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Backtracking search algorithm for solving economic dispatch problems with valve-point effects and multiple fuel options

Mostafa Modiri-Delshad [a, *], S. Hr. Aghay Kaboli [a], Ehsan Taslimi-Renani [a], Nasrudin Abd Rahim [a, b]

[a] UM Power Energy Dedicated Advanced Center (UMPEDAC), Level 4, Wisma R&D University of Malaya, Jalan Pantai Baharu, 59990 Kuala Lumpur, Malaysia

[b] Renewable Energy Research Group, King Abdulaziz University, Jeddah 21589, Saudi Arabia

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A B S T R A C T

This paper presents backtracking search algorithm (BSA) for solving economic dispatch (ED) problems with considering valve-point loading effects, prohibited operating zones, and multiple fuel options. The proposed method is an evolutionary technique of optimization with simple structure and single control parameter to solve numerical optimization problems. It is a powerful method for effectively exploring the search space of an optimization problem to find the optimal solution within a low computation time. Different test systems with up to 160 generating units have been used to show the performance of BSA to solve ED problems with high nonlinearities. The results are compared with several methods of optimization to verify the high performance of BSA for solving the ED problems. Statistical analysis of the results among 50 independent runs has been carried out to validate the BSA as a highly robust method.

1. Introduction

Economic dispatch (ED) is considered to be a fundamental economic operation issue in power systems. It aims to determine the schedule of generating units to supply a specific power demand subject to the network and generators' constraints.

Economic dispatch (ED) problem as an optimization problem is composed of an objective function and several constraints. Previous attempts to solve the ED problem have employed the classical methods of optimization known as conventional techniques. In these methods, technical and practical constraints of the generating units and the network have to be simplified/ignored owing to the limits of these methods. Such simplifications divide into two sections. One is associated to the accuracy of the cost model of the generating units especially for different types of fuels or to consider the valve-point loading effects [1]. Another relates to the network topology, either ignored or limited to considering only the total transmission network loss [2].

The objective of economic dispatch is usually to minimize the generation cost in the power system. Traditionally, the cost function of a generating unit is modeled by a quadratic cost function to make the ED a convex problem to be solved by the classical methods. In this case, an analytical solution is proposed in Ref. [3] for solving convex ED problem in a basic form without considering the transmission network loss. Another analytical approach is presented in Ref. [4] for solving the problem by incorporating the transmission loss. However, it has not produced accurate results because of an approximation technique used in the power balance equation. So, it is improved in Ref. [5] and is combined with an iterative method to produce the exact solution to the convex problem. Quadratic programming [6], interior point technique [7], fast lambda iteration [8], lagrange relaxation (LR) [9], and linear programming [10] are other examples of classical methods addressing the ED problems.

In the real world, an ED problem is non-convex with high complexity, so the application of the classical methods is restricted. Although Maclaurin series [11] approximation is employed to solve the non-convex ED problems, it leads to a non-optimal solution. In addition, Dynamic programing (DP) among the classical methods has been proposed to solve the ED problem with no restriction on

* Corresponding author.
E-mail addresses: modiri@siswa.um.edu.my (M. Modiri-Delshad), nasrudin@um.edu.my (N.A. Rahim).

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the forms of generators' cost functions; however, its performance is increasingly affected by problem size [12].

To look for another alternative, metaheuristic and evolutionary methods have been deployed to solve practical ED problems with a high degree of nonlinearity and more constraints than before. In this case, the application of the genetic algorithm (GA) [13] and particle swarm optimization (PSO) [14] showed promising solutions for complex ED problems, since they could handle various operating constraints, such as prohibited operating zones (POZ), generators' ramp-up and ramp-down. Other methods in this category, including cuckoo search algorithm (CSA) [15], chaotic teaching–learning-based optimization (CTLBO) [16], kinetic gas molecule optimization algorithm (KGMO) [17], chaotic bat algorithm (CBA) [18], Immune Algorithm (IA) [19], modified artificial bee colony algorithm (MABC) [20], oppositional invasive weed optimization (OIWO) [21], modified group search optimizer (MGSO) [22], modified symbiotic organisms search (MSOS) [23], grey wolf optimization (GWO) [24], hybrid grey wolf optimizer (HGWO) [25], crisscross optimization algorithm (CSO) [26], tournament-based harmony search (THS) [27], and seeker optimization algorithm (SOA) [28], have succeeded in considering an accurate generator cost function with multiple fuel options or valve-point loading effects.

Some metaheuristic methods suffer from premature convergence and high computation time in the case of increasing system size. In addition, the fairly high sensitivity of these methods to their control parameters has been a major drawback, which impedes their applications for real time operation. Therefore, the hybrid methods, such as the combination of two or more methods, have been proposed to eliminate each method's drawback. A few examples are modified sub-gradient combined with harmony search algorithms (MSG-HS) [29], chaotic local search integrated in honey bee mating optimization method [30], bacterial foraging and Nelder-Mead (BF-NM) [31], hybrid of harmony search with sequential quadratic programming method [32], hybrid of chemical reaction optimization with differential evolution (HCRO-DE) [33], continuous greedy randomized adaptive search procedure mixed with differential evolution (CGRASP–DE) [34], novel combination of differential evolution and particle swarm optimization (DE-PSO-DE) [35], and fuzzy adaptive chaotic ant swarm optimization algorithm combined with the sequential quadratic programming (FCASO-SQP) [36] which perform better than individual methods.

Methods of solving ED problems can also be categorized into another three groups. The first group includes the methods applied to ED problems in their original versions. Few examples are tabu search algorithm (TS) [37], particle swarm optimization (PSO) [12], differential evolution (DE) [38]. The methods of the second group are the modified versions of the first group including modified tabu search (MTS) [39], improved PSO (IPSO) [40], shuffled differential evolution (SDE) [41]. The last group consists of the hybrid methods as the combination of methods from the previous groups described above.

Inclusion of valve point loading effects and multiple fuel options in an ED problem makes it highly non-convex and finding a method to solve this type of problem is a challenge. According to the NFL theorem [42], all metaheuristic methods have the same performance when averaged over all possible objective functions. It means, one approach is superior to others when it has focused on a particular class of problems [43]. In this paper, backtracking search algorithm (BSA) as an evolutionary method has been proposed to solve highly non-convex ED problems with several operating constraints such as ramp-up, ramp-down, and prohibited operating zones. In the ED problem formulation, the valve-point loading effects and multiple fuel options have been considered in the generators' cost functions. Also, a suitable constraint handling mechanism is proposed and incorporated in BSA to provide feasible solutions for the optimizer within the optimization process. The proposed method has been applied to several case studies varied in size and complexity to demonstrate its feasibility for solving the practical ED problems.

The rest of this paper is organized as follows: Section 2 presents the proposed method's algorithm, Section 3 provides the mathematical model of the ED problems, Section 4 addresses the methodology of BSA for solving the ED problems, Section 5 presents and discusses the simulation results for the case studies, and the paper is concluded in Section 6.

2. Backtracking search optimization algorithm (BSA)

BSA is an evolutionary optimization tool developed by Civicioglu [44] to solve optimization problems. It is used to solve different types of engineering optimization problems such as surface wave analysis [45], wind power prediction [46], wind turbine power curve model [47], and economic/emission dispatch problems [48] due to its promising optimization performance. The structure of BSA is simple and it has a single control parameter which makes it a suitable approach to solve even multimodal optimization problems. The performance of BSA is not over sensitive to its control parameter and it does not suffer from high computation time or premature convergence unlike many evolutionary methods. BSA utilizes crossover and mutation operators to effectively explore the search domain. These operators are completely different from the ones used by other evolutionary methods, such as genetic algorithm and evolutionary programming. BSA also has the advantage of a memory that defines the search direction based on the previous generations.

Fig. 1 shows the flowchart of BSA, which comprises five main steps: initialization, selection-I, mutation, crossover, and selection-II, as mentioned next.

2.1. Initialization

The population and each individual are represented by $\mathbf{X} = [\mathbf{X}_1\mathbf{X}_2\ldots\mathbf{X}_{nPop}]'$ and $\mathbf{X}_i = [x_{i1}\ldots x_{ij}\ldots x_{i\,nVar}]'$ where i and j respectively denote the individual and element numbers. The

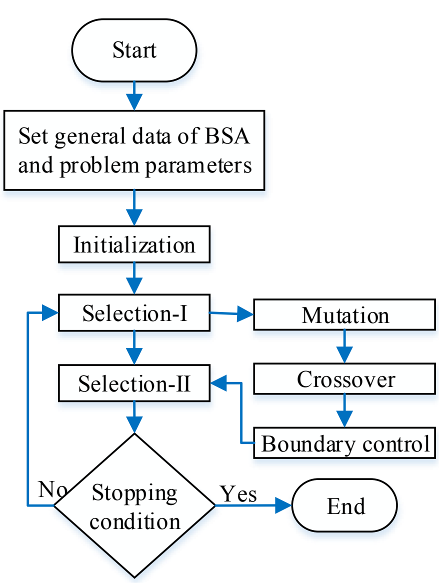

Fig. 1. Flowchart of BSA.