



# Multi-objective quasi-oppositional teaching learning based optimization for economic emission load dispatch problem



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## ARTICLE INFO

### Article history:

Received 4 February 2013

Received in revised form 5 May 2013

Accepted 9 June 2013

### Keywords:

Economic dispatch

Emission

Valve point loading

Pareto front

Opposition based learning

Teaching learning based optimization

## ABSTRACT

This paper proposes an efficient optimization approach, namely quasi-oppositional teaching learning based optimization (QOTLBO) for solving non-linear multi-objective economic emission dispatch (EED) problem of electric power generation with valve point loading. In this article, a non-dominated sorting QOTLBO is employed to approximate the set of Pareto solution through the evolutionary optimization process. The proposed approach is carried out to obtain EED solution for 6-unit, 10-unit and 40-unit systems. For showing the superiority of this optimization technique, numerical results of the four test systems are compared with several other EED based recent optimization methods. The simulation results show that the proposed algorithm gives comparatively better operational fuel cost and emission in less computational time compared to other optimization techniques.

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## 1. Introduction

Economic load dispatch (ELD) has acquired a great importance in operation and control in modern power system analysis. The economic emission load dispatch problem (EELD) is a combination of ELD problem and emission dispatch (ED) problem. In recent decades, with the increase of environmental pollution, EED has drawn much attention of researchers for reducing emission for environmental protection [1]. The objective of EED is to allocate optimal generation scheduling among all the available generating units in order to minimize the fuel cost as well as the environmental pollutant such as  $\text{NO}_x$  and  $\text{SO}_2$ , which releases to atmosphere through the emission produced by the combustion of fossil fuel. Environmental constraints impact in the production cost is first shown by Gent and Lamnot [2]. To solve EED problem, a number of conventional optimization techniques are proposed in the literature [3–5]. However, the practical EED problem, with the presence of valve point loading and other non-linear constraints, is a highly non-linear optimization problem. Therefore, conventional optimization methods that make use of derivatives are not able to produce the global optimum solution. If we take a look in the literature, we may observe that various heuristic optimization techniques are introduced by many researchers to overcome the drawbacks of conventional methods. Some of these techniques are evolutionary programming (EP) [6], genetic

algorithm (GA) [7], differential evolution (DE) [8], particle swarm optimization (PSO) [9], bacteria foraging optimization (BFO) [10], Seeker optimization algorithm (SOA) [11], chaotic ant swarm optimization (CASO) [12], tabu search (TS) [13], biogeography based optimization (BBO) [14], harmony search algorithm (HSA) [15], gravitational search algorithm (GSA) [16] and so on. Though, most of the methods mentioned above often provide fast and reasonable solutions but do not guarantee obtaining the global optimal solutions.

Multi-objective EED problem with two different conflicting objectives, namely fuel cost and emission is generally solved by different ways. Perez-Guerrero and Cedeno-Maldonado [17] proposed a method using price penalty factor after combining cost and emission dispatch objectives into a single function. Shaw et al. [18] applied oppositional GSA (OGSA) to solve EED problem using the concept of price penalty factor for simultaneous minimization of fuel cost and emission. Yasar and Ozyon [19] presented GA to solve multi-objective environmental economic power dispatch problem by converting the multi-objective problem into a single objective optimization problem via conic scalarization (CSM) and weighted sum (WSM). Bhattacharya and Chattopadhyay [20] proposed BBO to solve the economic and environmental objectives simultaneously by combining them linearly to form a single objective function. By varying the weight, the trade off between fuel cost and environmental cost was determined. Granelli et al. [21] handled EED problem by considering emission as a constraint with a permissible limit. Many researchers proposed multi-objective evolutionary algorithms such as the non-dominated

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sorting genetic algorithm (NSGA) [22], the strength Pareto evolutionary algorithm (SPEA) [23] to solve the EED problem by simultaneously considering the fuel cost and the emission as competing objectives. Kumar et al. [24] developed Pareto bee colony optimization algorithm to solve multi-objective economic emission power dispatch problem. The proposed algorithm was applied to the standard IEEE 30-bus six generator test system and it outperformed the classical methods as well as other multi-objective evolutionary algorithms. Mohamed and Koivo [25] implemented Pareto based multi-objective mesh adaptive direct search (MOMADS) method to solve EED problem of micro grid. An opposition based harmony search algorithm (OHSA) was introduced by Chatterjee et al. [26] to solve combined economic emission dispatch problem of power system. In this algorithm opposite numbers are utilized to improve the convergence rate of HSA which employed opposition based learning for harmony memory initialization. Dhanalakshmi et al. [27] developed Pareto based modified NSGA-II algorithm for economic and emission dispatch problem and the proposed algorithm was applied to standard IEEE 14 bus, IEEE 30-bus, IEEE 57-bus and IEEE 118-bus systems to verify its effectiveness. Mondal et al. recently presented GSA [28] to solve EED problem and they integrated wind power plant in the EED problem in order to save energy and reduce emission for electric power systems. Afzalan et al. proposed a novel  $\varepsilon$  dominance multi-objective GA [29] to solve small, medium and large scale EED problems. Jiang et al. in his most recent endeavor solved EED problem by modified adaptive multi-objective DE (MA-MODE) algorithm [30]. Ghasemi suggested Pareto based multi objective interactive honey bee mating optimization [31] for solving the EED problem. Zhang et al. introduced enhanced multi-objective cultural algorithm (EMOCA) [32] which integrated cultural algorithm and PSO to provide a global optimal solution for the EED problem. Silva et al. recently proposed Pareto dominance and crowding distance based improved scatter search (ISS) algorithm [33] to provide solution for multi-objective EED problem.

Teaching learning based optimization (TLBO) [34,35] is relatively a new, much simpler and more robust optimization algorithm compared to the many other well popular optimization methods proposed by past scholars. Though this technique has the ability to search near global optimal solution, nevertheless the algorithm requires further improvement to produce probable global optimal solutions in reasonable time. In this article, quasi-opposition based learning (QOBL) concept is integrated with original TLBO to accelerate the convergence speed of the original TLBO algorithm. The current study develops quasi-oppositional teaching learning based optimization (QOTLBO) method for solving EED problems with non-convex cost functions. The effectiveness and application of the proposed method are demonstrated by implementing it in standard 6-unit, 10-unit and 40-unit test systems.

This article is organized as follows: the EED model is first briefly described in Section 2; then the proposed TLBO is revealed in Section 3; Opposition based learning concept is briefly explained in Section 4; Section 5 presents the detailed design and application of QOTLBO technique. QOTLBO algorithm applied to EED problem is described in Section 6. In Section 7, through simulation study, the performance of the proposed algorithm is compared with GSA, DE, multi-objective DE (MODE), Pareto DE (PDE), non-dominated shorting genetic algorithm II (NSGA-II), strength Pareto evolutionary algorithm 2 (SPEA 2) by solving the multi-objective EED problem. Finally, the paper is concluded in Section 8.

## 2. Mathematical problem formulation

The main objective of EED is to determine the optimal operation strategy for allocation of generation of committed generating units

so as to meet the load demand that minimizes the fuel cost and pollutant emission simultaneously and subjected to various equality and inequality constraints. In essence, it is a multi-objective optimization problem with a mixture of linear and non-linear constraints which attempts to minimize both generation cost as well as emission.

The following objectives are considered in the formulation of EED problem.

### 2.1. Economic dispatch

The objective of economic dispatch may be stated as to find out the optimal power generations of thermal units that minimize the total fuel cost for thermal generations while satisfying load balance constraints. To consider the accurate cost curve of each generating unit, the valve-point effect must be included in the cost model. The fuel cost function of each generating unit is expressed in the sum of quadratic and sinusoidal form with the value point effect taken in to account. Thus, the total generation cost addressing valve point effect of generating unit is given by

$$FC(P_g) = \sum_{i=1}^n a_i P_{gi}^2 + b_i P_{gi} + c_i + \left| d_i \times \sin \left[ e_i \times \left( P_{gi}^{\min} - P_{gi} \right) \right] \right| \quad (1)$$

where  $n$  is the number of generating unit;  $a_i$ ,  $b_i$ ,  $c_i$ ,  $d_i$  and  $e_i$  are fuel cost coefficients of the  $i$ -th generating unit;  $P_{gi}$  is the real power output of the  $i$ th generating unit and  $P_{gi}^{\min}$  is the minimum capacity of the  $i$ th generating unit.

### 2.2. Emission dispatch

The objective of emission dispatch is to minimize the total pollutant emission due to the burning of fuels for production of power. The amount of pollutants from a fossil based generating units depend on the amount of power generated by that unit. The total emission may be expressed as:

$$E(P_g) = \sum_{i=1}^n E_i(P_{gi}) = \sum_{i=1}^n \left[ \alpha_i P_{gi}^2 + \beta_i P_{gi} + \gamma_i + \mu_i^* \exp(\lambda_i P_{gi}) \right] \quad (2)$$

where  $\alpha_i$ ,  $\beta_i$ ,  $\gamma_i$ ,  $\mu_i$ ,  $\lambda_i$  are the emission coefficients of the  $i$ th generating unit.

### 2.3. Economic and emission dispatch

A general multi-objective optimization problem consists of multiple objectives to be optimized simultaneously. In this article, to implement multi-objective QOTLBO algorithm for solving economic emission dispatch (EED) problem, Pareto-based approach is introduced to find the best compromising solutions. A set of points is said to be Pareto-optimal if any improvement in one of the objectives inevitably leads to the deterioration of other objective. In most cases, the Pareto-optimal solution set is on the boundary of the feasible region. A multi-objective EED problem may be expressed as follows:

$$EED(P_g) = \min[FC(P_g), E(P_g)] \quad (3)$$

The EED problem is subjected to the following constraints:

#### 2.3.1. Power balance constraint

The total power generated by all the generators must cover the total load demand and the real power loss at the transmission line network, i.e.

$$\sum_{i=1}^n P_{gi} = P_D + P_L \quad (4)$$

where  $P_{gi}$  is the active power generation of the  $i$ th generator;  $P_D$  is the total load demand and  $P_L$  is the power loss in the transmission

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