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Multi-objective artificial bee colony algorithm for short-term scheduling of hydrothermal system

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ABSTRACT

In this paper, we present a multi-objective artificial bee colony (MOABC) algorithm and compare its efficiency with other existing algorithms for short-term scheduling of hydrothermal systems. We formulate the short-term combined economic and emission dispatch of hydrothermal systems as a complicated nonlinear optimization problem with a group of complex constraints. We modify the select operator of artificial bee colony algorithm to adapt the multi-objective problem optimization, and change the employed bee phase and probability calculation of onlooker bee phase to avoid local maxima. Furthermore, we utilize a progressive optimality algorithm based method to enhance the local search ability of the MOABC. Moreover, the constraint handling method has been proposed to resolve the complex constraints. We demonstrate the performance of the MOABC algorithm and compare it with other existing algorithms using the data from a hydrothermal power system in three different cases. The results show that the MOABC can obtain better schedule results with less fuel cost and environment pollution, more close to the true Pareto front and better diversification of non-dominated solutions compared to other existing methods.

1. Introduction

Short-term hydrothermal scheduling (SHS) is an important issue in the economic operation of interconnected power systems. The goal of multi-objective short-term hydrothermal scheduling (MOSHS) is to minimize the both fuel cost and exhaust gas emission of hydrothermal system by determining the water releases of hydropower unit in each scheduling interval while satisfying the various complex constraints including power balance, generation limits, storage and discharge limits and hydraulic network balance. The scheduling period of MOSHS is often set as a day. Since the fossil fuel cost of hydropower unit is negligible, the fuel cost and exhaust gas emission of hydrothermal interconnected power system is related to the power generation of thermal unit. On the other hand, the power demand in each scheduling interval should be satisfied by the sum of hydropower generation and thermal generation while taking the power transmission loss into account.

SHS is an active research field in recent decades. Various optimization techniques have been developed to resolve the SHS problem. Traditional mathematical method including Lagrange relaxation (LR) [1–3], dynamic programming (DP) [4], network flow (NF) [5] had been applied for resolving this complex optimization problem. However, the SHS problem is a non-linear, non-convex, multi-dimensional problem with a set of complicated constraints. These traditional mathematical programming methods faced various weaknesses when they had been used to solve the SHS problem. LR suffered from the oscillation of initial solution, and the optimization effective greatly affected by the updating strategy of Lagrange multiple. The phenomenon named "Curse of the dimensionality" occurred when DP had been applied to resolve the SHS problem because the computational complexity increases dramatically while the dimension of interconnected power system increasing. When NF had been applied in modeling, the complex model would make the optimization of problem a difficult task.

In order to resolve the non-linear and non-convex characteristics of SHS, the modern heuristic stochastic search technique had been developed such as artificial neural network (ANN) [6,7], evolutionary programming (EP) [8–10], genetic algorithm (GA) [11–16], artificial immune system (AIS) [17], differential evolution (DE) [18–24], cultural algorithm (CA) [25,26], particle swarm optimization (PSO) [27–30], harmony search [31].

These methods do not require the continuous and differentiable properties of problem and perform well on solving SHS problem. However, the convergence of algorithm on finding the optimal solution in limited iteration number is irresponsible because of the characteristics of modern heuristic stochastic search technique. In another word, the algorithm is easy to be trapped in local optimal. Furthermore, all these methods motioned above are designed to solve the single object optimization problem.

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Some literatures [10,30,32–34] use the weighting method or constraints conversion to handle the MOSHS problem. The multi-objective problem had been converted to single objective problem through these methods. Thus, the optimization problem in these literatures is a single objective optimization problem essentially. The drawbacks of these methods are obvious. Only one non-dominated solution had been obtained by each computation. Moreover, multiple calculations are necessary so as to obtain the Pareto optimal front. Even so, the regional distribution of these Pareto optimal solutions cannot be guaranteed.

In order to overcome the drawbacks mentioned above and make a tradeoff between the conflicting objectives in the multi-objectives optimal problem, many modern heuristics multi-objective evolutionary algorithms (MOEA) had been developed such as non-dominated sorting genetic algorithm-II (NSGA-II) [35], enhanced strength Pareto evolutionary algorithm (SPEA2) [36] multi-objective particle swarm optimization algorithm (MOPSO) [37] multi-objective differential evolution algorithm (MODE) [38]. These methods had been applied to solve the multi objective optimization (MOO) problem and perform the effectiveness on some level. Instead of keeping only one optimal solution in each cycle, a group of Pareto optimal solutions named non-dominated set is adopted by MOEA to keep the Pareto optimal solutions. The non-dominated set mechanism ensures that the algorithm could keep the elite solution and increase the efficiency of computation. However, these methods still have some weakness and the performances are not good enough when they have been applied to resolve the MOSHS problem. Because of the algorithm is based on evolutionary mechanism, these methods still suffered from the premature convergence problem and the convergence rate and the distribution of non-dominated solutions are not satisfactory simultaneously. Above all, these methods cannot guarantee the non-dominated set converges to the true Pareto front due to their drawbacks. NSGA-II and SPEA2 draw inspiration from GA, the algorithm still suffered from premature convergence. MOPSO and MODE can deal the multi-objective optimization problem when dimension is low. However, when the dimension of problem increased, the population diversity gets worse dramatically.

Recently, a new swarm intelligence algorithm named artificial bee colony (ABC) [39] had been proved to be effective on solving the optimization problem. The ABC algorithm simulates the honey bee foraging behavior in natural environment and show the great potential and good performance for resolving optimization problem. Simulated with other swarm intelligent algorithm, ABC still suffered from the premature convergence. In order to handle this defect, some researchers [40–43], modified the operator of ABC and applied to resolve SHS problem. However, ABC algorithm is designed for single objective optimization problem, structure of algorithm need to be improved to adapt to the MOO problem. *Moreover, some researchers focus on the Pareto-based artificial bee algorithm. Literature [44] presented an MOABC algorithm which used ε-dominance method to update the archive and tested by a set of benchmark functions.* A *vector evaluated ABC are proposed in [45] and tested by the multi-objective composite design problem. The adaptive windowing mechanism and crowding distance mechanism were adopted in updating archive in the proposed MOABC [46] and verified by a set of test problems. A non-dominated sorting ABC was proposed in [47] and used to resolve the burdening optimization of copper strip production. The strategy of updating archive is crowding distance. In literature [48], crossover operator, local search and non-dominated sorting technique had been combined with ABC algorithm to resolve the flexible job shop scheduling problem. However, most these methods did not consider the local search mechanism in the MOABC and some methods only tested by benchmark functions, and the effectiveness needs to be proved by complex MOSHS issue such as hydrothermal scheduling. In addition, the constraint handling method is different because the various multi-objective optimization problems.* Thus, we propose the multi-objective artificial bee colony algorithm (MOABC) to cope with the MOO problem in this paper. The proposed method modifies the original ABC to enhance the efficiency of convergence and overcome the problem of premature convergence. Additionally, the global optimal solution has been replaced by an external archives set to reserve the elite solutions. The proposed algorithm has the ability to acquire as close as possible solutions to the real Pareto front due to the external archives set updating mechanism. In order to enhance the search ability of MOABC, a local search strategy based on progressive optimality algorithm (POA) has been adopted. In this paper, the proposed MOABC algorithm and previous study [49] both has been applied to solve the MOSHS problem of a hydrothermal interconnected power system including four hydro units and three thermal units. The results demonstrate the effectiveness and efficiency of MOABC algorithm on resolving the MOSHS problem.

The rest of paper is organized as follow: Section 2 is the problem formulation of multi-objective scheduling of hydro-thermal power system. An overview of artificial bee colony algorithm is given in Section 3. Section 4 is the detailed introduction of multi-objective artificial bee algorithm. Section 5 is the implementation processes of MOABC for MOSHS problem. The previous method and MOABC applying in an interconnected power system is compared and analyzed in Section 6. Section 7 is the conclusion of this article.

2. Problem formulation

Multi-objectives short-term hydrothermal scheduling problem of power system is a nonlinear optimization problem which takes both the economic and emission as objectives. Considering the various complex equality and inequality constraints, the goal of MOSHS problem is to find a set of water release of hydro units and power generation of thermal units in each scheduling interval, typically an hour, in order to minimize both the emission and fuel cost.

2.1. Objectives

2.1.1. Economy

Traditionally, economic object is minimizing the total fuel cost of hydrothermal power system through the whole scheduling period. The objective function can be formulated as a quadratic function of the thermal unit power as follow:

$$F_1 = \min \sum_{t=1}^{T}\sum_{i=1}^{N_s} a_i + b_i P_{si}^t + c_i (P_{si}^t)^2 \tag{1}$$

where T represents the total number of scheduling intervals. N_s is the total number of thermal units P_{si}^t is the output of thermal unit i in scheduling interval t, and a_i, b_i, c_i, represent the coefficient of thermal generating power respectively.

Nonetheless, the objective function above is out of accord with the real power generation situation. Considering the value point effects, the formulation of total fuel cost can be modified as below:

$$F_1 = \min \sum_{t=1}^{T}\sum_{i=1}^{N_s} \{a_i + b_i P_{si}^t + c_i (P_{si}^t)^2 + |d_i \sin[e_i(P_{si}^{\min} - P_{si}^t)]|\} \tag{2}$$

where d_i, e_i represents the value point effects coefficients of the thermal plant i. $P_{si}^{\min}$ is the minimal power generation limit of thermal plant i.