Chapter 9
Evolutionary Algorithms for Economic Load Dispatch Having Multiple Types of Cost Functions

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ABSTRACT

This chapter presents various novel evolutionary algorithms, namely Real Coded Genetic Algorithm (RGA), two variants of Biogeography-Based Optimization (BBO), and three variants of Particle Swarm Optimization (PSO) in order to find the optimal power generation scheduling to simultaneously optimize fuel cost and power loss for solving constrained economic load dispatch problems of all thermal systems, considering multiple fuel operation and valve point effect. The effectiveness of the proposed algorithms is demonstrated in five different ELD problems, considering different constraints such as transmission losses, ramp rate limits, multi-fuel options and valve point loading. Comparative studies are carried out to examine the effectiveness and superiority of the proposed approaches. A comparison of simulation results reveals optimization usefulness of the proposed BBO scheme over other well established population based optimization techniques. It is also found that the convergence characteristics of the BBO algorithm are better than other optimization methods.

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INTRODUCTION

Economic load dispatch (ELD) problem is an important issue of the power generation system operation and planning. The arrangement of the power generating units output to gather the power demand of the load at the least operating cost at the same time as satisfying overall inequality and equality constraints of the power system is the main objective of the ELD problem. Numerous classical methods like lambda iteration method (LIM) (Aravindhababu & Nayar, 2002; Chen & Wang 1993), Lagrangian multiplier method (Nanda, Hari & Kothari, 1994), classical technique based on co-ordination equations (El-Keib, Ma & Hart, 1994), quadratic programming (QP) (Fan & Zhang, 1998), gradient method (Dodu, Martin, Merlin & Pouget,1972), linear programming (LP) approach (Parikh & Chattopadhyay,1996) etc, have been applied to resolve ELD problem considering flat cost function. Excluding, these approaches are not feasible at the real power systems for the nonlinear characteristics of the cost function and nonlinear constraints of ELD problem. These classical optimization techniques frequently try to converge to local optimum or diverge altogether and highly penetrating to starting points. Therefore, several dominant mathematical optimization methods which are reliable and extremely fast, like nonlinear programming (NLP) (Han, Gooi & Kirschen, 2001) and dynamic programming (DP) (Liang & Glover, 1992) have been engaged to solve the problems of ELD. However, NLP methods have a disadvantage of algorithmic difficulty. DP enforces no boundaries on the character of the cost curves so it can resolve ELD problems having essentially nonlinear cost curves. Though, this process may face dimension problems which in turn increase the problem complexity. Moreover, this method suffers from the local optimality.

Due to nonconvex and nondifferential characteristics similar to valve point loading, discontinuous prohibited operating zones, ramp rate limits etc of a sensible ELD problem, the aforementioned techniques are infeasible and incapable for tracing the global optima. Complex ELD problems with constraints are resolved by many population-based evolutionary optimization techniques in the modern researches. Few popular population based well known optimization techniques are genetic algorithms (GA) (Chiang & Chao, 2005; Walters & Sheble, 1993), evolutionary programming (EP) (Park, Yang, Lee & Park, 1996), simulated annealing (SA) (Abido, 2000), particle swarm optimization (PSO) (Eberhart & Shi, 2001; Ho, Yang, Ni, Edward &Wang, 2005; Liu & Abraham, 2005; Naka, Genji, Yuru & Fukuyama, 2003), hybrid evolutionary programming (HEP) (Swain & Morris, 2000), bacteria foraging optimization (BFO) (Ghoshal, Chatterjee & Mukherjee, 2008), modified BFO (MBFO) (Hota, Barisal & Chakrabarti, 2010), artificial bee colony(ABC) (Kwannetr, Leeton & Kulworawanichpong, 2010), chaotic ant swarm optimization (CASO) (Cai et al., 2007),seeker optimization algorithm (SOA) (Shaw, Mukherjee & Ghoshal, 2011), civilized swarm optimization (CSO) Immanuel & Thanushkodi, 2009), tabu search (TS) (Sangiamvibool, Pothiya & Ngamroo, 2011), harmony search algorithm (HSA) (Sivasubramani & Swarup, 2011), PSO with crazy particles (Chaturvedi, Pandit & Srivastava), hybrid PSO (HPSO) (Haiyan, Pichet, Song & Dillon, 2010), anti-predatory PSO (APSO) (Immanuel & Thanushkodi, 2008), modified PSO (MPSO) (Neyestani, Farsangi & Nezamabadi, 2010), ant colony optimization (ACO) (Pothiya, Ngamroo & Kongprawechnon, 2010), random drift PSO (RDPSO) algorithm (Sun, Palade, Xiao & Fang, 2013), artificial bee colony algorithm with dynamic population size (ABCDP) (Aydin, Ozyon, Yas & Tianjun, 2014). Moreover, to solve non-linear ELD problems, the artificial intelligent methods like Hopfield neural networks (Park, Kim, Eom & Lee, 1998; Lee & Park, 1998; Su & Lin, 2000) have also been successfully applied. In the above population based algorithms, few methods suffer from settings of algorithm parameters and frequently revisit the same suboptimal solutions. Hence, the slow convergence of these methods reduces its search capability and degrades their performance.