Enhanced Bee Swarm Optimization Algorithm for Dynamic Economic Dispatch

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***Abstract*—This paper proposes an enhanced bee swarm optimization method to solve the dynamic economic dispatch problem of thermal units considering the valve-point effects, ramp-rate limits, and the transmission power losses. The bee swarm optimization algorithm unlike most of the population-based algorithms employs different moving patterns to search the feasible solution space. This property makes an effective balance between exploration and exploitation. Different modifications in moving patterns of the bee swarm optimization method are proposed to search the feasible space more effectively. The efficiency of the method is validated using three test systems with 10, 30, and 60 units, including 240, 720, and 1440 design variables. The latter can be considered as a large-scale power system. The results are compared with other reported works in this area and found to be superior.**

***Index Terms*—Dynamic economic dispatch (DED), enhanced bee swarm optimization (EBSO), ramp-rate limits, valve-point effects.**

Nomenclature

Indices

i	Thermal generating units (TGU) index.
t	Time interval (hour) index.
k	Iteration index of enhanced bee swarm optimization (EBSO).
v	Experienced forager bee index.
h	Onlooker bee index.
q	Scout bee index.
j	Bees index.

Constants

N	Number of TGUs.
NT	Number of time intervals.
$a_i, b_i, c_i, d_i, e_i, h_i$	Cost coefficients of the ith TGU.
$B_{i,j}$	Loss coefficients between ith and jth generators (MW^{-1}).
$p_{i\max}, p_{i\min}$	Maximum and minimum power output of the ith TGU, respectively (MW).
UR_i	Ramp-up rate of the ith TGU (MW/h).
DR_i	Ramp-down rate of the ith TGU (MW/h).
$p_{i\max}^t, p_{i\min}^t$	Maximum and minimum power output of the ith TGU at time t, respectively (MW).
$n(\zeta)$	Number of the experienced forager bees.
$Iter_{\max}$	Maximum iteration number.
$Iter$	Current iteration.

Variables

p_i^t	Generation output of the ith TGU at time t (MW).
P_D^t	Load demand at time t (MW).
P_{Loss}^t	The system total real power losses at time t (MW).
$F(\mathbf{P})$	Total fuel cost of generation of all TGUs through dispatch periods (\$).
$f_i(p_i^t)$	Total fuel cost of generation of ith TGU at time t (\$).
$P(\beta, j)^t$	Position of the jth bee in the set of β at time t.
$P(\zeta, v)^t$	Position of the vth bee in the set of ζ at time t.
$P(\chi, h)^t$	Position of the hth bee in the set of χ at time t.
$P(\vartheta, q)^t$	Position of the qth bee in set ϑ at time t.
w_b	Cognitive weight factor.
w_g	Social weight factor.
$w_{\text{bmin}}, w_{\text{bmax}}$	Minimum and maximum values of the cognitive weight factors, respectively.
$w_{\text{gmin}}, w_{\text{gmax}}$	Minimum and maximum values of the social weight factors, respectively.
r	Random number with uniform distribution between 0 and 1.

Sets

ϑ	Scout bees.
χ	Onlooker bees.
ζ	Forager bees.
β	Total number of the bees.

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I. Introduction

Dynamic economic dispatch (DED) is one of the major optimization issues in power system operations. Its objective is to allocate the forecasted load demand over a certain period of time among available generators in the best economical manner, while all physical and operational constraints are satisfied. Considering different constraints for the purpose of more precise modeling, the DED shows nonconvex characteristics [1], [2].

Different methods are proposed in the literature for coping with the DED problem. Traditional methods [3] and [4] fail to lead to optimal solutions because of nonlinear and nonconvex characteristics of the DED problem. In addition, they are computationally complex and may trap in local optima. Over the past few years, research has been using heuristic optimization methods in the DED problem [5]. Although these methods impose no restriction on the problem formulation, they are incapable to guarantee achieving global optimal solution. The main problem of these methods is the "curse-of-dimensionality," which leads to high computational cost.

More recent methods are hybrid methods. In this regard, evolutionary programming (EP) and particle swarm optimization (PSO) were combined with sequential quadratic programming (SQP) in [6]. Combining seeker optimization algorithm and SQP was introduced in [7]. However, regulation of the control parameters of these hybrid methods is a challenging and complicated task, so modified optimization algorithms such as modified differential evolution [2], adaptive hybrid differential evolution (AHDE) [8], improved chaotic PSO (ICPSO) [9], and quantum genetic algorithm [10] were developed.

The bee swarm optimization (BSO) algorithm is a population-based optimization technique, which is inspired by foraging behavior of the honey bees. To the best of our knowledge, a few algorithms have been developed based on this idea for numerical optimization. Artificial bee colony and virtual bee algorithm are two examples [11], [12]. These types of algorithms have been proved to have better performance compared to the other population-based algorithms, such as the ant colony optimization algorithm, the PSO, and the genetic algorithm (GA), for solving numerical optimization problems [11]–[13]. In most of the optimization algorithms, all individuals in the population use a homologous pattern to search the space and update their positions. Methods that use only one moving pattern may ignore regions, which possibly contain candidate optima. In order to solve this problem, it is essential to employ algorithms, which provide different moving patterns such as the BSO algorithm. Different behaviors of the bees in the BSO set up effective balancing mechanism between exploration and exploitation.

In this paper, an EBSO algorithm is proposed to solve the DED problem considering the ramp-rate limits, the valve-point effects, and the transmission power losses. The DED as a complex, nonconvex, high dimensional and extremely constrained problem is considered as a benchmark for testing effectively and applicability of the proposed EBSO algorithm.

Despite the mentioned advantages of the BSO, the original BSO suffers from premature convergence in a high dimensional complex problem like the DED. Therefore, in this paper, several valuable enhancements to the BSO are developed to improve search capability of the BSO and enhance calculation speed. These modifications were made to design a more powerful optimization technique in comparison with the other population-based techniques, such as the GA, PSO, and the differential evolution (DE).

The EBSO algorithm uses three types of bees to find the optimal solution of the DED problem. Each type of the bees employs a different moving pattern. Accordingly, the feasible region will be searched more effectively. The EBSO algorithm uses a set of approaches, including two novel moving patterns, a reformation technique, repulsion factor, and nonlinear adaptive weights. In addition, constraint-handling schemes are offered to manage equality constraints effectively without enforcing any restrictions.

The proposed EBSO is tested on two popular test systems implemented in much research in the area, including 10-unit test system and 30-unit large-scale power system. The 10-unit test system is studied under two cases by considering and neglecting transmission power losses. In addition, to validate the applicability of the proposed method for high dimensional optimization problems, a 60-unit power system including 1440 design variables is considered. The results are compared with the most recently published works, which solved the DED problem. The results confirm the superiority and effectiveness of the EBSO algorithm over the previous ones in solving the DED problem.

The remainder of this paper is organized as follows. Section II deals with the mathematical formulation of the DED problem. The proposed EBSO algorithm for the DED problem is described in Section III. The implementation of the EBSO algorithm to solve the DED problem is presented in Section IV. The feasibility and efficiency of the proposed method are assessed on three test systems in Section V. This paper concludes in Section VI.

II. Mathematical Description

A. Objective Function

$$\text{Minimize } F(\mathbf{P}) = \sum_{t=1}^{T}\sum_{i=1}^{N} f_i(p_i^t) \tag{1}$$

where $\mathbf{P} = \begin{bmatrix} P^1 & P^2 & \dots & P^{NT} \end{bmatrix}$ and $P^t = \begin{bmatrix} p_1^t & p_2^t & \dots & p_N^t \end{bmatrix}^{\mathrm{T}}$.

The above fuel cost function is comprised of two terms: the smooth quadratic function and the absolute value of sinusoidal function of valve-point effects as follows:

$$\begin{aligned} f_i(p_i^t) &= a_i + b_i p_i^t + c_i (p_i^t)^2 \\ &\quad + \left| e_i \times \sin(h_i \times (p_{i\,\min} - (p_i^t))) \right|. \end{aligned} \tag{2}$$

B. Constraint

The DED optimization problem is subject to the following constraints:

$$\sum_{i=1}^{N} p_i^t = P_D^t + P_{\text{Loss}}^t \qquad t = 1, 2, \dots, NT \tag{3}$$

$$P_{\text{Loss}}^t = \sum_{i=1}^{N}\sum_{j=1}^{N} p_i^t B_{ij}^t p_j^t \qquad t = 1, 2, \dots, NT \tag{4}$$

$$p_{i\,\min} \leq p_i^t \leq p_{i\,\max} \quad i = 1, 2, \dots, N \quad t = 1, 2, \dots, NT \tag{5}$$

$$p_i^t - p_i^{t-1} \leq UR_i \quad i = 1, 2, \dots, N \quad t = 1, 2, \dots, NT \tag{6}$$

$$p_i^{t-1} - p_i^t \leq DR_i \quad i = 1, 2, \dots, N \quad t = 1, 2, \dots, NT. \tag{7}$$