Electrical Power and Energy Systems 82 (2016) 264–273

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

# A discrete Teaching–Learning-Based Optimization algorithm to solve distribution system reconfiguration in presence of distributed generation

Arash Lotfipour, Hossein Afrakhte *

*Department of Electrical Engineering, Faculty of Engineering, University of Guilan, Rasht, Iran*

ARTICLE INFO

*Article history:*
Received 9 December 2014
Received in revised form 20 February 2016
Accepted 9 March 2016
Available online 29 March 2016

*Keywords:*
Discrete Teaching–Learning-Based Optimization algorithm
Distribution system
Distributed generation
Reconfiguration

ABSTRACT

Reconfiguration is an important way to increase the power distribution systems efficiency. The problem of reconfiguration is a complicated combinatorial optimization problem with discrete decision variables. To solve such problem, a powerful optimization technique is required. This paper presents a discrete Teaching–Learning-Based Optimization (DTLBO) algorithm for solving the distribution system reconfiguration (DSR) problem. The objectives are power loss minimization and voltage profile improvement in presence of distributed generation (DG). The proposed method is applied to 33-bus and 69-bus test systems and a part of the distribution network of Ahvaz, a city in the south of Iran. A comparison between the proposed algorithm and other existing methods shows the effectiveness and capability of the proposed method to reach the global optimum and rapid convergence to the optimal solution.



## Introduction

From the standpoint of utility, power losses have a significant effect on the distribution systems efficiency. Therefore, active power loss minimization is an important factor to enhance the efficiency of the distribution systems. There are many and various methods to reduce the power loss of distribution system and the three which are commonly used are the following [1]:

(1) Capacitor placement.
(2) DG allocation.
(3) Distribution system reconfiguration.

Distribution system reconfiguration (DSR) is a process which optimizes the operation of power distribution systems with different goals (such as active power loss minimization). The DSR is performed by changing the status of sectionalizing (normally closed) and tie (normally open) switches in such a way that the radiality of the system is maintained, all the loads are energized and other constraints are satisfied.

Recently, DSR has been the subject of many researches. A 0–1 integer programming method was employed in [2] to solve the DSR problem in order to loss minimization. Kashem et al. [3] proposed a geometric approach for solving the DSR in order to loss minimization. A refined genetic algorithm was stated by Zhu [4] to solve network reconfiguration problems. A DSR method to maximize loadability and improve voltage profile was suggested in [5]. Ref. [6] proposed a fuzzy mutated genetic algorithm for network reconfiguration with the objective of improving voltage profile and loss minimization. Das [7] proposed a fuzzy multi-objective approach for network reconfiguration and also used heuristic rules to minimize the number of tie-switch operations. A fuzzy genetic approach [8] and a heuristic method [9] have been presented to enhance voltage stability as the objective of network reconfiguration. Zhang et al. [10] have presented an improved tabu search (ITS) algorithm for reconfiguration in large-scale distribution systems. In [11], Particle Swarm Optimization (PSO) algorithm was used to solve the DSR problem in the presence of distributed generation (DG). Minimizing the total cost of the active power generated by DGs and distribution companies, the number of switching operations and bus voltage deviations were considered as objective function. Niknam and Farsani [12] have presented a hybrid self-adaptive particle swarm optimization and modified shuffled frog leaping algorithm to solve the DSR problem. In [13], DSR was studied with the objective of reducing power loss along with improving voltage profile by using Guaranteed Convergence Particle Swarm Optimization (GCPSO) and graph theory. The impact of load type on DSR problem was studied in [14]. The

* Corresponding author. Tel.: +98 131 6690274 8; fax: +98 131 669027 1.
*E-mail addresses:* a.lotfipour@outlook.com (A. Lotfipour), ho_afrakhte@guilan.ac.ir (H. Afrakhte).

http://dx.doi.org/10.1016/j.ijepes.2016.03.009
0142-0615/

results of this work show that if loads are modelled as constant power, the decrease in losses is equal to decrease of system intakes; but if loads are modelled as voltage dependent, the decrease in losses is equal to increase of system intakes. A binary particle swarm optimization algorithm (BPSO) [15] and an improved shuffled frog leaping algorithm (ISFLA) [16] were used to minimize losses and enhance reliability via reconfiguration in distribution system. Tow circular-updating hybrid heuristic methods [17] and a Binary Group Search Optimization (BGSO) algorithm [18] have been used only to reduce power loss as the objective of network reconfiguration. Ref. [19] presented an Improved Adaptive Imperialist Competitive Algorithm (IAICA) to solve the DSR with the aim of loss reduction and voltage profile improvement in presence of distributed generation. Also, proposed a heuristic method that always generates radial configurations. In [20] real time reconfiguration of distribution network was solved in presence of distributed generation. Ref. [21] proposed an Enhanced Gravitational Search Algorithm (EGSA) to solve the DSR in presence of distributed generation in order to minimize the losses, energy not supplied (ENS) and operational costs.

Recently, a new meta-heuristic optimization algorithm known as Teaching-Learning-Based Optimization algorithm (TLBO) has been introduced by Rao et al. [22]. One of the advantages of this algorithm is that it requires no parameters to be regulated except population size and convergence criterion, and the other is high speed of convergence to global optimum. Therefore, TLBO is easily adapted for different distribution systems. DSR is a discrete problem, while TLBO is a continuous optimization algorithm. This paper presents a method to change TLBO from a continuous algorithm to a discrete algorithm and solve the DSR using it. The proposed method is named discrete Teaching–Learning-Based Optimization (DTLBO) algorithm. The active power losses and voltage profile index are considered as the objective functions with and without distributed generation (DG). The proposed method is tested on 33-bus and 69-bus distribution systems and a part of the distribution network of Ahvaz, a city in the south of Iran. Simulation results verify the ability of the proposed method.

The paper is organized as follows: Section 'Problem formulation' presents the distribution system reconfiguration formulation. Teaching-Learning-Based Optimization algorithm is presented in Section 'Teaching-Learning-Based Optimization'. Section 'Proposed method' explains the proposed method and its application for solving the reconfiguration problem. Simulation results are discussed in Section 'Numerical results'. Finally, conclusion is presented in Section 'Conclusion'.

## Problem formulation

The DSR is an optimization problem and like other optimization problems, the reconfiguration problem has some objectives and constraints. The objective functions and constraints of DSR are as follows:

*Objective functions*

*Minimizing of active power losses*

$$f_1 = \sum_{i=1}^{N_{branch}} R_i \times |I_i|^2 \tag{1}$$

where $f_1$ is the total active power losses, $R_i$ is the resistance of the $i$th branch, $|I_i|$ is the absolute of current in $i$th branch, and $N_{branch}$ is the number of branches.

*Minimization of voltage profile index [19]*

$$f_2 = \sqrt{\frac{1}{N_{bus}} \times \sum_{i=1}^{N_{bus}} (v_i - v_p)^2} \tag{2}$$

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

where $f_2$ is the voltage profile index, $v_i$ is the voltage of the $i$th bus, $v_p$ is the average voltage of the buses, and $N_{bus}$ is the number of buses.

*Constraints*

*Bus voltage constraint*

$$v_i^{min} \leqslant v_i \leqslant v_i^{max} \quad i = 1, 2, \ldots, N_{bus} \tag{4}$$

where $v_i$ is the voltage of the $i$th bus, $v_i^{min}$ and $v_i^{max}$ are the minimum and maximum permitted voltage of the $i$th bus, respectively, and $N_{bus}$ is the number of buses.

*Line current constraint*

In order to prevent overload of the lines, the current of each branch must be kept below or equal to its maximum capacity.

$$|I_i| \leqslant |I_i^{max}| \quad i = 1, 2, \ldots, N_{branch} \tag{5}$$

where $|I_i|$ is the absolute value of current in $i$th branch, $|I_i^{max}|$ is the maximum permissible current of the $i$th branch, and $N_{branch}$ is the number of branches.

*Radial configuration of the system and isolation constraints*

Distribution system configuration must be radial and all buses must be contained. In this paper, configuration of the system is checked using proposed method in [13].

## Teaching-Learning-Based Optimization

Teaching-Learning-Based Optimization (TLBO) algorithm is a new meta-heuristic optimization technique which introduced by Rao et al. [22]. TLBO is based on the concept of teaching and learning process in a class. TLBO algorithm includes two phases. The first one is called 'teacher phase' and the second one is called 'learner phase'.

*Teacher phase*

In this part of algorithm, the learners learn through the teacher. During this phase, a teacher gives knowledge to the learners and tries to increase the average result of the class from initial to his level. Assume $X_i$ is a matrix consisting of decision variables that is called learner, $M_i$ is the average of the class and $X_i^{best}$ is the best learner that is called teacher at iteration $i$. The difference between teacher's level and the average of the class is expressed as:

$$Difference\_Mean_i = r_i \left( X_i^{best} - T_F M_i \right) \tag{6}$$

where $r_i$ is a random number between $(0, 1)$, $Difference\_Mean_i$ is the difference between mean and teacher, and $T_F$ is the teaching factor. The value of $T_F$ can be either 1 or 2 and is obtained randomly as follows:

$$T_F = round[1 + r_i] \tag{7}$$