Electrical Power and Energy Systems 62 (2014) 665–678

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Weight pattern evaluation for multiobjective hydrothermal generation scheduling using hybrid search technique

Nitin Narang [a,*], J.S. Dhillon [b], D.P. Kothari [c]

[a] Department of Electrical and Instrumentation Engineering, Thapar University, Patiala 147004, Punjab, India
[b] Department of Electrical and Instrumentation Engineering, Sant Longowal Institute of Engineering and Technology, Longowal, Sangrur 148106, Punjab, India
[c] MVSR Engineering College, Hyderabad, India

ARTICLE INFO

Article history:
Received 18 January 2014
Received in revised form 29 April 2014
Accepted 3 May 2014
Available online 11 June 2014

Keywords:
Predator-prey optimization
Hydrothermal generation scheduling
Multi-objective
Powell's pattern search
Weighting method

ABSTRACT

This paper presents best weight pattern evaluation approach to solve short-term multi-objective *hydrothermal generation scheduling* (HTGS) which determines the allocation of power demand among the committed generating units, to minimize operating cost and minimal impacts on environment subjected to physical and technological constraints. A multi-chain interconnected hydro system having non-linear relationship between water discharge rate and power generation is undertaken with due consideration of water transport delay between connected reservoirs. The best weights are computed by conventional statistical measures, which characterize the correlation coefficients matrix evolution. The solution methodology hybridizes global and local search techniques. *Predator-prey optimization* (PPO) is undertaken as a global search technique and *Powell's pattern search* (PPS) is exploited as a local search technique. The results among the competing objectives obtained by the proposed method are compared with various results reported in the literature. The sensitivity and robustness of the proposed technique are evaluated by performing statistical analysis of results obtained based on independent runs. The integration of PPO and PPS improves the quality of solution and convergence characteristics.

1. Introduction

The main objective of short-term HTGS is to minimize thermal units fuel cost by distributing generation to thermal and hydro units optimally while satisfying various equality and inequality constraints. The operating cost of hydro units is insignificant because the source of hydro generation is natural water resources. Thermal units produce significant amount of emission apart from heat, and because of harmful effects of emissions it is necessary to control it. So, HTGS problem should be viewed as *multi-objective optimization problem* (MOOP). Optimization techniques applied to solve HTGS problem are broadly divided into two main categories that are conventional search and global search techniques. Further, conventional search techniques are classified into gradient and direct search methods. Gradient based method requires information about the gradient and higher order gradients of objective functions and on the other side direct search method requires only objective function values to search the optimum solution. It is a known fact that gradient based methods are more efficient if gradient information of objective function is known. But most of the gradient methods are applied to solve the HTGS problem with number of simplifying assumptions in order to make the optimization problem more tractable and simple. Sometimes implications may lead to false global optimum solution by virtue of simplifications. Direct search techniques perform the search by explorative and pattern moves. One of the main disadvantages of direct search method is that when the search space is large or non-convex and function is multimodal, solution may converge to local solution. Several conventional methods have been used for HTGS under practical constraints such as *Dynamic programming* (DP) [1], mixed integer programming [2], Lagrangian relaxation technique [3] and gradient based technique [4]. The realistic models of thermal and hydro units are represented by non-smooth, non-convex characteristics. The conventional techniques are not able to handle these models so a robust solution methodology is required. To find global optimal solution is scrupulous tedious task especially in presence of high dimensionality, non-linearity and multimodality of objective function. In these days, heuristic algorithms are getting attention because of number of exclusive advantages. In the past, researchers have applied many heuristic methods to deal with

* Corresponding author. Tel.: +91 9876576364.
E-mail addresses: nitin.narang4@gmail.com (N. Narang), jsdhillonp@yahoo.com (J.S. Dhillon), dpk0710@yahoo.com (D.P. Kothari).

http://dx.doi.org/10.1016/j.ijepes.2014.05.026
0142-0615/

HTGS problem, such as *particle swarm optimization* (PSO) [5], *differential Evolution* (DE) [6], *clonal selection algorithm* (CSA) [7], *improved quantum PSO* (IQPSO) [8], *self-organizing hierarchical PSO technique with time-varying acceleration coefficients* (SOH-PSO_TVAC) [9], chaotic artificial bee colony [10], *real coded genetic algorithm* (RCGA) [11], with various degree of success.

One of the natural characteristics associated with real-world decision making problem is their inescapably diverse nature. One of the diverse characters of such problem is their multiple objectives that are conflict in nature. With multiple objectives, there is not one unique solution which is best with respect to all objectives but there is a set of solutions which cannot be dominated by any other solutions in the search space. In order to make a tradeoff between conflicting objectives in the multi-objective frame work, many recent heuristic multi-objective evolutionary algorithms have been developed. Several researchers have applied various heuristic techniques to solve multi-objective HTGS problem. Basu [11] and Ke et al. [12] have applied *multi-objective Differential Evolution* (MODE) and *DE based on ε-domination and orthogonal design* (ε-ODEMO) method, respectively to solve HTGS problem. Zhou et al. [13] have presented an algorithm for short-term HTGS problem. They have applied *multi-objective artificial bee colony algorithm* (MOABC) and to further enhance the local search ability of MOABC, progressive optimality algorithm based method is used. Lu and Sun [14] have proposed *quadratic approximation based DE with valuable trade off approach* (QADEVT) to solve the bi-objective HTGS problem. In the proposed approach, the local search *quadratic approximation* (QA) operator is employed along with DE technique to improve the search quality. Zhang et al. [15] have proposed *multi-objective cultural algorithm CA based on PSO* (MOCA-PSO) technique for scheduling problem. In the proposed technique, they have exploited history knowledge structure as a local search operator to search the promising area found by PSO. A *hybrid multi-objective cultural algorithm* (HMOCA) technique is presented to deal with HTGS problem [16]. The proposed method integrates DE algorithm into the framework of CA along with history knowledge structure as a local search operator.

Methodologies used for solving MOOPs, principally differ in two ways, the procedure used to generate non-inferior solutions and the ways and means used to interact with *Decision-maker* (DM) and the type of information made available to the DM such as trade-offs. There are various techniques for generating noninferior solutions [12,17], e.g., weighting method, ε-constraint method, noninferior set estimation method, etc. In weighting method, to obtain a set of non-dominated solutions a number of trails are required [18]. Other methods have been adopted by various researchers i.e., ε-constraint method, interactive fuzzy based method, goal attainment method, price penalty method, etc. provides a set of non-dominated solutions in a single run. The most obvious weakness of ε-constraint method is that it is time-consuming and trends to find weakly non-dominated solutions [18]. An extension of fuzzy interactive method to include more objectives is a very qualm fact. The main disadvantage of goal programming is that it demands a higher effort from the DM. Researchers [5,6] have applied price penalty factor to bundle the fuel cost and emission in HTGS problem. Price penalty factor does not address the conflict issue between different objectives. Marler and Arora [19] have presented concepts, advantages and limitations of current continuous nonlinear multi-objective optimization techniques.

Evolutionary algorithms (EAs) seem suitable to solve MOOPs because these techniques deal simultaneously with a set of possible solutions which allows finding an entire set of Pareto optimal solution in a single run of the algorithm. Additionally, EAs are less suitable to the shape of continuity of the Pareto front. *Non-dominated sorting genetic algorithm* (NSGA-II) encompasses advanced concepts like elitism, fast non-dominated sorting approach and diversity maintenance along the Pareto-optimal front; it still falls short in maintaining lateral diversity and obtaining Pareto-optimal with high uniformity [20]. MODE can deal with simple low-dimensional problem with a fast convergence rate. However, when applied to cope with complicated problems with multiple local optimal fronts, MODE may end up with premature convergence because of the significantly decreasing of population diversity caused by their fast convergence rate [16]. In *multi-objective EA* (MOEA) approach, for large the number of objectives of multiobjective problem, Pareto dominance-based ranking procedures become ineffective in sorting out the quality of solutions. Pierro et al. [21] have investigated the potential of using preference order-based approach as an optimality criterion in the ranking stage of MOEAs. Villalobos-Arias et al. [22] have proposed a mechanism to spread the solutions generated by a multi-objective evolutionary algorithm. The approach is based on the use of stripes that are applied in objective function space and is independent of the search engine adopted. A multiobjective programming algorithm may find multiple non-dominated solutions. If these solutions are scattered more uniformly over the Pareto frontier in the objective space, they are more different choices and so their quality is better. Leung and Wang [23] have proposed a quality measure to measure the uniformity of a given set of non-dominated solutions over the Pareto frontier.

In this article, the solution of MOOP is sought by solving single objective weighted problem. The weighting method [24] is the most common method used for solving MOOPs until recently. It simply assigns different weights to each objective function based on its importance and combines different objectives into single objective function. The association of weights in multi-objective problem is a critical stage of the whole decision making process. A major drawback of weighting method is that there is no rational basis of determining adequate weights. The objective function so formed may lose significance due to combining non-commensurable objectives. Messac [25] has suggested that weights must be functions of the original objectives, not constants, in order for a weighted sum to mimic a preference function accurately. Diakoulaki et al. [26] have proposed a method for determination of objective weights, based on the quantification of two fundamental notions of multi-objective decision method: the contrast intensity and the conflicting character of the evaluation criteria. The extraction and exploitation of these two features is beneficial in the decision making. Singh et al. [17] have evaluated the best weight pattern for multi-objective load dispatch.

Among different EAs, PSO is a salient optimizer which can be applied to a broad variety of highly nonlinear and complex problems. The PSO performance is superior from many other global search techniques because its ability to search optimum solution in a very short computation time [27,28] but it has few shortcomings also. The PSO particles may trap into divergent trajectories if parameters of algorithm have not been properly set [29]. The PSO technique suffers premature convergence when it is applied to solve high dimensional optimization problem [30]. Researchers aim to improve the PSO algorithm in various ways. These amelioration can be classified into five categories: (i) inertial weight varying strategy [30], (ii) parameter selection and convergence analysis [15], (iii) swarm topology structure [31], (iv) discrete PSO [32] and (v) hybrid PSO combined with some evolutionary computation operators and other methods [15]. In the conventional PSO, during the search process, particles may come together near a solution then it is very difficult for particles to get away from the