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Multi-strategy ensemble biogeography-based optimization for economic dispatch problems

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HIGHLIGHTS

- New method to solve convex and non-convex economic dispatch problems using MsEBBO.
- MsEBBO is able to balance the global exploration and the local exploitation.
- Considering valve-point effects, ramp rate limits, prohibited operating zones.
- An effective repair technique for handling different constraints is proposed.
- The sensitivity of MsEBBO to variations in population size is investigated.

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ABSTRACT

Economic dispatch (ED) is an important task in power system operation. It is able to decrease the operating cost, save energy resources, and reduce environmental load. In this paper, a multi-strategy ensemble biogeography-based optimization (MsEBBO) based method for ED problems is proposed. BBO is a population-based meta-heuristic algorithm inspired by the science of biogeography and mainly consists of three components: migration model, migration operator, and mutation operator. It has good local exploitation ability but lacks satisfactory global exploration ability. To keep a proper balance between exploration and exploitation, MsEBBO has three extensions to BBO's three components according to the no free lunch theorem. First, a nonlinear migration model based on sinusoidal curve is employed. Second, a backup migration operator through adopting a backup strategy to combine perturb operator and blended operator is presented. This operator can make the entire population fully exchange or share information and thus further strengthen the exploitation ability. Finally, both differential mutation and Lévy local search are embedded as mutation operator for MsEBBO using a similar backup strategy. Gaining from this mutation operator, MsEBBO can be accelerated to escape from local optima and perform efficient search within global range. Additionally, an effective repair technique is proposed to handle different constraints of ED problems. The performance of MsEBBO is tested on four ED problems with diverse complexities. Experimental results and comparisons with other recently reported ED solution methods confirm that MsEBBO is capable of yielding a good balance between exploration and exploitation, and obtaining competitive solution quality. Moreover, the sensitivity of MsEBBO to variations in population size is investigated as well.

1. Introduction

Shortage of energy resources, deterioration of environment, rising power generation cost, and increasing electric energy demand necessitate optimal economic dispatch (ED) in today's competitive power market. The objective of ED problem of electric power generation is to schedule the committed generators' outputs so as to meet the required load demand at minimum operating cost while satisfying all generator and system equality and inequality constraints [1]. Accurate and intelligent scheduling of the generators can not only save an enormous amount of revenue but also lead to massive reduction in greenhouse gas emission and in the rate of consumption of energy resources. As one of the key functions of the modern energy management system, ED has been seen as the kernel of a power system [2]. It is so important that many researchers have devoted themselves to design efficient and robust solutions. Up to now, existing methods can be roughly divided into two categories: conventional methods and modern heuristic methods. Conventional methods, including linear programming method,

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nonlinear programming method, lambda iteration method, Lagrange relaxation algorithm, etc., require that the incremental generation cost curves should be piecewise linear and monotonically increasing. Unfortunately, the practical ED problems exhibit heavily nonlinear and non-convex characteristics in virtue of valve-point effects, prohibited operating zones, etc. In this context, the aforementioned conventional methods are easy to be trapped into local optima or fail to offer adequate solutions at all. Although the dynamic programming method [3] can solve the ED problems without imposing any restrictions on the nature of the cost curves, it suffers from the "curse of dimensionality" resulting in enormous computational efforts.

As an alternative to the conventional methods, modern heuristic methods have gained much attention and been well developed for solving ED problems in the past two decades. Compared with the conventional methods, they have many advantages, such as global search capability, no requirement of specific domain information, no requirement for a differentiable or continuous objective function, and easy implementation. These methods include genetic algorithm [4–7], evolutionary programming [8], neural networks [9], particle swarm optimization [10–15], differential evolution [16], artificial bee colony [17], bacterial foraging [18], biogeography-based optimization [19,20], etc.

Biogeography-based optimization (BBO), which was introduced by Simon [21] in 2008, is a kind of optimization technique based on the equilibrium theory of island biogeography. BBO mainly consists of three components: migration model, migration operator, and mutation operator. In BBO, problem solutions are represented as islands. It operates by probabilistically sharing information between individuals in a population of candidate solutions just like species migrate back and forth between islands. It uses individuals' fitness values to calculate their immigration and emigration rates for each generation, making poor individuals have a high probability of accepting new features from good individuals to improve their quality.

For a population-based evolutionary algorithm, it is well known that both exploration (i.e. the global search) and exploitation (i.e. the local search) are crucial. Benefiting from efficient information sharing mechanism, i.e., migration operator, BBO has good exploitation ability. However, lacking satisfactory exploration makes it converge slowly and easy to fall into a local optimum. According to the no free lunch theorem [22], no single strategy can consistently perform the best for every problem throughout the evolution process. To balance the exploration and the exploitation of BBO, a multi-strategy ensemble BBO (MsEBBO) is proposed. Five strategies, i.e., sinusoidal migration model, perturb operator, blended operator, differential mutation, and Lévy local search, are imbedded into MsEBBO, bringing three extensions to the three aspects of BBO. The purpose of the ensemble, which is based on the no free lunch theorem, is efficient use of these five strategies to give full play to the roles of the migration model, migration operator, and mutation operator. In addition, since the ED problems have different constraints, such as active power balance constraint, generation capacity constraints, ramp rate limits, and prohibited operating zones, therefore, an effective repair approach is proposed to handle these constraints. The validity of the proposed MsEBBO method has been tested on four different ED problems.

The rest of this paper is organized as follows. Section 2 describes the formulation of ED problems. Section 3 gives simple description of BBO. The proposed method, MsEBBO, and its implementation for ED problems are elaborated in Sections 4 and 5, respectively. In Section 6, the MsEBBO is verified on four cases and Section 7 concludes this paper.

2. Formulation of ED problems

2.1. Objective function

2.1.1. Traditional objective function

The objective function of traditional ED problem can be approximately represented by a single quadratic function:

$$\min \quad cost = \sum_{i=1}^{N_g} F_i(P_i) \tag{1}$$

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \tag{2}$$

where $cost$ is the total generation cost (in \$/h); N_g is the number of generators; P_i is the power output of the ith generator (in MW); $F_i(P_i)$ is the fuel cost function of the ith generator (in \$/h); a_i, b_i, c_i are fuel cost coefficients of the ith generator.

2.1.2. Objective function with valve-point effects

In practice, the generators with multi-valve stream turbines have valve-point effects. Modelling valve-point effects on the performance and cost of power generators for ED problems is necessary [23]. The objective function of ED problem with valve-point effects can be written as follows:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + |e_i + \sin(f_i \times (P_{i,\min} - P_i))| \tag{3}$$

where e_i, f_i are non-smooth fuel cost coefficients of the ith generator with valve-point effects; $P_{i,\min}$ is the minimum power generation limit of the ith generator (in MW).

2.2. Equality and inequality constraints

The ED problems should satisfy the following equality and inequality constraints.

2.2.1. Active power balance constraint

The total generated power should be equal to the total system demand (P_D) plus the total transmission network loss (P_L):

$$\sum_{i=1}^{N_g} P_i = P_D + P_L \tag{4}$$

where P_L can be calculated using B coefficients as follows:

$$P_L = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_i B_{ij} P_j + \sum_{i=1}^{N_g} B_{0i} P_i + B_{00} \tag{5}$$

where B_{ij}, B_{0i}, B_{00} are loss coefficients.

2.2.2. Generation capacity constraints

The power output of each generator should be within its minimum and maximum limits, i.e.,

$$P_{i,\min} \leqslant P_i \leqslant P_{i,\max} \tag{6}$$

2.2.3. Ramp rate limits

The adjustment of generation output should be in an acceptable range and is limited by the corresponding ramp rate limits, i.e.,

$$P_i - P_i^{\mathrm{pr}} \leqslant UR_i \quad \text{and} \quad P_i^{\mathrm{pr}} - P_i \leqslant DR_i \tag{7}$$

where P_i^{pr} is the previous generation output of the ith generator; UR_i and DR_i are the up-ramp and down-ramp limits of the ith generator, respectively.

When simultaneously considering the ramp rate limits and generation capacity constraints, (6) and (7) can be merged and rewritten as follows:

$$\max\{P_{i,\min}, P_i^{\mathrm{pr}} - UR_i\} \leqslant P_i \leqslant \min\{P_{i,\max}, P_i^{\mathrm{pr}} + DR_i\} \tag{8}$$