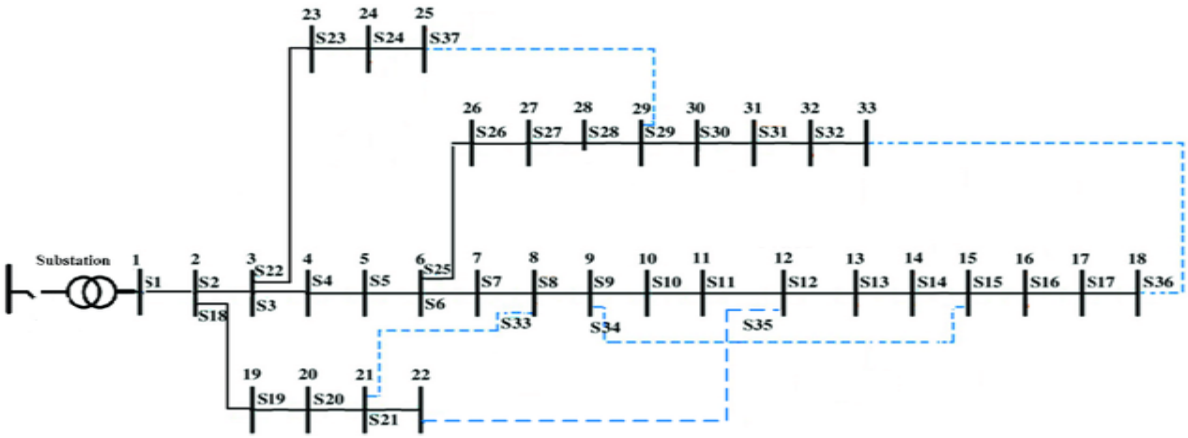

Fig. 1: The 33-bus distribution system.

TABLE I
RESULTS OF APPLYING THE PROPOSED METHOD IN ALL CASES

Case Number	Open Switches	Loss (kW)	Number of Population	Maximum Iteration
Case I	33 - 34 - 35 - 36 - 37	202.6	-	-
Case II	7 - 9 - 14 - 32 - 37	124.8	20	20
Case III	11 – 14 – 17 – 33 - 37	103.97	20	20
Case IV	9 – 14 – 16 – 25 - 32	79.67	50	50

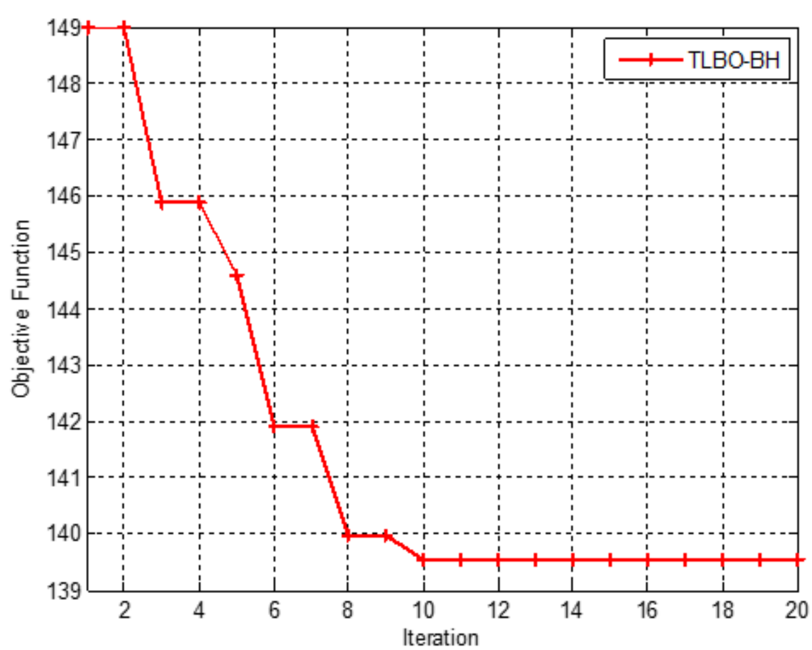

Fig. 2: The convergence curve of the hybrid TLBO-BH algorithm in case II.

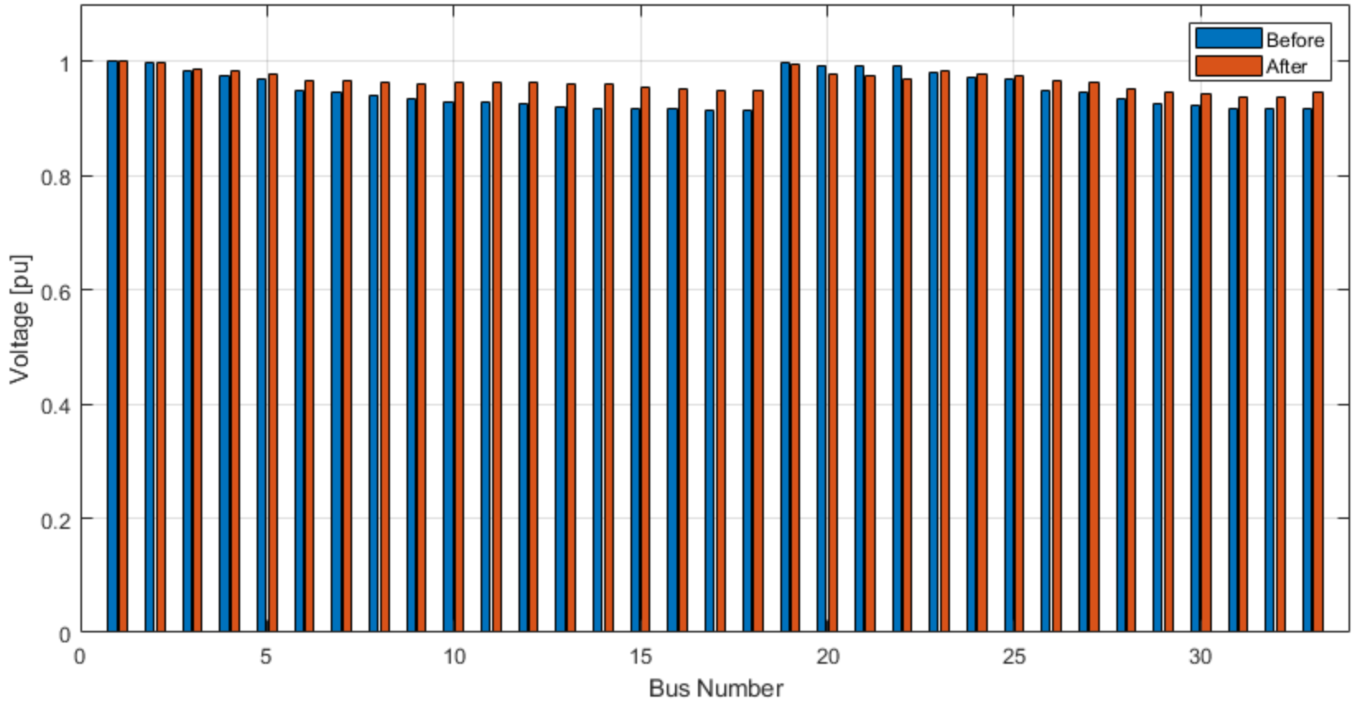

Fig. 3: The network voltage profile using hybrid TLBO-BH algorithm in case II.

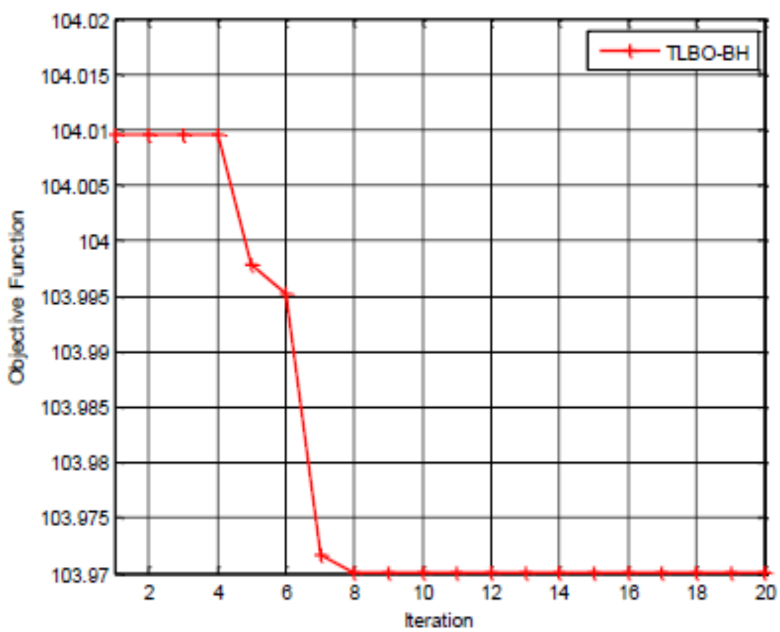

Fig. 4: The convergence curve of the hybrid TLBO-BH algorithm in case III.

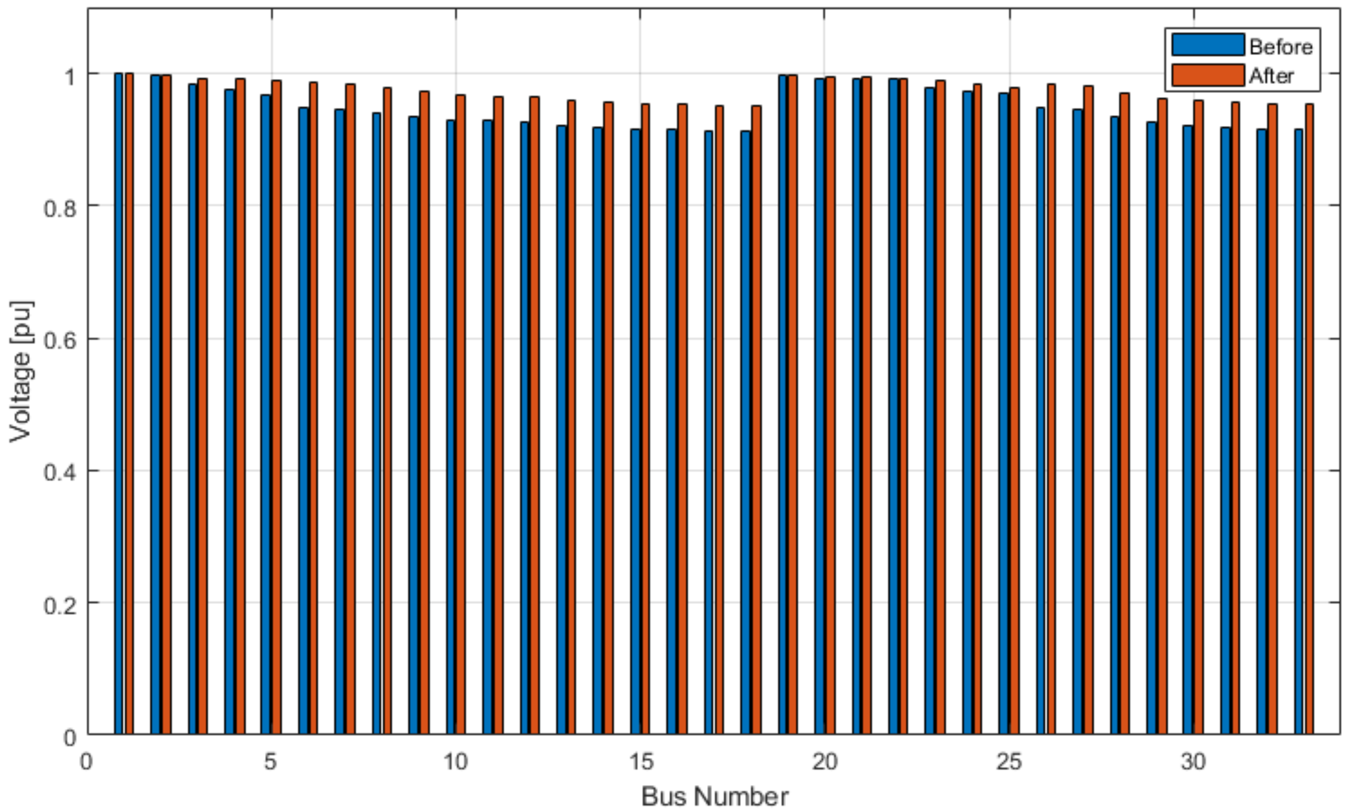

Fig. 5: The network voltage profile using hybrid TLBO-BH algorithm in case III.

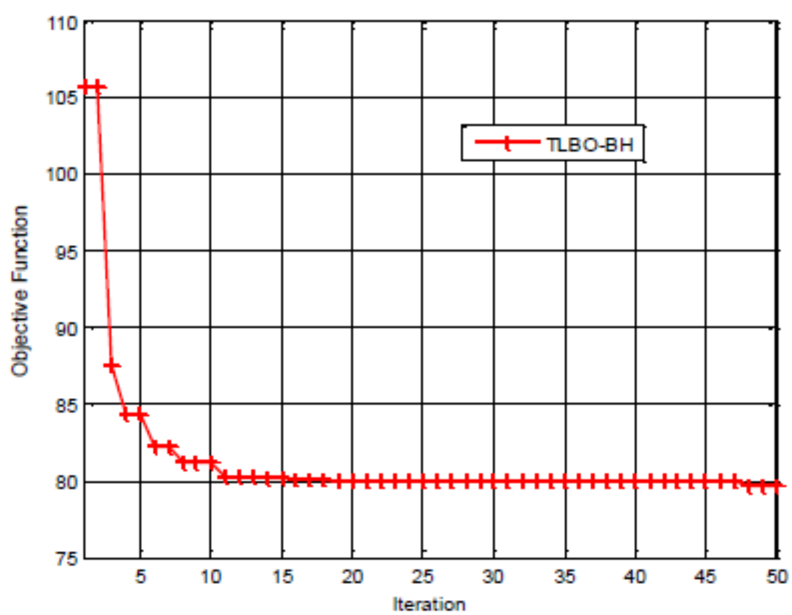

Fig. 6: The convergence curve of the hybrid TLBO-BH algorithm in case IV.

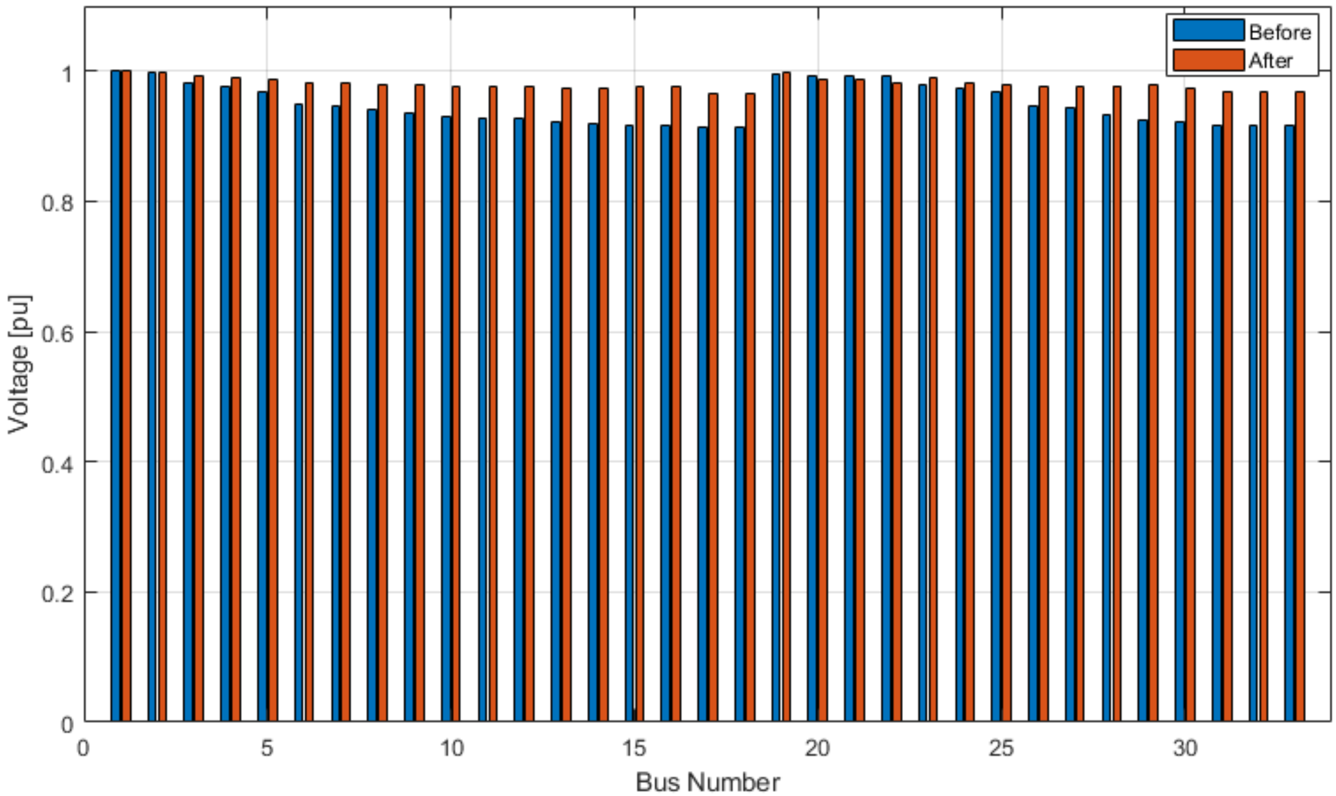

Fig. 7: The network voltage profile using hybrid TLBO-BH algorithm in case IV.

V. Conclusion

In this paper, a new method based on the combination of the Teaching-learning-based-optimization (TLBO) and Black-hole (BH) algorithm has been proposed to reconfiguration of distribution networks in order to reduce active power losses and improve voltage profiles in the presence of distributed generation sources. The proposed method has been tested on the IEEE 33-bus radial distribution system in different cases. The obtained results show that the hybrid TLBO-BH algorithm has high efficiency on loss reduction and voltage profile improvement and can coverage to global optimum very fast.

Conflict of Interest

The authors have no conflict of relevant interest to this article can be used.

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