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Cultural quantum-behaved particle swarm optimization for environmental/economic dispatch☆

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ABSTRACT

In this paper, a novel CMOQPSO algorithm is proposed, in which cultural evolution mechanism is introduced into quantum-behaved particle swarm optimization (QPSO) to solve multiobjective environmental/economic dispatch (EED) problems. There are growing concerns about the ability of QPSO to handle multiobjective optimization problems. Two important issues in extending QPSO to multiobjective context are the construction of exemplar positions for each particle and the maintenance of population diversity. In the proposed CMOQPSO, one particle is measured for multiple times at each iteration in order to enhance its global searching ability. Belief space, which is based on cultural evolution mechanism and contains different types of knowledge extracted from the particle swarm, is adopted to generate global best positions for the multiple measurements of each particle. Moreover, to maintain population diversity and avoid premature, a novel local search operator, which is based on the knowledge in belief space, is proposed in this paper. CMOQPSO is compared with several state-of-art algorithms and tested on EED systems with 6 and 40 generators respectively. The comparative results demonstrate the effectiveness of the proposed algorithm.

1. Introduction

Economic dispatch (ED) can be formulated as a nonlinear constraint problem which aims to minimize the total fuel cost while satisfying several equal and unequal constraints by operating electric power systems. However, power generators using fossil fuel release some contaminants, which are the major contributors to air pollution. With the rising of public awareness of environmental protection, air pollution has become another important consideration in allocating optimal outputs of power generators. In this case, ED has been changed into an environmental/economic dispatch (EED) [1] problem. EED minimizes total fuel cost and pollution emission simultaneously and can be seen as a nonlinear multiobjective optimization problem with several constraints.

Various algorithms have been proposed to solve EED problems. These algorithms can be classified into two categories. For the first category, EED has been treated as a single objective problem by using different strategies. In [2], EED has been reduced to a single objective problem by considering pollution emission as a constraint. The algorithm is implemented without considering the tradeoff between fuel cost and emission. In addition, only a single solution can be obtained in an independent run by the algorithm. In [3], ϵ-constraint method has been proposed to solve multiobjective problems. In ϵ-constraint method, the most preferred objective is optimized and the other objectives are treated as constraints bounded by allowable levels. In [4], a new algorithm based on ϵ-constraint method is proposed to solve EED problems. The most obvious weakness of the algorithm is that it is time-consuming and tends to find weakly nondominated solutions. In [5–7], EED is treated as a single objective optimization problem by the linear combination of all the objectives. A set of nondominated solutions can be obtained by using different weight parameters. So in order to get a Pareto front, multiple runs are required. The algorithms belong to the second category deal with the two objectives in EED simultaneously. In [8], a fuzzy satisfaction-maximizing decision approach has been proposed to solve EED problems. In [9], a multiobjective stochastic search technique has been introduced for solving EED. The major drawback of the technique is that it is time-consuming and easily trapped into local optima. Because of the robustness and parallelism, evolutionary algorithms (EAs) have been applied to solve various kinds of optimization problems

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successfully [10–13]. Recently, using multiobjective EAs to solve EED problems has aroused general concern. Many evolutionary algorithms have been adopted to solve EED problems successfully, such as niched Pareto genetic algorithm (NPGA) [14], strength Pareto evolutionary algorithm (SPEA) [15], non-dominated sorting genetic algorithm (NSGA) [16], differential evolution algorithm (DE) [17–19], estimation of distribution algorithm (EDA) [20], and so on.

Particle swarm optimization (PSO), a population-based stochastic searching technology, was firstly proposed in 1995 [21]. Owing to its simplicity and facile realization, PSO has been widely used in dealing with many real-world problems [22–29]. However, some studies have demonstrated that global convergence cannot be guaranteed in a PSO system [30,31]. In order to overcome this disadvantage of PSO, quantum-behaved particle swarm optimization (QPSO) is proposed [32]. QPSO has been proved to be global convergent according to the analysis in [33]. Recently, quantum-behaved particle swarm optimization (QPSO) has attracted more and more attention. In QPSO, a significant parameter that can influence the measurement (update) of a particle is its attractor position, which is constructed by the particle's personal and global best positions. In multiobjective optimization, it is hard to find the best individual which could optimize all the objectives simultaneously, since the objectives are mutually conflictive. So, how to obtain particles' personal and global best positions is the major problem needs to be solved in extending QPSO to multiobjective context. In [34], a classic multiobjective QPSO, called MOQPSO, is proposed. In MOQPSO, a modified sigma method is adopted to generate the global best position for each particle. Another problem that can affect the performance of QPSO in optimizing multiobjective problems is the population diversity. With poor population diversity, it is easy for QPSO to fall into local optima and run into premature.

In this paper, a novel CMOQPSO algorithm is proposed, in which cultural evolution mechanism [35] is introduced into QPSO to solve the two above-mentioned problems. The main differences between CMOQPSO and traditional QPSO are listed below.

(a) Inspired by cultural evolution mechanism, belief space, which contains three types of knowledge extracted from particle swarm, is adopted in CMOQPSO.
(b) In CMOQPSO, each particle is measured for multiple times at a single iteration. If the tested problem has M objectives, then each particle will be measured for $M+1$ times. The first M measurements only consider one objective separately. For example, the 1st measurement focuses on the 1st objective, the 2nd measurement focuses on the 2nd objective, and so on. The last measurement (($M+1$)th measurement) takes into account all the objectives. For each particle, the global best positions of the $M+1$ measurements can be obtained by using the knowledge in belief space. Multiple measurements can enhance the global searching ability of the algorithm.
(c) A novel local search operator, which is guided by the knowledge in belief space, is proposed to maintain population diversity and avoid premature convergence in this paper.

To summarize, in the proposed CMOQPSO, each particle is measured for multiple times. The global best position for each measurement can be obtained according to the knowledge in belief space. So, there exists a continuous cycle between particle swarm and belief space. Specifically, the knowledge in belief space is extracted from particle swarm and then the particles are measured (updated) according to the knowledge stored in belief space. Moreover, a local search operator, which is guided by the knowledge in belief space, is proposed to maintain population diversity and avoid premature convergence. In this paper, belief space contains three types of knowledge, namely situational knowledge, topographical knowledge and history knowledge. Situational and topographical knowledge is used to generate global best position for each measurement. Topographical knowledge is adopted in the proposed local search operator. The detailed description of CMOQPSO has been given in Section 3.3.

The proposed algorithm is adopted to solve EED problems and tested on two EED systems. The contents of this paper are organized as follows. Section 2 introduces the formulation of EED problems. Section 3 gives the detailed description of CMOQPSO for solving EED problems. Section 4 shows the comparative experiments and achieved results. Section 5 draws the concluding remarks.

2. Formulation of EED problems

EED can be formulated as a constrained multiobjective problem which minimizes two conflicting objectives, i.e. the total fuel cost and the emission of harmful pollutants of the tested power system.

2.1. Objective functions

2.1.1. Fuel cost function

The total fuel cost can be calculated as a quadratic function, which is shown in Eq. (1). Where, P_i and $F(P_i)$ are the power output and the fuel cost of the ith generator respectively. N_g is the number of generators in power system.

$$\min \sum_{i=1}^{N_g} F(P_i) = \sum_{i=1}^{N_g} (a_i + b_i P_i + c_i P_i^2) \tag{1}$$

Taking into account the practical operating conditions of power generators, the fuel cost function can be modified by adding a nonlinear sinusoid function as shown in Eq. (2) [36]. Where, a_i, b_i, c_i, d_i and e_i are the fuel cost coefficients of the ith generator. $P_i^{\min}$ is the minimized power output of the ith generator.

$$\min \sum_{i=1}^{N_g} F(P_i) = \sum_{i=1}^{N_g} (a_i + b_i P_i + c_i P_i^2 + |e_i \sin(d_i(P_i^{\min} - P_i))|) \tag{2}$$

2.1.2. Emission function

The total emission of harmful pollutants can be calculated by Eq. (3) [37]. Where, α_i, β_i, γ_i, ε_i and λ_i are the emission coefficients of the ith generator.

$$\min \sum_{i=1}^{N_g} E(P_i) = \sum_{i=1}^{N_g} (\alpha_i + \beta_i P_i + \gamma_i P_i^2 + \varepsilon_i e^{\lambda_i P_i}) \tag{3}$$

2.2. Constraints

2.2.1. Output constraint of each generator

The output of each generator must be within the given range. That is, the following constraint, as shown in Eq. (4), must be satisfied for each generator. Where, $P_i^{\min}$ and $P_i^{\max}$ are the boundary values. P_i is the output of the ith generator.

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{4}$$

2.2.2. Power balance constraint of system

The power balance constraint can be formulated as Eq. (5). P_D is total demand and P_{Loss} is total transmission loss.

$$\sum_{i=1}^{N_g} P_i = P_D + P_{Loss} \tag{5}$$