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Economic dispatch using chaotic bat algorithm

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ABSTRACT

This paper presents the application of a new metaheuristic optimization algorithm, the chaotic bat algorithm for solving the economic dispatch problem involving a number of equality and inequality constraints such as power balance, prohibited operating zones and ramp rate limits. Transmission losses and multiple fuel options are also considered for some problems. The chaotic bat algorithm, a variant of the basic bat algorithm, is obtained by incorporating chaotic sequences to enhance its performance. Five different example problems comprising 6, 13, 20, 40 and 160 generating units are solved to demonstrate the effectiveness of the algorithm. The algorithm requires little tuning by the user, and the results obtained show that it either outperforms or compares favorably with several existing techniques reported in literature.

1. Introduction

ED (Economic Dispatch) is an important optimization problem in electric power systems which aims at allocating optimum generation values to minimize the cost while simultaneously satisfying several equality and inequality constraints. A naive approach would be to consider the cost curve as continuous and quadratic in nature. In practice, thermal power plants have a non-smooth and non-convex cost curve due to valve point loading effects [1] and discontinuities due to POZs (prohibited operating zones).

Given the importance of the ED problem, several attempts have been made to solve it using a variety of methods, classical and non-classical. Classical, gradient based methods like linear programming, Base-Point and Participation Factors, λ-iteration method [1], gradient method [2], branch and bound [3], quadratic programming [4] were initially proposed. The presence of POZs and multiple fuel options make the ED problem discontinuous [5]; this is a complication that gradient based methods find difficult to deal with, since gradient based methods are for smooth and continuous objective functions. Several modifications to the gradient based methods have been presented recently, to address these complications, like the dimensional steepest decline method [5] and Big-M method [6]. These involve additional computation to account for these complications.

Non-classical, metaheuristic methods owe their popularity to their ability to deal easily with these difficulties in the ED problem. The metaheuristic methods include the GA (Genetic Algorithm) [8,9], EP (Evolutionary Programming) [10], PSO (Particle Swarm Optimization) and its variants [11–15], neural networks [16,17], DE (Differential Evolution) [18] and so on.

The metaheuristic techniques in turn can be loosely classified into several categories like evolutionary algorithms, SI (swarm intelligence) and immune algorithms. SI techniques are inspired by the flocking behavior of agents like birds, bees and bats. In these techniques, the agents belonging to the swarm or population interact locally with each other and their environment in an organized and decentralized fashion to reach the required optimum solution.

Several SI algorithms have been developed and applied to solve the ED problem like the PSO [11], FA (Firefly Algorithm) [19], Bat Algorithm [20], DS (Differential Search) [21], and ABC (Artificial Bee Colony Algorithm) [22].

A recent advancement in optimization using metaheuristic algorithms has been to enhance existing algorithms by using chaotic sequences to tune the parameters that control the performance of the algorithm to improve diversity and avoid premature convergence [23], [24]. Chaos is characterized by ergodicity, stochastic

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Table 1
Table of abbreviations.

Optimization technique/algorithm	Abbreviation
Artificial Bee Colony	ABC
Backtracking Search Algorithm	BSA
Bat Algorithm	BA
Biogeography-Based Optimization	BBO
Chaotic Bat Algorithm	CBA
Chemical Reaction Optimization	CRO
Classical Evolutionary Programming	CEP
Conventional Genetic Algorithm with Multiplier Updating	CGA_MU
Cross-Entropy Method and Sequential Quadratic Programming	CE-SQP
Differential Evolution	DE
Differential Evolution with Biogeography-Based Optimization	DE/BBO
Differential search	DS
Dimensional Steepest Decline Method	DSD
Distributed Auction-Based Algorithm	AA(Dist.)
Evolutionary Programming	EP
Evolutionary Programming with Sequential Quadratic Programming	EP-SQP
Firefly Algorithm	FA
Genetic Algorithm – Ant Colony Optimization (special class)	GA-API
Genetic Algorithm – Binary	GA Binary
Group Search Optimizer	GSO
Hopfield Modeling	HM
Hybrid Chemical Reaction Optimization with Differential Evolution	HCRO-DE
Hybrid Differential Evolution	HDE
Improved Fast Evolutionary Programming	IFEP
Improved Genetic Algorithm with Multiplier Updating	IGA_MU
Modified Artificial Bee Colony Algorithm	MABC
Multiple Tabu Search	MTS
New Particle Swarm Optimization with Local Random Search	NPSO-LRS
Oppositional Real Coded Chemical Reaction Optimization	ORCCRO
Particle Swarm Optimization	PSO
Particle Swarm Optimization with the Sequential Quadratic Programming	PSO-SQP
Passive Congregation-based Particle Swarm Optimization	PC-PSO
Quantum Particle Swarm Optimization	QPSO
Random Drift Particle Swarm Optimization	RDPSO
Real Coded Chemical Reaction Optimization	RCCRO
Self-Tuning Hybrid Differential Evolution	STHDE
Self-Organizing Hierarchical Particle Swarm Optimization	SOH-PSO
Simple Particle Swarm Optimization	SPSO
Simulated Annealing	SA
Society-Civilization Algorithm	SCA
Species-based Quantum Particle Swarm Optimization	SQPSO
Tabu Search	TS
θ-Particle Swarm Optimization	θ –PSO

properties, and regularity [25]. Chaotic maps or sequences have been used instead of random numbers in different stages of an algorithm to improve the performance [26]. Several chaos based algorithms have been presented to solve various engineering optimization problems including the ED problem [27,28].

This paper presents the application of one such chaos based metaheuristic algorithm, the CBA (Chaotic Bat Algorithm), a SI algorithm to the ED problem. Five test systems of varying complexities have been solved by CBA to demonstrate its performance. The CBA is easy to implement and shows promising results.

Table 2
Optimal generations and cost obtained by the CBA for Test System 1 (6 generators with loss, POZ and ramp rate limits).

Unit	P_j^{min}	P_j^{max}	POZ	Generation
1	100	500	[210, 240]; [350, 380]	447.4187
2	50	200	[90, 110]; [140, 160]	172.8255
3	80	300	[150, 170]; [210, 240]	264.0759
4	50	150	[80, 90]; [110, 120]	139.2469
5	50	200	[90, 110]; [140, 150]	165.6526
6	50	120	[75, 85]; [100, 105]	86.7652
Cost ($/hr)			15,450.2381	
Transmission loss (MW)			12.9848	

The rest of the paper is organized as follows. Section 2 describes the ED problem, Section 3 introduces the CBA algorithm, and Section 4 explains its application to the ED problem. Section 5 presents the results of the CBA applied to five test systems, and Section 6 concludes the paper.

2. ED problem formulation

The objective of the ED problem is to minimize the fuel cost of thermal power plants for a given load demand subject to various constraints.

2.1. Objective function

The objective is to minimize the quadratic fuel cost function of the thermal units, given by

$$\min_{P\in R^{N_g}} \quad F = \sum_{j=1}^{N_g} F_j(P_j) = \sum_{j=1}^{N_g} \left(a_j + b_jP_j + c_jP_j^2\right) \tag{1}$$

where N_g is the total number of generating units, $F_j(P_j)$ is the fuel cost of the jth generating unit in $/hr, P_j is the power generated by the jth generating unit in MW, and a_j, b_j and c_j are cost coefficients of jth generator.