Chapter 7

Swarm-Based Mean-Variance Mapping Optimization ($MVMO^S$) for Solving Non-Convex Economic Dispatch Problems

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ABSTRACT

The practical Economic Dispatch (ED) problems have non-convex objective functions with complex constraints due to the effects of valve point loadings, multiple fuels, and prohibited zones. This leads to difficulty in finding the global optimal solution of the ED problems. This chapter proposes a new swarm-based Mean-Variance Mapping Optimization ($MVMO^S$) for solving the non-convex ED. The proposed algorithm is a new population-based meta-heuristic optimization technique. Its special feature is a mapping function applied for the mutation. The proposed $MVMO^S$ is tested on several test systems and the comparisons of numerical obtained results between $MVMO^S$ and other optimization techniques are carried out. The comparisons show that the proposed method is more robust and provides better solution quality than most of the other methods. Therefore, the $MVMO^S$ is very favorable for solving non-convex ED problems.

INTRODUCTION

The economic dispatch (ED) is one of essential optimization problems in power system operation. Its objective is to allocate the real power output of the thermal generating units at minimum fuel production cost while satisfying all units and system contraints (Xia & Elaiw, 2010).

Traditionally, the cost function objective of the ED problem is the quadratic function approximations and this problem is solved by using mathematical programming methods such as lambda iteration method, Newton's method, gradient search, dynamic programming (Wollenberg & Wood, 1996), linear

DOI: 10.4018/978-1-4666-8291-7.ch007

programming (Parikh & Chattopadhyay, 1996), non-linear programming (Nanda, Hari, & Kothari, 1994), quadratic programming (Fan & Zhang, 1998), and Maclaurin series-based Lagrangian (MSL) method (Hemamalini & Simon, 2009). Among of them, the linear programming methods have fast computation time with reliable solution. However, they suffers the main disadvantage associated with the piecewise linear cost approximation. The non-linear programming methods suffer problems in convergence and algorithm complexity. The Newton-based algorithms have difficulty in handling a large number of inequality constraints (Al-Sumait, Al-Othman, & Sykulski, 2007). MSL method can directly deal with the non-convex ED problem by using the Maclaurin expansion of non-convex terms in the objective function. Although this method can quickly find a solution for the problem, the obtained solution quality is not high, especially for the large-scale systems. In general, the conventional methods are not capable for solving non-convex ED problems (Dieu, Schegner, & Ongsakul, 2013).

The quadratic function is not exactly representing the practical ED problem which can contain non-convex and nonlinear objective and constraints. The effects of valve point loadings, multiple fuels, or prohibited operating zones can cause the input-output curve of thermal generators more complicated. For this reason, the practical ED problem should be formulated as non-convex objective function. More advanced methods based on artificial intelligence have been previously developed to deal with ED problems such as Hopfield neural network (HNN) (Lee, Sode-Yome, & Park, 1998; P Vasant, Ganesan, Elamvazuthi, et al., 2012), evolutionary programming (EP) (Sinha, Chakrabarti, & Chattopadhyay, 2003), differential evolution (DE) (Noman & Iba, 2008), genetic algorithm (GA) (Chiang, 2005), ant colony optimization (ACO) (Pothiya, Ngamroo, & Kongprawechnon, 2010), artificial immune system (AIS) (Panigrahi, Yadav, Agrawal, & Tiwari, 2007), biogeography-based optimisation (BBO) (Padmanabhan, Sivakumar, Jasper, & Victoire, 2011), particle swarm optimization (PSO) (Ganesan, Vasant, & Elamvazuthy, 2012; Mahor, Prasad, & Rangnekar, 2009; P Vasant, Ganesan, & Elamvazuthi, 2012), and artificial bee colony (ABC) algorithm (Le, Vo, & Vasant). Among of these methods, the HNN method based on the minimisation of its energy function can be only applied to the convex optimization problems. This method can be easily implemented on large-scale systems but it suffers long computational time and local optimum solution (Dieu, Schegner, et al., 2013). The GA method is critically dependent on the fitness function and sensitive to the mutation and crossover rates, the encoding scheme of its bits, and the gradient of the search space curve leading toward solutions. The EP method may prove to be very effective in solving nonlinear ED problems without any restrictions on the shape of the cost curves. However, a solution by EP method may get trapped in a suboptimal state for large-scale problems. In general, these methods also involve a large number of iterations and their optimal solutions are susceptible to the related control parameters (J.-B. Park, Lee, Shin, & Lee, 2005). The DE method is a population-based stochastic parallel search technique which has the advantages such as simple and compact structure, few control parameters, and high convergence characteristic. However, there is no guaranty for this method to always get optimal solution. Moreover, the DE method suffers slow computation when dealing with large-scale problems. Recently, PSO is the most popular method applied for solving the ED problems. It can be applied to global optimization problems with non-convex or non-smooth objective functions. Although this method can provide high-quality solutions with short computational time and stable convergence property (Eberhart & Shi, 1998), it seems to be susceptible to the tuning of some weights or parameters. The PSO method is continuously improved for dealing with large-scale and complex problems in power systems. Although these artificial intelligence methods do not always guarantee to find the best global optimal solution in finite computational time, they can find near global optimal solution for non-convex optimization problems.