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A modified particle swarm optimization for economic dispatch with non-smooth cost functions

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ABSTRACT

This paper presents a new approach to economic dispatch (ED) problems with non-smooth cost functions using a particle swarm optimization (PSO) technique. The practical ED problems have non-smooth cost functions with equality and inequality constraints, which makes the problem of finding the global optimum difficult when using any mathematical approaches. Since, standard PSO may converge at the early stage, in this paper, a modified PSO (MPSO) mechanism is suggested to deal with the equality and inequality constraints in the ED problems. To validate the results obtained by MPSO, standard particle swarm optimization (PSO) and guaranteed convergence particle swarm optimization (GCPSO) are applied for comparison. Also, the results obtained by MPSO, PSO and GCPSO are compared with the previous approaches reported in the literature. The results show that the MPSO produces optimal or nearly optimal solutions for the study systems.

1. Introduction

Economic dispatch (ED) is one of the most important problems to be solved in the operation and planning of a power system (Wood and Wollenberg, 1996). The primary objective of the ED problem is to determine the optimal combination of power outputs of all generating units so that the required load demand at minimum operating cost is met while satisfying system equality and inequality constraints. In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function and is solved using mathematical programming based on the optimization techniques such as lambda-iteration method, gradient method, and dynamic programming method, etc. However many mathematical assumptions such as convex, quadratic, differentiable and linear objectives and constraints are required to simplify the problem.

The practical ED problem with ramp rate limits, prohibited operating zones, valve-point effects and multifuel options is represented as a non-smooth or non-convex optimization problem with equality and inequality constraints and this makes the problem of finding the global optimum difficult and cannot be solved easily by traditional methods.

A considerable amount of work has been adopted by researches to solve a practical ED problem by considering different non-convex cost functions using various heuristic approaches (Chen and Chang, 1995; Chiang, 2003, 2005; Gaing, 2003; Jayabarathi and Sadasivam, 2000; Lee et al., 1998; Lin, et al., 2001, 2002; Orero and Irving, 1996; Park, et al., 2005, 2007, 1993; Selvakumar and Thanushkodi, 2007; Sinha et al., 2003; Walters and Sheble, 1993; Wong and Wong, 1994; Wong and Fung, 1993; Yang, et al., 1996). This paper introduces a modified PSO (MPSO) and its solution to the non-convex ED problems. Two types of non-smooth ED problems; ED with ramp rate limits and prohibited operating zones and ED with combined valve-point loading effects and multifuel options will be considered.

The PSO has been proven to be very effective for static and dynamic optimization problems. But in some cases, it converges prematurely without finding local optimum. In PSO algorithm, it is possible for the inertia weight to drive all velocities to zero before the swarm manages to reach a local extremum. Thus, in this paper MPSO is introduced to address the issue of premature convergence to solutions that are not guaranteed to be local extrema.

To validate the results obtained by the MPSO, the problem is solved by PSO. Also, the GCPSO, which is introduced by Van den Bergh and Engelbrecht (2002) to address the issue of premature convergence of PSO, is applied to validate the results. Furthermore, the results obtained by MPSO, PSO and GCPSO are compared with those obtained by other approaches reported

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in the literature. To make a proper background, PSO, GCPSO and the proposed modified PSO (MPSO) are explained in the next Section.

2. PSO, GCPSO and MPSO algorithms

2.1. PSO algorithm

The particle swarm optimizer is a population based optimization method that was introduced by Kennedy and Eberhart (1995). In PSO, each particle moves in the search space with a velocity according to its own previous best solution and its group's previous best solution. The dimension of the search space can be any positive integer. Each particle updates its position and velocity with the following equations:

$$X_i(t+1)=X_i(t)+V_i(t+1) \tag{1}$$

where $X_i(t)$and $V_i(t)$ are vectors representing the position and velocity of the ith particle, respectively and

$$V_{i,j}(t+1)=wV_{i,j}(t)+c_1r_{1,j}(pb_{i,j}-X_{i,j}(t))+c_2r_{2,j}(gb_j-X_{i,j}(t)) \tag{2}$$

where $j\in 1, 2,\ldots,d$ represents the dimension of the particle; $0\leq w<1$ is an inertia weight determining how much of particle's previous velocity is preserved; c_1 and c_2 are two positive acceleration constants; $r_{1,j}$, $r_{2,j}$ are two uniform random sequences sampled from U(0, 1); pb_i is the personal best position found by the ith particle; and gb is the best position found by the entire swarm so far.

The PSO has been proven to be very effective for static and dynamic optimization problems. But in some cases, it converges prematurely without finding even a local optimum. Standard PSO may converge at the early stage: the best particle moves based only on the inertia term since $X_i=pb_i=gb$ at the time step when it became the best. Later, its position may improve where $X_i=pb_i=gb$ holds again. Also, its position will worsen, where it will be drawn back to $pb_i=gb$ by the social component. Therefore, it is possible for the inertia weight to drive all velocities to zero before the swarms manage to reach a local extremum. When all the particles collapse with zero velocity on a given position in the search space, then the swarm has converged, but this does not mean that the algorithm has converged to a local extremum. It merely means that all the particles have converged on the best position discovered so far by the swarm. This phenomenon is referred to as *stagnation*. Thus, it is possible for the standard PSO to converge prematurely without finding even a local extremum. The MPSO is introduced in the next section to address the issue of premature convergence to solutions that are not guaranteed to be local extrema.

2.2. GCPSO algorithm

GCPSO was introduced by Van den Bergh and Engelbrecht (2002) to address the issue of premature convergence to solutions that are not guaranteed to be local extrema. The modifications to the standard PSO involve replacing the velocity update (2) of only the *best* particle with the following equation:

$$V_{i,j}(t+1)=wV_{i,j}(t)-X_{i,j}(t)+pb_{i,j}+\rho(t)r_j \tag{3}$$

where r_j is a sequence of uniform random numbers sampled from $U(-1,1)$ and $\rho(t)$ is a scaling factor determined using

$$\rho(0)=1.0$$

$$\rho(t+1)=\begin{cases} 2\rho(t) & \text{if successes} > s_c \\ 0.5\rho(t) & \text{if failures} > f_c \\ \rho(t) & \text{otherwise} \end{cases} \tag{4}$$

where s_c and f_c are tunable threshold parameters.

Whenever the best particle improves its personal best position, the success count is incremented and the failure count is set to 0 and vice versa. The success and failure counters are both set to 0 whenever the best particle changes. These modifications cause the best particle to perform a directed random search in a non-zero value around its best position in the search space.

2.3. The proposed modified PSO (MPSO) algorithm

MPSO differs from PSO by controlling the diversity of a small population, thereby avoiding premature convergence. Assuming in the PSO algorithm, n particles are generated randomly. The modifications to the standard PSO involve generating one-third of n, randomly and generating two-third of n by the following equations:

$$X_{i+n/3,j}(t)=X_{i,j}(t)+r(X_{\max j}-X_{i,j}(t)) \tag{5}$$

$$X_{k+n/3,j}(t)=X_{k,j}(t)-r(X_{k,j}(t)-X_{\min j}) \tag{6}$$

where $j\in 1, 2,\ldots,d$ represents the dimension of the particle; $i\in 1,2,\ldots,n/3$ and $k\in 1,2,\ldots,n/3$ represent the two-third of n; $X_{\min j}$,$X_{\max j}$ represent the minimum and maximum value related to the jth particle; r is a parameter in the interval [0, 1].

The generated populations are evaluated by the fitness (objective) function. Then one-third of the evaluated population with the best fitness is selected as the next generation followed by finding the pb_i and gb for the particles in the selected population. The position and velocity of the ith particle in the selected population are updated according to (1) and (2). Then two-third of the population (or two-third of n) will be generated based on (5) and (6). In MPSO the exploration is controlled by r and should vary linearly in the interval [0, 1]. As it increases the exploration will be increased and the algorithm avoids the premature convergence.

By the above mechanism, the diversity of the population is controlled. In other words, the exploration and exploitation of the search space are increased, resulting in avoiding premature convergence.

3. Problem formulation

For convenience in solving the ED problem, the unit generation output is usually assumed to be adjusted smoothly and instantaneously. Practically, the operating range of all online units is restricted by their ramp rate limits by forcing the units to operate continually between two adjacent specific operation zones. In addition, the prohibited operating zones, valve-point effects and multifuel options must be taken into account. The traditional and practical ED is explained below.

3.1. Traditional ED problem with smooth cost functions

In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function. The primary objective of the ED problem is to determine the optimal combination of power outputs of all generating units so that the required load demand at minimum operating cost is met while satisfying system equality and inequality constraints. Therefore, the ED problem can be described as a minimization problem with the following objective:

$$\min\ F=\sum_{i=1}^{N_G}F_i(P_{Gi})=\sum_{i=1}^{N_G}(a_iP_{Gi}^2+b_iP_{Gi}+c_i) \tag{7}$$