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A social spider algorithm for solving the non-convex economic load dispatch problem

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ABSTRACT

Economic Load Dispatch (ELD) is one of the essential components in power system control and operation. Although conventional ELD formulation can be solved using mathematical programming techniques, modern power system introduces new models of the power units which are non-convex, non-differentiable, and sometimes non-continuous. In order to solve such non-convex ELD problems, in this paper we propose a new approach based on the Social Spider Algorithm (SSA). The classical SSA is modified and enhanced to adapt to the unique characteristics of ELD problems, e.g., valve-point effects, multi-fuel operations, prohibited operating zones, and line losses. To demonstrate the superiority of our proposed approach, five widely adopted test systems are employed and the simulation results are compared with the state-of-the-art algorithms. In addition, the parameter sensitivity is illustrated by a series of simulations. The simulation results show that SSA can solve ELD problems effectively and efficiently.

1. Introduction

Economic Load Dispatch (ELD) is a fundamental problem in power system control and operation. The goal of ELD is to find a best feasible power generation schedule with a minimal fuel cost, while satisfying the generation constraints of the power units [1]. In the canonical formulation of ELD, the fuel costs of power units are represented by quadratic functions, which are convex and can be easily solved using mathematical programming methods. Many classical methods have been employed to solve ELD in the past decades, e.g., the gradient method [2], the lambda iteration method [3], and quadratic programming [4]. These methods have also been employed to solve other optimization problems in power system like the Unit Commitment problem [5] and the Optimal Power Flow problem [6].

Although the convex, differentiable, and monotonically increasing canonical formulation of ELD is simple to solve, it is unrealistic because valve-point effects (VPE), multi-fuel options (MFO), and prohibited operating zones (POZ) are not considered. However, all these factors shall be accounted for in the real-world industrial production process. Incorporating these factors, the modern ELD is represented by a non-convex, non-continuous, and non-differentiable optimization problem with many equality and inequality constraints, making it very challenging to find the global optimum solution. For the sake of simplicity, ELD is used to refer to the modern formulation of the problem hereafter.

Despite the complexity of the problem, a number of techniques have been devised to solve ELD in the past decade, e.g., Tabu search [7], Taguchi method [8], and variants of particle swarm optimization [9,10]. Evolutionary algorithms (EAs) also play an important role in solving ELD problems. Currently most state-of-the-art solvers for ELD are EAs and their variants according to the analysis in [11].

Social Spider Algorithm (SSA) is a recently proposed evolutionary algorithm to solve global numerical optimization problems [12]. By mimicking the foraging behavior of the social spiders, SSA explores and exploits the solution space in an iterative manner. In the formulation of SSA, searching information is propagated among the individuals, i.e., spiders, through the means of vibrations, which are lossy. In addition to this lossy information feature, SSA also incorporates a new social animal foraging model, namely, the information sharing model [13]. In this model, individuals in a population perform searching and joining behaviors simultaneously, which could potentially result in improved searching efficiency [12,14]. The reasons leading to the outstanding performance of SSA have been investigated in [12], and the improvements are mainly credited to the unique design of the information loss scheme and the searching pattern. Besides its superiority in solving optimization benchmark problems [12], SSA has also demonstrated its potential to be applied to address real world complex optimization problems [15]. This makes it a good candidate to generate outstanding power schedules for ELD.

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In this paper, we propose a variant of SSA to solve ELD problem, accounting for VPE, MFO, POZ, and power line loss. The advantage of our proposed algorithm is that it can generate more cost-efficient power schedules when compared with other algorithms. The rest of the paper is organized as follows. We first introduce the related work in Section 2. Section 3 presents the formulation of ELD with VPE, MFO, POZ, and power line loss. Our proposed algorithm is elaborated in Section 4, and simulation problems, results, and comparisons are shown in Section 5. Finally we conclude this paper in Section 6.

2. Related work

Over the past decades, many methods have been developed to solve ELD. Lin and Viviani proposed a hierarchical numerical method to solve the economic dispatch problem with piecewise quadratic cost functions [16]. In this work the authors considered multiple intersecting cost functions for each generator, which is an analogy of MFO. A similar formulation of the problem is addressed by Park et al. [17] with hopfield neural networks. This work is among the first attempts of adopting computational intelligence methodologies in solving ELD. Lee et al. later proposed an adaptive hopfield neural network to solve the same problem [18]. Their algorithm introduced a slope adjustment and bias adjustment method to speed up the convergence of the hopfield neural network system with adaptive learning rates. Lee and Breipohl proposed a decomposition technique to solve ELD with POZ [19]. Their algorithm decomposes the nonconvex decision space into subsets which can be solved via the conventional Lagrangian relaxation approach. Binetti proposed a distributed algorithm based on the auction techniques and consensus protocols to solve ELD [20]. In their work, each power unit locally evaluates its possible fuel costs as bids. The bids are later employed in the auction mechanism to come up with a consensus. A very recent work by Zhan et al. proposed a dimensional steepest decline method [11]. This method utilizes the local minimum analysis of the ELD problem to reduce the solution space to singular points.

Besides the above non-EA approaches, many EA methods have also been developed to solve various formulations of ELD. Orero and Irving proposed a simple Genetic Algorithm (GA) to solve ELD with POZ [21]. Besides the standard GA, this work also devised a deterministic crowding GA model to solve the problem. Chiang developed an improved GA with the multiplier updating scheme for ELD with VPE and MFO [22]. In this work, the proposed GA is incorporated with an improved evolutionary direction operator. In addition, the tailor-made migration operator efficiently searches the solution space. He et al. proposed a hybrid GA approach to solve ELD with VPE [23]. The algorithm proposed is a hybrid GA with differential evolution (DE) and sequential quadratic programming (SQP). Sinha et al. developed an Evolutionary Programming (EP) method to solve ELP with VPE [24]. Pereira-Neto et al. proposed an Evolutionary Strategy (ES) method to solve ELP with VPE and POZ [25]. DE has also been adapted to solve ELD [26,27].

Swarm Intelligence (SI), a branch of EA, has also attracted researchers' attention. Particle Swarm Optimization (PSO) has made a significant contribution in solving ELD problems. Selvakumar and Thanushkodi proposed a "new PSO" based on the classical PSO for ELD with VPE, MFO, and POZ [28]. They manipulated the cognitive searching behavior in PSO to facilitate the solution space exploration. They also proposed an anti-predatory PSO in [29]. In this algorithm, a new anti-predator scheme is modeled and introduced in the classical PSO. Chaturvedi et al. proposed a hierarchical PSO for ELD with VPE and POZ [30]. In this work, a time-varying acceleration coefficient is introduced to act as the inertia factor of PSO. Meng et al. proposed a Quantum PSO for ELD with VPE [31]. Their algorithm demonstrated strong searching ability and fast convergence speed, which are contributed by the introduction of quantum computing theory, self-adaptive probability selection, and chaotic sequence mutation. Safari and Shayeghi developed an Iteration PSO for ELD with VPE and POZ [32]. Besides the conventional global best (*gBest*) and personal best (*pBest*) positions considered in canonical PSO, the proposed algorithm also considers an iteration best (*iBest*) position in the searching process. Nature-inspired EAs also yield satisfactory results in solving ELD variants. Some outstanding ones are Bee Colony Optimization Algorithm [33], Biogeography-Based Optimization [34], Ant Swarm Optimization [35], Harmony Search Algorithm [36], and Chemical Reaction Optimization [37].

3. Economic load dispatch problem

The objective of the ELD problem is to find an optimal power generation schedule with minimal fuel cost while satisfying different power system operating constraints, including power unit and load balancing constraints. In this paper we adopt the formulation described in [11] and [37]. The problem is formulated on one-hour time spans.

3.1. Objective function

The objective function of ELD is defined as follows:

$$\min_{P} \sum_{i=1}^{n} F_i^c(P_i), \tag{1}$$

where n is the total number of power units, $F_i^c(P_i)$ is the fuel cost function for the ith power unit, and P_i is the power generation for the ith power unit according to the power generation schedule.

3.1.1. Valve-point effect

Conventionally the fuel cost of power units are formulated by a quadratic function with the following form:

$$F_i^c = a_i + b_i P_i + c_i P_i^2, \tag{2}$$

where a, b, and c are constant coefficients determined by the physical characteristics of the power units. However, the fuel cost function exhibits a larger variation in practice due to VPE, which generates ripple like effect during the valve-opening process of multi-valve units. A more precise formulation with both a quadratic component and a rectified sinusoidal component is adopted. In (1), the fuel cost is defined by

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

where e and f are new coefficients describing VPE, and P_i^{min} is the minimum power generation for the ith power unit in the system.

3.1.2. Multi-fuel options

Modern power units can be operated with multiple fuels [11], and each fuel has a different fuel cost function. The unit will always utilize the fuel with a minimum fuel cost given a specified power generation requirement. Thus the fuel cost defined in (3) is further modified to reflect the effects of multiple fuel options. A piecewise quadratic function is adopted to calculate the fuel cost of such power units, defined as follows:

$$\begin{aligned} F_i^c = \min(&a_{i,1} + b_{i,1} P_i + c_{i,1} P_i^2 + |e_{i,1} \sin(f_{i,1}(P_i^{min}) - P_i)|, \\ &a_{i,2} + b_{i,2} P_i + c_{i,2} P_i^2 + |e_{i,2} \sin(f_{i,2}(P_i^{min}) - P_i)|, \\ &\ldots, \\ &a_{i,h} + b_{i,h} P_i + c_{i,h} P_i^2 + |e_{i,h} \sin(f_{i,h}(P_i^{min}) - P_i)|), \end{aligned} \tag{4}$$

where $a_{i,k}$, $b_{i,k}$, $c_{i,k}$, $e_{i,k}$, and $f_{i,k}$ are the fuel cost coefficients of the kth fuel option of the ith power unit, and h is the total number of fuel options. Note that our formulation of MFO is different from