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Large scale economic dispatch of power systems using oppositional invasive weed optimization

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ABSTRACT

This paper presents an evolutionary hybrid algorithm of invasive weed optimization (IWO) merged with oppositional based learning to solve the large scale economic load dispatch (ELD) problems. The oppositional invasive weed optimization (OIWO) is based on the colonizing behavior of weed plants and empowered by quasi opposite numbers. The proposed OIWO methodology has been developed to minimize the total generation cost by satisfying several constraints such as generation limits, load demand, valve point loading effect, multi-fuel options and transmission losses. The proposed algorithm is tested and validated using five different test systems. The most important merit of the proposed methodology is high accuracy and good convergence characteristics and robustness to solve ELD problems. The simulation results of the proposed OIWO algorithm show its applicability and superiority when compared with the results of other tested algorithms such as oppositional real coded chemical reaction, shuffled differential evolution, biogeography based optimization, improved coordinated aggregation based PSO, quantum-inspired particle swarm optimization, hybrid quantum mechanics inspired particle swarm optimization, modified shuffled frog leaping algorithm with genetic algorithm, simulated annealing based optimization and estimation of distribution and differential evolution algorithm.

1. Introduction

Economic load dispatch (ELD) is one of the power system optimization problems has high dimensional, high constraints, non-convex, non-smooth and nonlinear characteristics and requires an efficient optimization technique to be solved. The modern power systems encounter numerous technical and economical difficulties under competitive deregulated environment. The ELD problem is usually a sub problem of unit commitment and also a constrained optimization task. The prime requirement of ELD is to allocate the optimal generation levels of online generating units so as to accomplish the load demand at the minimum operating cost under various system constraints. Over the years, various mathematical programming methods and nature inspired meta-heuristic optimization techniques have been successfully employed to solve the ELD problems. The conventional methods include classical calculus method [1], base point and participation factor method, gradient search method, linear programming [2], nonlinear programming etc. A dynamic programming (DP) method can solve such problems in different formulations [3]. However, the drawback of the DP is its huge computational overburden when applied to practical sized ELD problems in stipulated time zones. These numerical methods require the incremental cost curves to be monotonically increasing or piece wise linear. However, these methods have difficulties and are not suitable to address nonlinear and discontinuous characteristics [4] of actual practical problems rather complicating the problem solutions.

The great attempts of researchers across the globe to overcome the limitations of conventional mathematical programming are leaded to introduce meta-heuristics algorithms like genetic algorithm (GA) [4–6], simulated annealing (SA) [7], evolutionary programming (EP) [8] and hierarchical method [9] may prove to be very efficient in solving complex power system problems but, these heuristic methods do not always guarantee the globally optimal solution. In recent years, differential evolution (DE) [10,11], Ant colony optimization [12], artificial immune systems (AIS) [13], bacteria foraging optimization [14] modified genetic algorithm [15,16], modified particle swarm optimization (PSO) [17–21] and biogeography based optimization (BBO) [25] have been successfully applied to ELD problems. Quite promising results in terms of fuel cost savings and faster convergence have been obtained by these techniques.

However, SA algorithm finds the solution trapped by local optimum rather than at the global optimum. Moreover, tuning of its relevant control parameters is a difficult task. The recent research has identified few drawbacks of the stochastic methods like GA of its premature convergence causing degradation in performance and reduction in its search capability and unsuitable when applied to multimodal objective functions. The main drawback of SA, GA, EP and AIS, is their slow convergence toward optimal solution, which is not suitable for real time operation. Though the convergence characteristic of PSO is fast and acceptable when applied to large-scale real time ELD problems still, the generation schedule obtained is not always global best solution; rather they often achieve a near global optimal solution.

Within the last few years, new optimization methods with modifications of existing methods have been applied in order to obtain the global or nearly global optimal solutions to ELD problems. These modified meta-heuristic algorithms like, GA based ant colony optimization algorithm [5], Nelder–Mead based BFA (BFA-NM) [14], modified shuffled frog leaping algorithm with genetic algorithm (MSFLA& GA) [15], quantum-inspired particle swarm optimization (QPSO) [18], hybrid quantum mechanics inspired particle swarm optimization (HQPSO) [19], improved coordinated aggregation based PSO (ICA-PSO) [20], an improved particle swarm optimization (IPSO) [21], shuffled differential evolution (SDE) [22], DE with

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generators of chaos sequences and sequential quadratic programming (DEC-SQP) [23], variable scaling hybrid differential evolution (VSHDE) [24], hybrid differential evolution with BBO [25] known as (DE/BBO) [26] and oppositional real coded chemical reaction optimization (ORCCRO) [27] have been successfully applied in constrained ELD problems. The opposition based learning (OBL) [28] have been incorporated in chemical reaction optimization to improve the convergence rate of the algorithm. However, this ORCCRO algorithm requires a lots of control parameters tuning which is a difficult task. The advantages of these algorithms that they do not have any or fewer restrictions on the shape of cost function curves or problem constraints. However, they are quite sensitive to various parameters tuning, their solution is not unique for each trial run and also the problem of large execution time.

The first application of oppositional based learning and back propagation in neural network was proposed by Ventresca and Tizhoosh [29]. Since then, it has been applied to many soft computing techniques such as DE [30], PSO by Wang et al. [31], ant colony optimization [32,33], biogeography based optimization [34], gravitational search algorithm [35], harmony search algorithm [36] and teaching learning based optimization [37]. It has been proved that a quasi opposite number is usually closer than an opposite number to the solution. This paper utilizes the improved computational efficiency of quasi opposition based learning concept in the proposed invasive weed optimization algorithm. This evolutionary algorithm known as invasive weed optimization (IWO), is a more robust, stochastic and derivative free optimization tool for the solution of complex real world problems. The algorithm is based on the invasive habits of growth of weeds in nature and having excellent exploration and exploitation ability in the search area. It was first developed by Mehrabian and Lucas [38] and since then, many applications have been found of this algorithm such as recommender system design [39], antenna system design [40], state estimation of nonlinear systems [41] and unit commitment problem solution [42].

Furthermore, oppositional based learning empowers the proposed IWO algorithm to obtain best solution in lesser time. The proposed algorithm is tested on five different test systems breaking down the previous best results in all cases. The simulation results so obtained show its reliability and superiority in solving constrained ELD problems.

2. Problem formulation

2.1. ELD with smooth cost function

The prime objective of the ELD problem is to determine the most economic loadings of generators to minimize the generation cost such that the load demands P_D in the scheduling horizon can be met and simultaneously, the power balance constraint and generating limit constraints are satisfied. Here, this constrained optimization problem can be written as:

$$\text{Minimize} \quad F_{Total} = \sum_{i=1}^{d} F_i(Pg_i) \tag{1}$$

In general, the cost function of ith unit $F_i(Pg_i)$ is a quadratic polynomial and is expressed as:

$$F_i(P_i) = a_i + b_iP_i + c_iP_i^2 \tag{2}$$

where a_i, b_i and c_i are fuel cost coefficients of ith unit, and d is the total number of committed units.

(a) Active power balance constraint or demand constraint: The total generation $\sum_{i=1}^{d}(Pg_i)$ should be equal to the total system demand P_D and total transmission loss P_{Loss}. That is represented as

$$\sum_{i=1}^{d}(Pg_i) = P_D + P_{Loss} \tag{3}$$

(b) The generator limits: The power output of each generator should vary within its minimum and maximum limits. That is, the following inequality constraint for each generator should be defined for each generator:

$$Pg_{i\,\min} \le Pg_i \le Pg_{i\,\max} \tag{4}$$

P_i is the power output of ith generator and $Pg_{i\min}$, $Pg_{i\max}$ are the minimum and maximum real power output of ith generator.

2.2. ELD with non-smooth cost functions

Practically, the ELD problems are inherently highly non linear and discontinuous in nature. Moreover, the cost functions have discontinuities corresponding to the change of fuels and also due to valve point effects that make the problem multimodal. Therefore, most of the techniques fail to obtain global solution instead of quasi-global optimums to power system optimization problems.

2.2.1. Non-smooth cost function with valve point effects

The generators with multiple valve steam turbines possess a wide variation in the input–output characteristics due to wire drawing effects. The valve point effect introduces ripples in the heat rate curves and cannot be represented by the polynomial function as in (2). Therefore, the accurate cost curve is a combination of sinusoidal functions and quadratic functions represented by Eq. (5).

$$F_i(Pg_i) = a_i + b_iPg_i + c_iPg_i^2 + |e_i \times \sin(f_i \times (Pg_{i\,\min} - Pg_i))| \tag{5}$$

where e_i, f_i are the constants of the ith unit with valve point effects.

2.2.2. Cost function with change of fuels

Generally, the dispatching units are practically supplied with multi-fuel sources, each unit should be represented with several piecewise quadratic functions reflecting the effect of fuel type changes, and the generator must identify the most economic fuel to burn. The generator with multiple fuel options [9] has different input–output curve. Therefore, it is more appropriate to represent the cost functions with piecewise quadratic functions described in (6).

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2 & \text{if} \quad P_{i\,\min} \le P_i \le P_{i1}, fuel-1 \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2 & \text{if} \quad P_{i1} \le P_i \le P_{i2}, fuel-2 \\ \ldots & \\ \ldots & \\ a_{im} + b_{im}P_i + c_{im}P_i^2 & \text{if} \quad P_{im-1} \le P_i \le P_{i\,\max}, fuel-m \end{cases} \tag{6}$$

where a_{ij}, b_{ij}, c_{ij} are cost coefficients of unit i for the jth fuel type and $P_i = Pg_i$, m = (number of generators).

2.2.3. Cost function with valve point effects and change of fuels

In reality, the objective function of the practical economic dispatch problem has non-differentiable points according to valve point loadings and multiple fuels. Therefore, the objective function should be composed of a set of non-smooth functions to obtain an accurate and practical economic dispatch solution. The cost function is framed by combining both valve point loadings and multi-fuel options which can be realistically represented as shown below in (7).

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2 + |e_{i1} \times \sin(f_{i1} \times (P_{i1\,\min} - P_{i1}))|, & \text{for } fuel1, \quad P_{i1\,\min} \le P_i \le P_{i1} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2 + |e_{i2} \times \sin(f_{i2} \times (P_{i2\,\min} - P_{i2}))|, & \text{for } fuel2, \quad P_{i2\,\min} \le P_i \le P_{i2} \\ \vdots & \vdots \qquad \vdots \\ a_{im} + b_{im}P_i + c_{im}P_i^2 + |e_{im} \times \sin(f_{im} \times (P_{im\,\min} - P_{im}))|, & \text{for } fuel.m, \quad P_{im\,\min} \le P_i \le P_{im} \end{cases} \tag{7}$$