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Fuzzy-TLBO optimal reactive power control variables planning for energy loss minimization

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ABSTRACT

This paper offers a new approach to the problem of optimal reactive power control variables planning (ORPVCP). The basic idea is division of Load Duration Curve (LDC) into several time intervals with constant active power demand in each interval and then solving the energy loss minimization (ELM) problem to obtain an optimal initial set of control variables of the system so that is valid for all time intervals and can be used as an initial operating condition of the system. In this paper, the ELM problem has been solved by the linear programming (LP) and fuzzy linear programming (Fuzzy-LP) and evolutionary algorithms i.e. MHBMO and TLBO and the results are compared with the proposed Fuzzy-TLBO method. In the proposed method both objective function and constraints are evaluated by membership functions. The inequality constraints are embedded into the fitness function by the membership function of the fuzzy decision and the problem is modeled by fuzzy set theory. The proposed Fuzzy-TLBO method is performed on the IEEE 30 bus test system by considering two different LDC; and it is shown that using this method has further minimized objective function than original TLBO and other optimization techniques and confirms its potential to solve the ORPCVP problem with considering ELM as the objective function.

1. Introduction

Reactive power control variables planning (RPCVP) is an optimization problem solved by finding an optimal solution that minimizes an objective function as well as the constraints. The purpose of RPCVP problem is mainly improving any change of voltage in the system due to changing in power demands by adjusting the control variables properly [1]. In many previous works, the optimal reactive power has been done with power loss minimization, voltage deviation or voltage stability index by adjusting the optimal control variables such as voltage magnitudes of generator buses, shunt capacitors/reactors, output of static reactive power compensators, transformer tap-settings [2–8]. Also, many of the articles by subject of the reactive power planning, deals with allocation of reactive power sources and minimize of the costs associated with the location and size of them as the objective function [9–12].

In the past, several methods have been proposed to solve the reactive power planning problem. One of the well-known methods is linear programming. Mamandur and Chenoweth [2], presented a mathematical formulation suitable for LP and developed a systematic algorithm. There are some drawbacks for LP method such as: inaccurate evaluation of system losses, insecure convergence properties and insufficient ability to find an exact solution [1]. For this reasons, fuzzy linear programming is proposed in [13] in order to improve the result of LP method by formulating the fuzzy mathematical programming of the reactive power control as a linear programming problem and used λ-formulation method for solving it.

In recent years, heuristic optimization techniques, such as differential evolution (DE) [14], particle swarm optimization (PSO) [15], gravitational search algorithm (GSA) [16,17], modified Honey Bee Mating Optimization (MHBMO) [18] and teaching learning based optimization (TLBO) [19] due to their robustness, flexibility and simplicity in finding the global optimal solution, have generated intense interest to the researchers. These methods are much better than linearization methods in obtaining the global optimum and in handling non-convex objective functions. A fuzzy adaptive PSO (FAPSO) is proposed in [20] to improve the performance of PSO with employing a fuzzy system to adaptively adjust the parameters of PSO during the evolutionary process. Niknam et al. [18] presented a new method based on modified HBMO algorithms to investigate the distribution feeder reconfiguration. Optimal reactive power flow based on artificial bee colony (ABC) algorithm to minimize active power loss in power system is studied in [21]. Khazali et al. presented harmony search algorithm (HSA) [22] to solve optimal reactive power dispatch problem and compared the obtained simulation results to other algorithms. Niknam et al. [23] improved the efficiency of GSA algorithm by the

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proposed opposition-based self-adaptive modified gravitational search algorithm (OSAMGSA) for optimal reactive power dispatch and voltage control in power system operation. Mandal and Roy [19] presented a newly developed teaching learning based optimization (TLBO) algorithm to solve multi-objective optimal reactive power dispatch problem by minimizing real power loss, voltage deviation and voltage stability index and incorporated quasi-opposition based learning (QOBL) concept in the original TLBO algorithm to accelerate the convergence speed.

In the method which is proposed in this paper, the load of the system is modeled as a Load Duration Curve and for this time-varying load the total energy loss is minimized. Demand of the system in every interval considers the mean variation of load and assumed constant but different from next interval. It should be noted that the energy loss as the objective function is the innovation of this work while the former methods of reactive power optimization have not addressed this issue. Moreover, a new TLBO approach is developed to solve the ORPCVP problem. The effectiveness of the proposed Fuzzy-TLBO algorithm is shown by the simulation results of the IEEE 30-bus power systems with two different load levels. The simulation results of the proposed method are compared with other well popular algorithms like LP, Fuzzy-LP, MHBMO and TLBO.

The rest of the paper is organized as follows: ELM problem is formulated in Section 2. In Section 3, the original TLBO algorithm is described briefly. The proposed Fuzzy-TLBO algorithm is described in Section 4. The approach of solving the ELM problem is briefly explained in Section 5. The system simulation is given in Section 6. The conclusion is made in Section 7.

2. Energy loss minimization

In the proposed method, the total energy loss in the power system is minimized and the initial setting of control variables is planned for the whole of the time according to the minimized energy.

In the formulation of the problem, we first determine the number of load levels with the same interval time in LDC, then calculate the power loss at each interval. It is assumed that demand and thereby voltage of load buses remain constant during each period. The total energy loss is a summation of power loss multiplied by time interval. Therefore, the total energy loss can be formulated as:

$$E_L = T_D \times \sum_{k=1}^{l} P_L^k = \frac{T \times \sum_{k=1}^{l} P_L^k}{l} \tag{1}$$

where E_L is the total energy loss of the system and l is the number of load levels. T is the total time which the system will be planned for it and T_D is the time interval. For time interval of k, P_L^k can be given by:

$$P_L = \sum_{i=1}^{n} P_i \tag{2}$$

For the ELM problem, after calculating the power loss, the energy loss optimization process is performed once for all the time intervals. The objective function may be expressed as:

$$\begin{aligned} &\min \quad f(X) = E_L(X) \\ &\text{subjected to}: \\ &\qquad H(X,u) = 0 \\ &\qquad G(X,u) \leqslant 0 \end{aligned} \tag{3}$$

X is the control variable vector consisting of generator voltages, shunt VAR compensations, and transformer tap settings. $H(X, u)$ and $G(X, u)$ are the compacts form of equality and inequality constraints respectively, as follows.

2.1. Equality constraints

The real and reactive power balance equations are the equality constraints of ELM problem and are expressed as follows:

$$\begin{cases} \Delta P^k = 0 & \text{for } k = 1,2,\ldots,l \\ \Delta Q^k = 0 & \text{for } k = 1,2,\ldots,l \end{cases} \tag{4}$$

where ΔP^k and ΔQ^k are active and reactive power mismatch at all buses except slack bus for every time interval of k, respectively.

2.2. Inequality constraints

The generator voltages V_G, shunt VAR compensations Q_C, transformer tap settings Tap, generator reactive power outputs Q_G and load bus voltages V_L are considered as follows:

$$\begin{cases} V_{Gi}^{\min} \leqslant V_{Gi}^k \leqslant V_{Gi}^{\max} & i = 1,2,\ldots,N_G \\ Q_{Ci}^{\min} \leqslant Q_{Ci}^k \leqslant Q_{Ci}^{\max} & i = 1,2,\ldots,N_C \\ Tap_i^{\min} \leqslant Tap_i^k \leqslant Tap_i^{\max} & i = 1,2,\ldots,N_{Tap} \quad \text{for } k = 1,2,\ldots,l \\ Q_{Gi}^{\min} \leqslant Q_{Gi}^k \leqslant Q_{Gi}^{\max} & i = 1,2,\ldots,N_G \\ V_{Li}^{\min} \leqslant V_{Li}^k \leqslant V_{Li}^{\max} & i = 1,2,\ldots,N_L \end{cases} \tag{5}$$

where N_G, N_C, N_{Tap} and N_L are the total number of generators, shunt VAR compensations (SVCs), on-load tap changer (OLTC) transformers and load buses, respectively.

3. The original TLBO

A new evolutionary algorithm called teaching–learning-based optimization is used in order to solve non-linear optimization problem and introduced by Rao et al. [24]. This algorithm is designed on the basis of the behavior of the students in a class and the TLBO population is described as the class of learners. The teacher plays the role of best solution obtained so far. TLBO algorithm requires very few input parameters which need tunning and this is one of the important advantages of it. TLBO algorithm divided into two basic operations: teacher phase and learner phase. The output solutions of the teacher phase are the input for the learner phase.

3.1. Teacher phase

The global search of the TLBO algorithm occurs in this operation. The task of the teacher is to improve the average result of the class room from initial level to his own level. So the solution is updated according to the difference between teacher's knowledge level and the mean of the class at any iteration of k, shown by the following equation:

$$X_{Diff}^k = rand \times (T^k - t_f M^k) \tag{6}$$

where T^k and M^k are the teacher and average at iteration of k; respectively. Rand is a random number in the range [0, 1] and t_f is the teaching factor which is evaluated randomly using:

$$t_f = round[1 + rand(0,1)] \tag{7}$$

This difference modifies the existing solution according to the following expression:

$$X_{new}^{k+1} = X_{old}^k + X_{Diff}^k \tag{8}$$

3.2. Learner phase

The local search of the TLBO algorithm occurs in this operation. In this phase of the algorithm, each student chooses another