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A modified teaching–learning based optimization for multi-objective optimal power flow problem

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ABSTRACT

In this paper, a modified teaching–learning based optimization algorithm is analyzed to solve the multi-objective optimal power flow problem considering the total fuel cost and total emission of the units. The modified phase of the optimization algorithm utilizes a self-adapting wavelet mutation strategy. Moreover, a fuzzy clustering technique is proposed to avoid extremely large repository size besides a smart population selection for the next iteration. These techniques make the algorithm searching a larger space to find the optimal solutions while speed of the convergence remains good. The IEEE 30-Bus and 57-Bus systems are used to illustrate performance of the proposed algorithm and results are compared with those in literatures. It is verified that the proposed approach has better performance over other techniques.

1. Introduction

Optimal power flow (OPF) is a non-linear programming problem that specifies the optimal control points of a power network to minimize a desired objective, commonly cost of generation, subject to a set of certain system constraints [1]. Generally, the OPF problem is a large-scale highly constrained non-linear non-convex optimization problem [2]. There are some mathematical techniques to solve this problem such as linear and non-linear programming [3–6], quadratic programming [7], and the interior point method [8,9]. All of these methods may be trapped in local minima that prevent the algorithm reaching the true optimal solution. Other disadvantages of these techniques are enormous computational effort and time consumption. Recent methods to deal with the shortcomings of these mathematical approaches are evolutionary algorithms such as genetic algorithm (GA), tabu search (TS), particle swarm optimization (PSO) and ant colony optimization (ACO).

One of the recently proposed techniques to solve the optimization problems is the teaching–learning based optimization (TLBO) [10]. This technique is a new efficient optimization algorithm that has been inspired by learning mechanism in a class. The main advantage of this method over the other evolutionary algorithms is that TLBO is an algorithm-parameter-free technique and the effectiveness of the method is not affected by the algorithm parameters such as those in GA, PSO and ACO. [11]. This algorithm is used to solve the economic dispatch problem [12] but there is no research on solving the OPF problem by this method.

The OPF problem may have various objective functions. The most commonly used objective is the minimization of the overall fuel cost of generators. However, other traditional objectives are minimization of active power loss, bus voltage deviation, emission of units, number of control actions, and load shedding [13]. A multi-objective optimal power flow (MO-OPF) problem is made if more than one of these objective functions should be optimized [14].

Several techniques are used to solve a multi-objective optimization problem (MOP). One method is combining all objective functions into one objective function using weighting factors. It finds just one solution for the problem that is very dependent on the weighting factors and this is the main disadvantage of this technique. Another way to deal with a multi-objective problem is solving all objective functions simultaneously using evolutionary methods. Since these algorithms are population-based techniques, multiple Pareto-optimal solutions can be found in one program run [15].

The aim of this paper is to solve the MO-OPF problem using the modified TLBO algorithm. A self-adaptive mutation wavelet technique is proposed to deal with the search capability, population diversity, and convergence speed. An external repository is utilized to save all non-dominated optimal solutions during the process. Then a fuzzy decision making method is applied to sort these solutions according to their importance and decision makers can choose the desired solution between the Pareto-optimal solutions by applying this fuzzy decision making mechanism. Furthermore,

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a fuzzy clustering approach is employed to decrease size of the repository without losing its characteristics. Also, a smart population selection is used to choose population of the next iteration of the algorithm efficiently. Simulations are done on the standard IEEE 30-Bus and 57-Bus systems and results are compared with the conventional TLBO and other evolutionary methods. The effectiveness and advantages of the proposed method is verified by various criterions.

The rest of the paper is organized as follows. In Section 2, mathematical formulation of the OPF objective functions are reviewed. In Section 3, the TLBO algorithm and its proposed modification are described in details, while Section 4 consists of some overview on the multi-objective problems. Moreover, the utilized fuzzy method and the smart population selection are described in this section. Application of the proposed algorithm for the MO-OPF is determined in Section 5 followed by some case studies and simulations in Section 6. Finally, Section 7 concludes the discussion.

2. Mathematical formulation

In this section a brief review on the objective functions of the OPF problem is presented. The total cost of generation and the total emission from units are two objective functions that are used in this paper.

2.1. Generation cost function

It is necessary to consider the valve-point effect of generators to obtain a more accurate model [16–18]. Thus, the ripple curve created by the valve-point effect is modeled in this paper and the total cost of generation can be formulated as follows:

$$F_1(\boldsymbol{X}) = \sum_{i=1}^{N_g} \begin{pmatrix} a_i P_{gi}^2 + b_i P_{gi} + c_i \\ + \left| d_i \sin\left[e_i \left(P_{gi}^{\min} - P_{gi} \right) \right] \right| \end{pmatrix} \tag{1}$$

$$\boldsymbol{X} = [\boldsymbol{P}_g, \boldsymbol{V}_g, \boldsymbol{T}, \boldsymbol{Q}_c]_{1\times N} \tag{2}$$

$$\boldsymbol{P}_g = [P_{g1}, P_{g1}, \ldots, P_{g(N_g-1)}]_{1\times(N_g-1)} \tag{3}$$

$$\boldsymbol{V}_g = [V_{g1}, V_{g1}, \ldots, V_{gN_g}]_{1\times N_g} \tag{4}$$

$$\boldsymbol{T} = [T_1, T_2, \ldots, T_{N_t}]_{1\times N_t} \tag{5}$$

$$\boldsymbol{Q}_c = [Q_{c1}, Q_{c2}, \ldots, Q_{cN_c}]_{1\times N_c} \tag{6}$$

$$N = (N_g - 1) + N_g + N_t + N_c \tag{7}$$

where $F_1(\boldsymbol{X})$ is the total cost of generation (\$/h), a_i, b_i, c_i are the fuel cost coefficients of the ith generator, d_i and e_i shows the valve-point effect of generators. P_{gi} is the generated active power of the ith unit and P_{gi}^{min} is its lower margin. Control variables of the optimization problem is named as $\boldsymbol{X}$ that includes the generated active power vector, $\boldsymbol{P}_g$, the voltage magnitude vector of units, $\boldsymbol{V}_g$, the tap of transformers vector, $\boldsymbol{T}$, and the reactive power vector of shunt capacitances, $\boldsymbol{Q}_c$. Furthermore N_g, N_t, and N_c are the total number of generators, the total number of tap transformers, and the total number of shunt capacitances in the power system, respectively.

2.2. Emission function

The emission objective function can be represented as below:

$$F_2(\boldsymbol{X}) = \sum_{i=1}^{N_g} (\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi} + \xi \exp(\lambda_i P_{gi})) \tag{8}$$

where $F_2(\boldsymbol{X})$ is the total emission of units (ton/h), α_i, β_i, γ_i, ξ_i, and λ_i are the emission coefficients of the ith generator.

2.3. Equality constraints

The OPF equality constraints show the power flow feasibility that can be expressed as:

$$P_{gi} - P_{di} - \sum_{j=1}^{N_b} V_i V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) = 0 \tag{9}$$

$$Q_{gi} - Q_{di} - \sum_{j=1}^{N_b} V_i V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) = 0 \tag{10}$$

where $i = 1,2,\ldots,N_b$ and N_b is the number of buses. P_{gi} and Q_{gi} are the generated active and reactive power at the ith bus. Also P_{di} and Q_{di} are the active and reactive power demand at the ith bus. V_i and V_j are the voltage magnitude at the ith and jth buses and $\theta_{ij} = \theta_i - \theta_j$ is the difference between the voltage angle of these buses. The mechanism of handling the equality constraint is shown in Fig. 1. It is worthwhile to note that this constraint should satisfy the equality of generation level with the load level plus losses in the system. The process of the algorithm is started by choosing generator output powers randomly within their limits. The difference of the total power generation from the total demand plus losses is generated by the slack. If slack is reached to its limits, the algorithm chooses another generator randomly to help the slack satisfying the equality constraint. For each population member of the optimization algorithm, his process is repeated until the equality constraint is satisfied.

2.4. Inequality constraints

Limits of the OPF variables are expressed by inequality constraints as follows:

$$P_{gi}^{\min} \leqslant P_{gi} \leqslant P_{gi}^{\max}, \quad i = 1, 2, \ldots, N_g \tag{11}$$

$$Q_{gi}^{\min} \leqslant Q_{gi} \leqslant Q_{gi}^{\max}, \quad i = 1, 2, \ldots, N_g \tag{12}$$

$$V_i^{\min} \leqslant V_i \leqslant V_i^{\max}, \quad i = 1, 2, \ldots, N_L \tag{13}$$

$$T_i^{\min} \leqslant T_i \leqslant T_i^{\max}, \quad i = 1, 2, \ldots, N_t \tag{14}$$

$$Q_{ci}^{\min} \leqslant Q_{ci} \leqslant Q_{ci}^{\max}, \quad i = 1, 2, \ldots, N_c \tag{15}$$

$$|P_{ij}| \leqslant P_{ij}^{\max} \tag{16}$$

where N_L is the total number of load buses and P_{ij} is the active power flows between bus i and bus j. The superscript min and max shows the lower and upper limits of their respected variables.

3. Teaching–learning based optimization

TLBO is a new population based optimization algorithm with efficient calculation demand. It is inspired by the influence of a teacher on his learners in a class [10]. The conventional algorithm has two modes: (1) teacher phase and (2) learner phase. However a third phase is added to the algorithm in the modified TLBO (MTLBO) method.

3.1. Teacher phase

The teacher is considered as the most knowledgeable person in a class who shares his knowledge with the students to improve the