

Reconfiguration of Smart Distribution Network in the Presence of Renewable DG's Using GWO Algorithm

M. Siavash¹, C. Pfeifer¹, A. Rahiminejad², B. Vahidi³

1 Department of Material Science and Process Engineering, University of Natural Resources and Life Sciences, Vienna, Austria

2 Department of Electrical and Computer Science, Esfarayen University of Technology, Esfarayen, North Khorasan, Iran

3 Department of Electrical Engineering, Amirkabir University of Technology, Tehran, Iran

E-mail: majid.siavash@students.boku.ac.at

Abstract. In this paper, the optimal reconfiguration of smart distribution system is performed with the aim of active power loss reduction and voltage stability improvement. The distribution network is considered equipped with wind turbines and solar cells as Renewable DG's (RDG's). Because of the presence of smart metering devices, the network state is known accurately at any moment. Based on the network conditions (the amount of load and generation of RDG's), the optimal configuration of the network is obtained. The optimization problem is solved using a recently introduced method known as Grey Wolf Optimizer (GWO). The proposed approach is applied on 69-bus radial test system and the results of the GWO are compared to those of Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). The results show the effectiveness of the proposed approach and the selected optimization method.

1. Introduction

Considering three major crises of human societies including financial, energy, and environmental issues, the presence of distributed generation especially renewable ones are increased dramatically in distribution networks. These kinds of resources could enhance the performance of the distribution networks from different aspects such as loss reduction, voltage profile and stability improvement, and reliability increase [1]. However, to achieve these improvements, optimal placement and scheduling of distributed generation are required [2].

Since the output power of Renewable Distributed Generations (RDG) such as solar cells and wind turbines depend on ambient conditions, their production could not be dispatched [3]. In other words, the RDGs output generation fluctuates which causes the operation point of distribution network moving away from the optimal point.

Reconfiguration of distribution networks is an effective and low cost method for enhancing the distribution system performance. The problem of optimal reconfiguration is a discrete optimization problem by which the configuration of the distribution network is changed optimally by altering the state of open/closed switches [4].

The two important issues related to this problem are determining the objective function and the solving algorithm. There are different target functions for the problem of reconfiguration including power loss minimization [5] voltage profile improvement [6], reliability increase [7], and voltage stability enhancement [8]. In this paper, the problem is solved with the aim of power loss reduction and voltage stability improvement. There are different methods proposed for solving the



reconfiguration problem in the literature such as genetic algorithm [9], Big Bang–Big Crunch algorithm [10], firefly algorithm [11], cuckoo search algorithm [6], plant growth simulation algorithm [12], Teaching–Learning–Based Optimization algorithm [13], bacterial foraging optimization algorithm [5], and Artificial immune algorithm [14]. Different methods have advantages from different aspects such as final results, time of convergence, convergence behaviour, and robustness.

In this paper, a recently introduced method known as Grey Wolf Optimizer (GWO) [15] is proposed for solving the distribution system reconfiguration problem. The suggested approach is applied on a distribution network equipped with renewable energy resources consists of solar cells and wind turbine. The reconfiguration problem is solved hourly in a day considering the hourly variation of load demand, wind speed, solar irradiance, and temperature. The distribution system is considered equipped by smart metering devices which provide accurate information of network conditions in any moment. The problem is solved with the aim of power loss reduction and voltage stability enhancement.

2. Problem formulation

Distribution networks consist of two types of switches including sectionalizing and tie switches which the former are normally close and the later are normally open. Changing the status of these switches changes the configuration of the system and the power flow path which may result in loss reduction, voltage profile improvement, voltage stability enhancement and etc. Depending on a target, the configuration of the system could be obtained optimally; thus, reconfiguration could be considered as an optimization problem as follow:

$$\begin{aligned} \min \quad & f(x) \\ \text{s.t.} \quad & h(x) = 0 \\ & g(x) \leq 0 \end{aligned} \quad (1)$$

where x is decision variables (status of switches), f is objective function, h and g are equality and inequality constraints, respectively.

2.1. Objective function

As mentioned before, the problem of reconfiguration in this paper is solved for two objectives as loss reduction and voltage stability enhancement. Herein, these two objective functions are explained.

2.1.1. Loss reduction

The first objective function is active power loss reduction which is the wasted power through feeders. The total power loss can be calculated as follow:

$$P_{loss} = \sum_{k=1}^{N_b} R_k I_k^2 \quad (2)$$

$$I_k = \frac{V_j - V_i}{R_k + jX_k} \quad (3)$$

where P_{loss} is the total power loss of the network, N_b is the total number of branches, I_k , R_k and X_k are current, resistance and inductance of branch k , and V_i and V_j are the voltages at sending and receiving end of branch k .

2.1.2. Voltage stability enhancement

Voltage stability is a factor which determines the weak buses which are sensitive to load changes and may cause voltage collapse. There are different indices introduced for voltage stability determination such as Shin criterion [16], Aman criterion [17], Kayal criterion [18]. In this paper, the Kayal criterion is used as the Voltage Stability Factor (VSF) which is as follow:

$$VSF_{total} = \sum_{m=1}^{N-1} (2 \times V_{m+1} - V_m) \quad (4)$$

where N is the total number of buses, V is voltage, VSF_{total} is the total VSF of the system. A higher value of VSF means a more stable network.

In order to add the two mentioned objectives for simultaneous optimization of both targets, the objective functions are normalized as follow:

$$\begin{aligned} f &= f_1 + f_2 \\ f_1 &= \frac{P_{loss}}{P_{loss}^0} \\ f_2 &= \frac{VSF_{total}^0}{VSF_{total}} \end{aligned} \quad (5)$$

where P_{loss}^0 and VSF_{total}^0 are the values of loss and voltage stability factor in the base case of the network.

2.1.3. Constraints

During the optimization procedure, there are some constraints which must be satisfied. These constraints are as follow:

Power balance: for any proposed configuration of distribution network, the power balance equation must be checked using power flow program.

Voltage magnitude: the magnitude of bus voltages must be remained in a predefined range

$$V_i^{\min} < V_i < V_i^{\max} \quad (6)$$

Thermal limit of feeders: the power flows through the feeders must be lower than their thermal limit

$$S_i < Limit_i \quad (7)$$

where S_i and $Limit_i$ are power flow and thermal limit of feeder i .

Radial structure: for any suggested configuration, the structure of the network must be remained radial.

3. Grey Wolf Optimizer (GWO)

Grey Wolf Optimizer (GWO) algorithm is a population based algorithm which was introduced by Mirjalili in 2014 [15]. This method simulates the hunting procedure of a wolf pack. The leadership hierarchy of the wolf pack is modeled by defining the wolves α , β , δ , and ω . The first level of leadership is the wolf α which is responsible for lots of decisions such as hunting, sleeping place, and time of wake. Mathematically, the best solution of the populations is considered as the wolf α . The second level of hierarchy is the wolf β which is the second best solution of the population. The third best solution is δ and the other wolves are considered as lowest ranking wolves ω . The wolves ω are the last group of wolves which are allowed to eat. These wolves are always ready to submit to higher ranking level wolves.

The main phases of hunting procedure are as follows:

- 1- Tracking, chasing, and approaching the prey
- 2- Pursuing, encircling, and harassing the prey until it stops moving
- 3- Attack towards the prey

Grey wolves encircle the prey before attacking to it. The encircling procedure could be mathematically modelled using the following equations.

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_P(t) - \vec{X}(t) \right| \quad (8)$$

$$\vec{X}(t+1) = \vec{X}_P(t) - \vec{A} \vec{D} \quad (9)$$

where t is iteration number, \vec{A} and \vec{C} are coefficient vectors, \vec{X}_P is prey position, and \vec{X} is the position of grey wolf. The coefficient vector can be calculated as follow:

$$\vec{A} = 2\vec{a}r_1 - \vec{a} \quad (10)$$

$$\vec{C} = 2\vec{r}_2 \quad (11)$$

where \vec{r}_1 and \vec{r}_2 are random vectors in the range of $[0, 1]$, and \vec{a} is vector which reduces from 2 to 0 during the iterations.

As mentioned before, the first three high ranking wolves (α , β , and δ) have a better knowledge of the prey location. Thus, these three wolves are remained unchanged in the current iteration and the other

wolves position updated based on the position of three first wolves. The updated procedure of wolves ω is as follows:

$$\bar{D}_\alpha = |\bar{C}_1 \bar{X}_\alpha - \bar{X}|, \bar{D}_\beta = |\bar{C}_2 \bar{X}_\beta - \bar{X}|, \quad (12)$$

$$\bar{D}_\delta = |\bar{C}_3 \bar{X}_\delta - \bar{X}|$$

$$\bar{X}_1 = \bar{X}_\alpha - \bar{a}_1 \bar{D}_\alpha, \bar{X}_2 = \bar{X}_\beta - \bar{a}_2 \bar{D}_\beta, \quad (13)$$

$$\bar{X}_3 = \bar{X}_\delta - \bar{a}_3 \bar{D}_\delta$$

$$\bar{X}(t+1) = \frac{\bar{X}_1 + \bar{X}_2 + \bar{X}_3}{3} \quad (14)$$

The final position would be in a random place within a circle which is defined by the positions of alpha, beta, and delta in the search space. In other words alpha, beta, and delta estimate the position of the prey, and other wolves updates their positions randomly around the prey.

4. Simulation and results

In this section the proposed approach is applied on 69-bus radial test system which the single line diagram of the network is depicted in Figure 1. The system was used in many previous researches [19]-[22] and the line and bus data of this system can be found in [20].

This system has a total load of 3802.2 kW and 2694.6 kVAR which is considered as the peak load situation. In this situation the total active power loss is 224.98 kW and the minimum voltage is 0.9092 (in p.u.). In addition, the total VSF for this network in the peak situation is 66.04. The daily load profile of this network is depicted in Figure 2 which is a percentage of peak load demand.

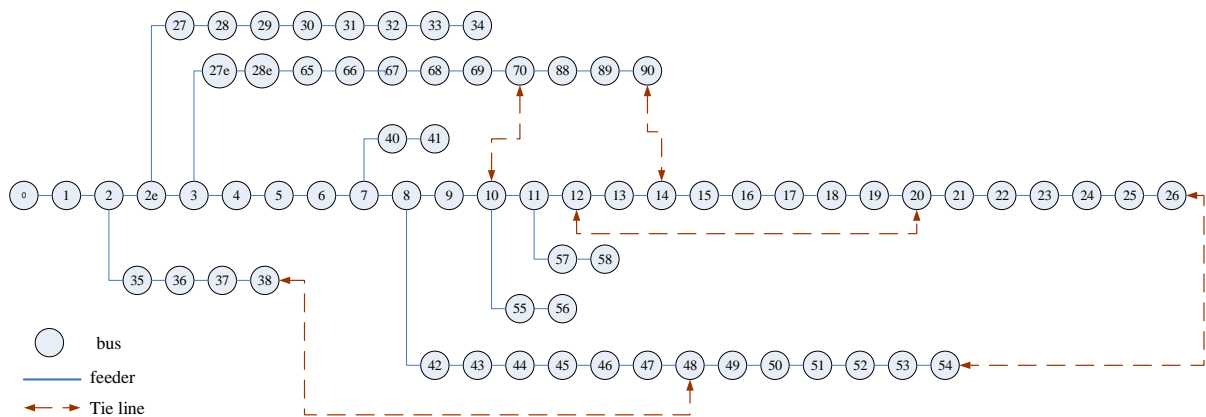


Figure 1. Single line diagram of 69 bus test system

4.1. Presence of RDG's

In order to investigate the effect of RDG's on network performance a 500 kW set of PV array and a 800 kW wind turbine are added to the buses 17 and 50 respectively. The location of RDG's are the optimal location based on [23]. The hourly variation of wind power generation and PV power output are depicted in Figure 3. In the presence of these resources the active power loss, minimum voltage, and total VSF at the peak hour are, respectively, 176.5, 0.9198, and 66.4. Thus, it can be concluded that the presence of RDG' improves the performance of the network. However, because of output fluctuation of RDG's, the performance of the network may move away from the best operation point. Thus, optimal reconfiguration is performed.

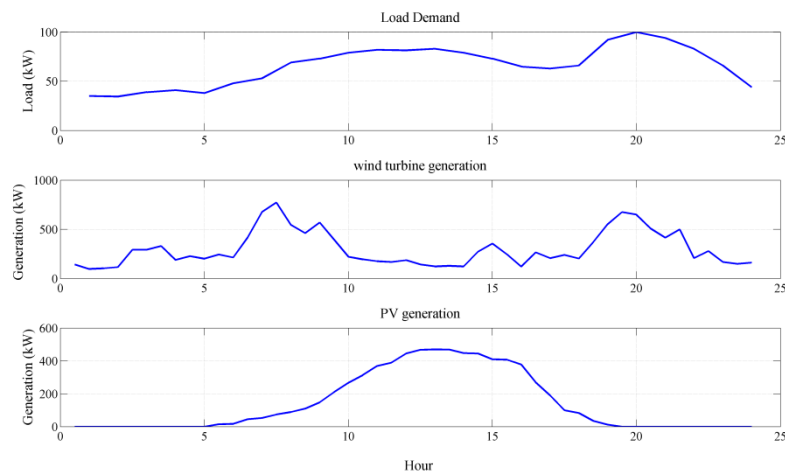


Figure 2. Hourly load profile and generation profile of wind turbine and PV array

4.2. Optimal reconfiguration

In order to enhance the network performance in the presence of RDG's, optimal network reconfiguration is performed hourly using GWO. As mentioned before, the objective functions of optimization problem are loss reduction and voltage stability enhancement.

The hourly loss of the system in three cases (i.e., before RDG's, after RDG's and no reconfiguration, and reconfiguration in the presence of RDG's) are depicted in Figure 3. As it is obvious, by the placing the RDG's, loss of the system is decreased. It also can be concluded that the reconfiguration of distribution network enhances the system performance dramatically from loss reduction point of view. Figures 4, and 5 depict the minimum voltage and total VSF in different hours in different cases. It also can be concluded that the proposed approach moves the operation point of the system to the optimal point.

The percentage of loss reduction is illustrated in Table 1. As it is obvious, the presence of RDG's results in loss reduction. However, using network reconfiguration, the network performance is highly improved and optimized. Thus, it can be concluded that using the proposed approach, not only the advantages of renewable resources are achieved, but also the network operation point is optimized in different ambient conditions.

In order to demonstrate the better performance of the selected optimization algorithm, the network reconfiguration results in peak load situation using GWO are compared to those of GA, and PSO. The convergence behaviours of these three algorithms are compared in Figure 6. As it is obvious, the proposed method not only reaches the better results, but also finds the best answer in lower iterations. In other words, the selected method outperforms the GA.

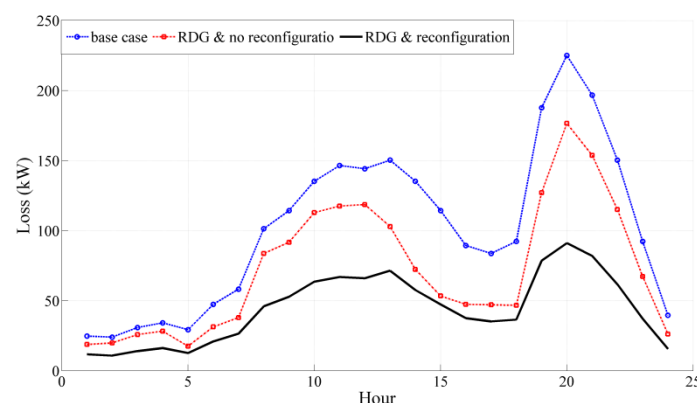


Figure 3. Hourly loss of the system in different cases

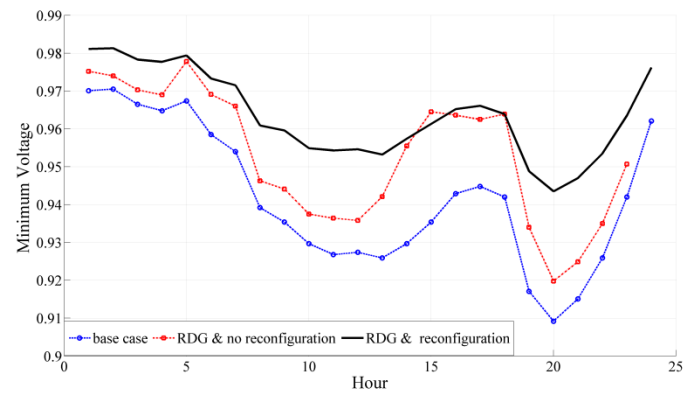


Figure 4. Hourly minimum voltage in different cases

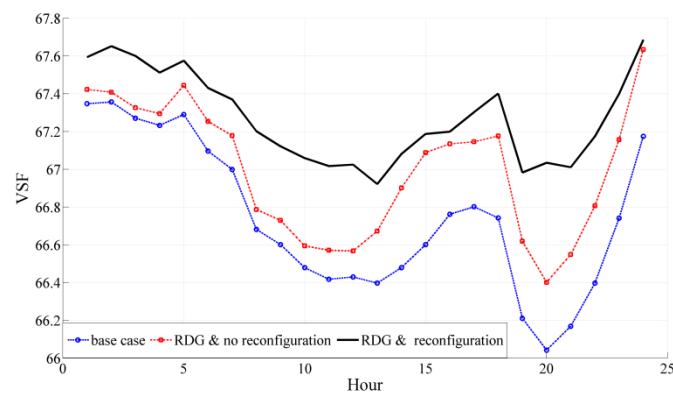


Figure 5. Hourly total VSF in different cases

Table 1. Style and Font Size

hour	PLR* Case 1	PLR Case 2	Hour	PLR Case 1	PLR Case 2
1	24.1	52.6	13	31.5	52.5
2	17.3	55	14	46.5	57.4
3	16.5	54.7	15	53.3	58.6
4	17.6	52.7	16	47	58
5	40.2	57	17	43.7	58
6	34	55.9	18	49.4	60.5
7	34.8	54.6	19	32.2	58.2
8	17.4	54.7	20	21.5	59.5
9	19.7	53.8	21	21.8	58.3
10	16.6	53	22	23.5	59
11	19.8	54.3	23	27.1	59.7
12	17.8	54.2	24	33.9	60.6

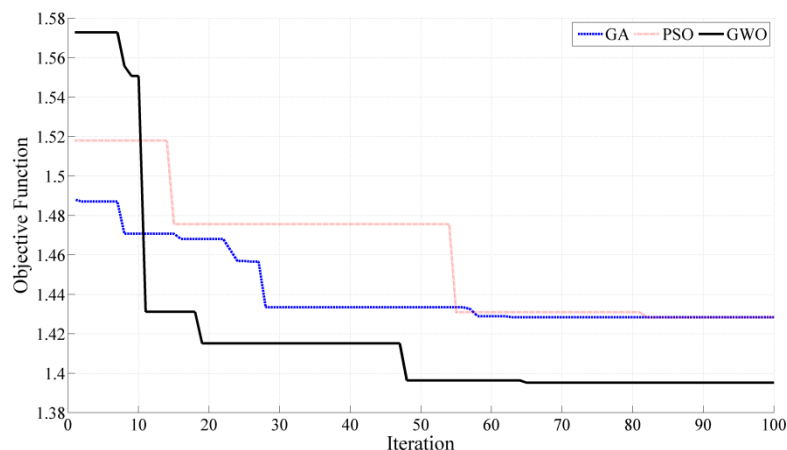


Figure 6. convergence behaviour of different methods

5. Conclusion

In this paper, the reconfiguration of distribution network in the presence of renewable distributed generation (RDG) is performed. It is obvious that the RDG's improve the network performance; however, since the output generation of these kinds of resources are fluctuated by the ambient conditions variation, the network operation point may move away from the optimal point. Thus, reconfiguration of distribution network as a low cost tool is employed to enhance the network performance in different conditions. In this paper, the distribution network is considered to be equipped with smart metering devices; thus, the network conditions (i.e., the load demand, wind speed, and solar irradiance) are known in any moment. The hourly optimal reconfiguration of network is implemented using a recently introduced method known as Grey Wolf Optimizer (GWO). The results show that by the proposed approach, the network performance is highly improved. In addition, by comparison of the results of the GWO with those of some other methods, it is concluded that the GWO outperforms other methods from final results and convergence behaviour points of view.

The future studies can be performed on the integration and optimal management of storage systems considering the variable output of RDGs. Moreover, the other objective functions such as reliability, voltage profile improvement, and energy cost minimization could be taken into account. The novel optimization methods can also be employed for possible better answers.

6. References

- [1]. Georgilakis PS, Hatziargyriou ND. Optimal distributed generation placement in power distribution networks: models, methods, and future research. 2013 *IEEE Trans Power Syst.*;28(3):3420-8.
- [2]. Shaaban MF, El-Saadany EF. Optimal allocation of renewable DG for reliability improvement and losses reduction. In: *Power and Energy Society General Meeting, 2012 IEEE*. IEEE; 2012:1-8.
- [3]. Rahiminejad A, Faramarzi D, Hosseini SH, Vahidi B. An effective approach for optimal placement of non-dispatchable renewable distributed generation. 2017 *J Renew Sustain Energy*;9(1):15303.
- [4]. Rao RS, Ravindra K, Satish K, Narasimham SVL. Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation. 2013 *IEEE Trans power Syst.*;28(1):317-25.
- [5]. Naveen S, Kumar KS, Rajalakshmi K. Distribution system reconfiguration for loss minimization using modified bacterial foraging optimization algorithm. 2015 *Int J Electr Power Energy Syst.*;69:90-7.

- [6]. Nguyen TT, Truong AV. Distribution network reconfiguration for power loss minimization and voltage profile improvement using cuckoo search algorithm. 2015 *Int J Electr Power Energy Syst.*;68:233-42.
- [7]. López JC, Lavorato M, Rider MJ. Optimal reconfiguration of electrical distribution systems considering reliability indices improvement. 2016 *Int J Electr Power Energy Syst.*;78:837-45.
- [8]. Sahoo NC, Prasad K. A fuzzy genetic approach for network reconfiguration to enhance voltage stability in radial distribution systems. 2006 *Energy Convers Manag.*;47(18):3288-306.
- [9]. Nara K, Shiose A, Kitagawa M, Ishihara T. Implementation of genetic algorithm for distribution systems loss minimum re-configuration. 1992 *IEEE Trans Power Syst.*;7(3):1044-51.
- [10]. Sedighzadeh M, Bakhtiary R. Optimal multi-objective reconfiguration and capacitor placement of distribution systems with the Hybrid Big Bang–Big Crunch algorithm in the fuzzy framework. 2016 *Ain Shams Eng J.*;7(1):113-29.
- [11]. Shareef H, Ibrahim AA, Salman N, Mohamed A, Ai WL. Power quality and reliability enhancement in distribution systems via optimum network reconfiguration by using quantum firefly algorithm. 2014 *Int J Electr Power Energy Syst.*;58:160-9.
- [12]. Rajaram R, Kumar KS, Rajasekar N. Power system reconfiguration in a radial distribution network for reducing losses and to improve voltage profile using modified plant growth simulation algorithm with distributed generation (dg). 2015 *Energy Reports.*;1:116-22.
- [13]. Lotfipour A, Afrakhte H. A discrete Teaching–Learning–Based Optimization algorithm to solve distribution system reconfiguration in presence of distributed generation. 2016 *Int J Electr Power Energy Syst.*;82:264-73.
- [14]. Souza SSF, Romero R, Pereira J, Saraiva JT. Artificial immune algorithm applied to distribution system reconfiguration with variable demand. 2016 *Int J Electr Power Energy Syst.*;82:561-8.
- [15]. Mirjalili S, Mirjalili SM, Lewis A. Grey wolf optimizer. 2014 *Adv Eng Softw.*;69:46-61.
- [16]. Shin J-R, Kim B-S, Park J-B, Lee KY. A new optimal routing algorithm for loss minimization and voltage stability improvement in radial power systems. 2007 *IEEE Trans Power Syst.*;22(2):648-57.
- [17]. Aman MM, Jasmon GB, Mokhlis H, Bakar AHA. Optimal placement and sizing of a DG based on a new power stability index and line losses. 2012 *Int J Electr Power Energy Syst.*;43(1):1296-304.
- [18]. Kayal P, Chanda CK. Placement of wind and solar based DGs in distribution system for power loss minimization and voltage stability improvement. 2013 *Int J Electr Power Energy Syst.*;53:795-809.
- [19]. Huang Y-C, Yang H-T, Huang C-L. Solving the capacitor placement problem in a radial distribution system using tabu search approach. 1996 *IEEE Trans power Syst.*;11(4):1868-73.
- [20]. Baran ME, Wu FF. Optimal capacitor placement on radial distribution systems. 1989 *IEEE Trans power Deliv.*;4(1):725-34.
- [21]. Injeti SK, Kumar NP. Optimal planning of distributed generation for improved voltage stability and loss reduction. 2011 *Int J Comput Appl.*;15(1):40-6.
- [22]. Abdelaziz AY, Mohamed FM, Mekhamer SF, Badr MAL. Distribution system reconfiguration using a modified Tabu Search algorithm. 2010 *Electr Power Syst Res.*;80(8):943-953.
- [23]. Rahiminejad A, Hosseini SH, Vahidi B, Shahrooyan S. Simultaneous Distributed Generation Placement, Capacitor Placement, and Reconfiguration using a Modified Teaching-Learning-based Optimization Algorithm. 2016 *Electr Power Components Syst.*;44(14).