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Multiobjective scatter search approach with new combination scheme applied to solve environmental/economic dispatch problem

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A B S T R A C T

The environmental/economic dispatch (EED) is an important daily optimization task in the operation of many power systems. It involves the simultaneous optimization of fuel cost and emission objectives which are conflicting ones. The EED problem can be formulated as a large-scale highly constrained nonlinear multiobjective optimization problem. In recent years, many metaheuristic optimization approaches have been reported in the literature to solve the multiobjective EED. In terms of metaheuristics, recently, scatter search approaches are receiving increasing attention, because of their potential to effectively explore a wide range of complex optimization problems. This paper proposes an improved scatter search (ISS) to deal with multiobjective EED problems based on concepts of Pareto dominance and crowding distance and a new scheme for the combination method. In this paper, we have considered the standard IEEE (Institute of Electrical and Electronics Engineers) 30-bus system with 6-generators and the results obtained by proposed ISS algorithm are compared with the other recently reported results in the literature. Simulation results demonstrate that the proposed ISS algorithm is a capable candidate in solving the multiobjective EED problems.

1. Introduction

Environmental/economic dispatch (EED) problem is one of the most important problems in power systems management. It consists of scaling the outputs of thermoelectric generators, in a thermal power plant, such that a power demand is supplied while satisfying equality and inequality constraints. Each generation unit has particular aspects in the cost of the fuel spent and the pollutants emitted.

Fossil-fired electric power plants cause pollution emission while they operate. The emission control results from the requirement for power utilities to reduce their pollutant levels below the annual emission allowances assigned for the affected fossil units. The total emission can be reduced by minimizing the major pollutants; this is one objective of the EED problem. There are two objectives to be optimized in this kind of EED problem: the cost of the generation and the total emission. Both objectives must be minimized, however they are conflicting, i.e. if there is an optimal solution it is impossible to optimize an objective without worsen other objective. Thus, there is not only one solution but a set of solutions that form the Pareto optimal set.

Pareto optimality is a measure of efficiency in multi-criteria and multi-objective situations. A state *A* (a set of object parameters) is said to be Pareto optimal, if there is no other state *B* dominating the state *A* with respect to a set of objective functions. A state *A* dominates a state *B*, if *A* is better than *B* in at least one objective function and not worse with respect to all other objective functions.

Many researchers have tackled this problem in the past. The first use of multiobjective programming with power systems has been addressed by Cheong and Dillon [1]. However, it is realized that

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conventional mathematical techniques, such as gradient method, linear programming algorithm, quadratic programming, Lagrange relaxation algorithm, become very complicated when dealing with increasingly complex dispatch problems, and are further limited by their lack of robustness and efficiency in a number of practical applications [2]. Therefore, because of its particularities, an efficient technique must be used to provide good solutions for the EED optimization problems.

In this context, more and more often, metaheuristics are used to find solutions of complex EED optimization problems. Metaheuristics are approximate, heuristic or general-purpose algorithms for solving complex optimization problems, with continuous and/or discrete variables. The use of metaheuristic search algorithms have gained attention in the recent decades due to the failure of conventional methods to solve NP-hard (Non-Polynomial hard) combinatorial and difficult continuous optimization problems. In general, metaheuristics are suitable for solving hard and/or large-size instances of an optimization problem for which there is no efficient exact algorithm available.

Over the last few years, metaheuristics such as genetic algorithms [3], differential evolution [4,5], particle swarm optimization [6,7], bacterial foraging algorithm [8], shuffled frog leaping algorithm [9], seeker optimization algorithm [10], biogeography-based optimization algorithm [11], chaotic ant swarm optimization [12], artificial bee colony optimization [13], harmony search [14,15], self-organizing migrating strategy [16], quantum-inspired evolutionary algorithm [17], artificial immune systems [18], imperialist competitive algorithm [19], charged system search algorithm [20], fuzzy adaptive chaotic ant swarm optimization [12], have been used to solve economic dispatch problems. In Ref. [21], a summary of EED algorithms is also given.

On the other hand, multiobjective EED optimization involves the simultaneous optimization of several incommensurable and often competing objectives. Recently, the research focus has shifted towards handling both the objectives simultaneously. Over the past decade, this option has received much interest due to the development of a number of multiobjective search strategies based on metaheuristics. Many examples of metaheuristic optimization approaches applied to multiobjective EED optimization problems are given in Refs. [22–36].

In this context, a metaheuristic method called scatter search (SS) can be useful. The scatter search methodology was first introduced in 1977 [37–39] as a heuristic for integer programming; it is a population-based metaheuristic method that uses a set of reference solutions to create new improved solutions by intelligently combining and improving others in a set of good and disperse solutions. The reference set is formed based on quality and diversity of the solutions. Initially, the best solutions are added to the reference set, and then the most diversified solutions, based on the distance to the already added solutions, are included in the set. The algorithm combines these solutions to create new ones and achieve a desirable result.

From the standpoint of metaheuristic classification, scatter search may be viewed as an evolutionary algorithm [40] because it builds, maintains and evolves a set of solutions throughout the search. However, scatter search differs from other population-based evolutionary heuristics like genetic algorithms mainly in its emphasis on generating new elements of the population mostly by deterministic combinations of previous members of the population as opposed to the more extensive use of randomization.

The two principles that govern SS are i) intensification, and ii) diversification. Intensification refers to the role of isolating the best performing solutions from the populations in order to obtain a group of good solutions. Diversification in turn isolates the solutions which are the furthest from the best solutions and combine them with the best solutions. This new pool of solutions is the reference set where crossover occurs in order to create solutions from new solution regions by the combination of the intensified solutions and diversified solutions. Intensification and diversification are commonly termed as adaptive memory programming [41]. These principles help to increase the exploration and the exploitation capabilities of the algorithm in finding solutions, which is very desirable in complex problems such as EED problem because the search space is generally wide and there are several local optimal points that can prevent the algorithm to advance.

Nevertheless, the original approach does not consider multiple objectives, so some modifications must be done in order to apply it to solve the EED problem. Our interest here is to adapt the well-known scatter search template to multiobjective optimization and the proposition of improvements in the scatter search design. Scatter search has been found to be successful in a wide variety of optimization problems [42–45]. Moreover, recently it had been extended to deal with multiobjective optimization problems (see examples in Refs. [46–49]).

Scatter search uses improvement strategies to efficiently produce the local tuning of the solutions, and a remarkable aspect concerning scatter search is the trade-off between the exploration abilities of the combination method and the exploitation capacity of the improvement mechanism. This paper proposes an improved scatter search (ISS) methodology to deal with multiobjective EED problems based on concepts of Pareto dominance and crowding distance [50] and a new scheme for the combination method.

The results of the original SS and proposed ISS approaches are compared to other techniques presented in the recent literature about EED. The mentioned algorithms have been implemented on standard IEEE (Institute of Electrical and Electronics Engineers) 30-bus six-generators system in order to obtain the trade-off between the cost and emission. Results show that the modifications proposed increased the performance of the scatter search algorithm.

The remainder of the paper is organized as follows: Section 2 presents the concepts of scatter search. Section 3 provides the description of the scatter search algorithm and the proposed approach. The description of the formulation of the optimization problem is mentioned in Section 4. Finally, Sections 5 and 6 present the results and conclusions, respectively.

2. Fundamentals of the scatter search

Scatter search is a metaheuristic algorithm that can be considered an evolutionary algorithm in the sense that it incorporates the concept of population. However, SS approaches usually avoid using typical evolutionary operators such as mutation or crossover operators.

SS derives its foundations from earlier strategies for combining decision rules and constraints. Historically, the antecedent strategies for combining decision rules were introduced in the context of scheduling methods to obtain improved local decision rules for job shop scheduling problems. New rules were generated by creating numerically weighted combinations of existing rules, suitably restructured so that their evaluations embodied a common metric [38].

The original SS algorithm has five procedures: i) a diversification generation method to randomly generate diversified trial solutions; ii) an improvement method to converge the current solutions toward the optimum; iii) reference set update method to renew the set of reference solutions with the best ones; iv) a subset generation method to create subsets for the combination method; and v) a combination method to combine the reference solutions and generate new offspring. Next subsections describe each procedure.