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An Improved Attractive and Repulsive Particle Swarm Optimization for Nonconvex Economic Dispatch Problems

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Abstract: This paper presents an improved attractive and repulsive particle swarm optimization (ARPSO) algorithm for nonconvex economic dispatch problem. The ARPSO algorithm enhances the exploration and exploitation behaviors of a particle by observing a diversity factor. This paper develops an improved ARPSO by introducing a penalty factor that forces each particle to repulse from the global worst particle. The advantage of the improved ARPSO is demonstrated numerically in comparison with the basic PSO and other variation of ARPSO.

Keywords: PSO, ARPSO, non-convex optimization, economic dispatch, heuristic algorithm.

1. INTRODUCTION

Particle Swarm Optimization (PSO) is one of the heuristic optimization techniques introduced in 1995 by James Kennedy and Russell Everhart. They observed birds and fishs' surviving strategy and moving path and formulated their movement. This technique is based on the observation that particles share individual experiences and the group experience for the migration of the group.

Since the introduction of the basic PSO (BPSO) many researchers have introduced improved algorithms, such as fuzzy PSO (Shi & Eberhart, 2001), hybrid PSO (Ciuprina et al., 2002), intelligent PSO (Trelea 2003), a queen-added PSO (Kennedy, 1997). When a PSO algorithm determines a particle's next position, it generally uses the particle's own experience such as the particle's best position (pbest) and the group's global best position (gbest). Riget and Vestterstorm (2002) introduced the attractive and repulsive PSO (ARPSO) to avoid the premature convergence problems. This Algorism uses a diversity alternative to enhance each particle's exploring and exploiting behavior, which improves the efficiency of the PSO algorism.

Niu et al. (2010) introduced a simple and effective modified PSO and called MARPSO(Modified Attractive and Repulsive Particle Swarm Optimization). MARPSO improved ARPSO to make the convergence rate faster, and make the capability of the global search better.

In this paper, we have introduced a new penalty factor to improve the ARPSO. When a particle determines a next move, it considers three kind of experiences, such as the particle's best position, the global best position, and the global worst position. Giving penalty to a particle close to the global worst position makes the particle to have repulsive behavior from the worst particle.

Park et al. (2005) show for the first time how nonconvex economic dispatch problem can be solved with the PSO algorithm. Vu et al. (2010), based on improving the function of weight parameters, presented a novel weight-improved particle swarm optimization (WIPSO) method for computing the optimization problems of the optimal power flow (OPF) and the economic load dispatch(ELD) with valve-point effects (Krost et al., 2008). They compared with WIPSO, PSO, and genetic algorism (GA), and introduced relationships between economic dispatch and valve point effects.

In this paper, we simulated nonconvex economic dispatch to use basic PSO (BPSO), added penalty PSO (PPSO), attractive and repulsive PSO (ARPSO), added penalty attractive and repulsive PSO (PARPSO).

The organization of this paper is as follows: Section 2 will be the brief introduction of the nonconvex economic dispatch problem. The improved ARPSO to use penalty factor method and basic PSO, penalty PSO, and ARPSO are introduced in Section 3. And compared with each PSO method in Section 3. Numerical results of economic dispatch problem using the proposed method on the IEEE 40-unit systems will be presented in Section 4. Finally, conclusion will be drawn in Section 5.

2. NON-CONVEX ECONOMIC DISPATCH PROBLEMS

Economic dispatch problem is formulated as follows:

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The objective function to be minimized is

$$C_i = \sum_{j=1}^{N} F_i(P_j) \tag{1}$$

where $F_i(P_i)$ is fuel cost function of unit i and P_i is generation of unit j.

The power balance constraints without transmission losses is formulated as follows:

$$\sum_{j=1}^{N} P_j = D \cdot \tag{2}$$

where D is the total demand and it is equal to total generation. Each generator unit has minimum and maximum generating capacity constraints:

$$P_{j,min} \le P_j \le P_{j,max} \quad ; \; j = 1, 2, \dots, N \tag{3}$$

General fuel cost function that is not considered valve points is as follows:

$$F_i(P_j) = a_j P_j^2 + b_j P_j + c_j \tag{4}$$

where N is the number of generating unit, P is power output and a_j, b_j, c_j are cost coefficients of the j -th unit.

Heat rate function of generating units have valve point by mechanical reason. Real fuel cost function is in the form of non-convex function due to the valve point effects. A typical fuel cost curve with valve points is shown in Fig.1.

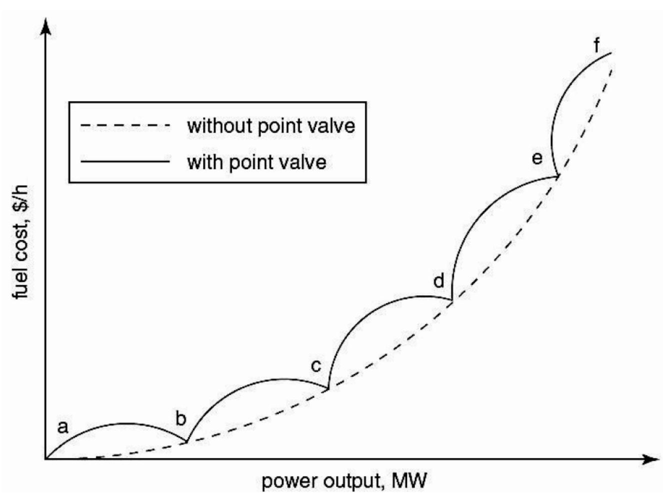

Fig. 1. Curve of cost function with 6 valves (Thanushkodi & et al., 2008).

Non-convex curve with multi-valve point effect is formulated as follows:

$$F_i(P_j) = \sum_{j=1}^{N} a_j + b_j P_j + c_j P_j^2 + \left| e_j \times sin\left(f_j \times (P_{j,min} - P_j)\right)\right| \cdot \tag{5}$$

Where a_i b_i c_i e_i f_i are cost coefficients of the j -th unit. the economic dispatch problem. For optimization of the economic dispatch problem, we used the improved penalty attractive and repulsive particle swarm optimization (PARPSO).

3. COMPARRISON OF BASIC PSO AND ARPSO, PENALTY ARPSO

3.1 Basic PSO (BPSO)

Particle Swarm Optimization (PSO) is an optimization technique introduced by Kennedy and Everhart in 1995. The basic PSO (BPSO) has three parts to make a next move. It has particles and particle group (swarm). Each particle in the group is moving in the direction of the particle that has a best value in the next step. If each particle's minimum value of experience position is *pbest* and each group's minimum value of experience position is *gbest,* this velocity definition is as follows:

$$V_i^{k+1} = wV_i^k + c_1 r_1 (pbest_i^k - x_i^k) + c_2 r_2 (gbest^k - x_i^k). \tag{6}$$

$$x_i^{k+1} = x_i^k + V_i^{k+1}. \tag{7}$$

where x_i^k is the k-th step of the i -th particle. Equation (6) is the velocity step size at the step $k+1$. The first term in the right-hand side is the inertia of the previous velocity and second term is in the direction of *pbest* and third term is in the direction of *gbest*. Acceleration constants c_1, c_2 (Eberhart & Shi, 2001) and inertia weight w (Shi & Eberhart, 1998) are predefined by the user and r_1, r_2 are the uniformly generated random numbers in the range of [0, 1] (Niu et al., 2010).

3.2 ARPSO and MARPSO

ARPSO and MARPSO used particle's attractive and repulsive behavior. MARPSO improved ARPSO by modifying the diversity definition.

Diversity determines each particle's exploring and exploiting behavior. Distance from each particle to the global best particle is changed every step so diversity is also changed every step. Diversity definition is as follows:

$$diversity^k(S) = 1/|S| \sum_{i=1}^{|S|} div_i^k. \tag{8}$$

$$div_i^k = \begin{cases} 0, \text{ if } \left|pbest_i^k - P_i\right| < \left|gbest^k - P_i\right|. \\ 1, \text{ therewise} \end{cases} \tag{9}$$

Diversity is a variable to control each particle's behavior. Equation (8) and (9) explain how to determine diversity value. In this paper, i is particle. S is the swarm and $|S|$ is swam size as the number of particles. If most particles are close to $pbest$, diversity will have a small value. Diversity is an average value of div and it has 0 to 1 value.