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Research Article

An Improved Particle Swarm Optimization with Biogeography-Based Learning Strategy for Economic Dispatch Problems

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Economic dispatch (ED) plays an important role in power system operation, since it can decrease the operating cost, save energy resources, and reduce environmental load. This paper presents an improved particle swarm optimization called biogeography-based learning particle swarm optimization (BLPSO) for solving the ED problems involving different equality and inequality constraints, such as power balance, prohibited operating zones, and ramp-rate limits. In the proposed BLPSO, a biogeography-based learning strategy is employed in which particles learn from each other based on the quality of their personal best positions, and thus it can provide a more efficient balance between exploration and exploitation. The proposed BLPSO is applied to solve five ED problems and compared with other optimization techniques in the literature. Experimental results demonstrate that the BLPSO is a promising approach for solving the ED problems.

1. Introduction

Economic dispatch (ED) is an important optimization task in power system operation and planning. The main objective of ED problems is to allocate generation among the committed generating units so as to meet the required load demand at minimum operating cost, with various physical constraints [1]. The cost of power generation is high, and economic dispatch can help in saving a significant amount of revenue [2].

In the original ED problem, the cost function for each generation unit is approximately represented by a single quadratic function, and traditional approaches based on mathematical programming techniques have been utilized to solve the ED problem, including the lambda-iteration method, gradient method, Newton's method, linear programming, interior point method, and dynamic programming [3–5]. Usually, these methods are highly sensitive to starting points and rely on the assumption that the cost function needs to be continuous and convex. However, the practical ED problems exhibit nonconvex and nonsmooth characteristics because of valve-point effects, ramp-rate limit, multifuel cost, prohibited operating zones, and so on [6]. The traditional methods are not capable of efficiently solving the ED problems with these characteristics.

In the past decades, more and more researchers are turning to metaheuristic search (MS) algorithms for solving the ED problems. These methods have the ability to identify higher-quality solutions and can be grouped into three categories, as original, improved, and hybrid MS algorithms.

The first category consists of methods applied in their original version, such as genetic algorithm (GA) [7], particle swarm optimization (PSO) [8], differential evolution (DE) [9], ant colony optimization (ACO) [10], harmony search (HS) [11], artificial bee colony (ABC) [12], teaching-learning-based optimization (TLBO) [13], gravitational search algorithm (GSA) [14], firefly algorithm (FA) [15], biogeography-based optimization (BBO) [16, 17], bacterial foraging optimization (BFO) [18], imperialist competitive algorithm (ICA) [19], seeker optimization algorithm (SOA) [20], grey wolf optimization (GWO) [21], backtracking search algorithm (BSA) [22], and root tree optimization (RTO) [23].

The second refers to improved or modified methods derived from the original version, and the following are included: self-adaptive real-coded genetic algorithm (SARGA) [24], random drift PSO (RDPSO) [25, 26], fuzzy adaptive modified PSO (FAMPSO) [27], improved differential evolution (IDE) [28], shuffled differential evolution (SDE) [29], improved harmony search (IHS) [30], modified artificial bee colony (MABC) [31], incremental artificial bee colony (IABC) [32], ramp-rate biogeography-based optimization (RRBBO) [33], dynamic nondominated sorting biogeography-based optimization (Dy-NSBBO) [34], multistrategy ensemble biogeography-based optimization (MsEBBO) [35], and modified group search optimizer (MGSO) [36].

The third is the hybrid method in which two or more optimization techniques are combined, including hybrid genetic algorithm (HGA) [37], chaotic PSO with sequential quadratic programming (CPSO-SQP) [38], hybrid PSO and gravitational search algorithm (HPSO-GSA) [39], hybrid differential evolution algorithm based on PSO (DEPSO) [40], hybrid differential evolution with biogeography-based optimization (DE/BBO) [41], hybrid chemical reaction optimization with differential evolution (HCRO-DE) [42], and hybrid imperialist competitive-sequential quadratic programming (HIC-SQP) [43].

In this paper, an improved PSO algorithm with biogeography-based learning strategy is proposed to solve the ED problems. The main contributions of this paper are listed as follows:

(1) A biogeography-based learning particle swarm optimization (BLPSO) algorithm which employs a biogeography-based learning strategy (BLS) is presented. The computational complexity of BLPSO is also analyzed.

(2) By combining the feature of ED problems, the BLPSO-based economic dispatch method is developed.

(3) BLPSO is applied to solve five ED problems with various practical constraints, and the experimental results demonstrate that the proposed method can obtain promising results for ED problems.

This paper is organized as follows: Section 2 briefly introduces the formulation of ED problems. Section 3 introduces the original PSO and its three variants. In addition, a biogeography-based learning particle swarm optimization algorithm is presented in this section. Section 4 addresses the implementation of BLPSO for solving ED problems. Section 5 provides the experimental results on five test systems. Finally, the paper is concluded in Section 6.

2. Formulation of ED Problems

The objective of the ED problem is to minimize the fuel cost of thermal power plants for a given load demand subject to various physical constraints.

2.1. Objective Function. The traditional fuel cost or objective function of the ED problem is the quadratic fuel cost equation of the thermal generating units and is given by

$$\min \quad F = \sum_{j=1}^{N_g} F_j(P_j) = \sum_{j=1}^{N_g} \left(a_j + b_j P_j + c_j P_j^2\right), \tag{1}$$

where N_g is the total number of generating units or generators, $F_j(P_j)$ is the cost function of the jth generating unit ($/hr), P_j is the real output of the jth generating units (in MW), and a_j, b_j, and c_j are fuel cost coefficients of the jth generator.

In some ED problems, the admission valves control the steam entering the turbine through separate nozzle groups. When the valve opens, the fuel cost will increase dramatically because of the wire drawing effect, and this makes the practical objective function have many nondifferentiable points [44]. Therefore, the fuel cost function often contains many nonsmooth ripple curves due to the presence of valve-point effects. The objective function when the valve-point effect is taken into account is represented as

$$\begin{aligned} \min \quad F = \sum_{j=1}^{N_g} F_j(P_j) = \sum_{j=1}^{N_g} \left(a_j + b_j P_j + c_j P_j^2\right) \\ + \left| e_j \sin\left(f_j\left(P_j^{\min} - P_j\right)\right)\right|, \end{aligned} \tag{2}$$

where e_j and f_j are nonsmooth fuel cost coefficients of the jth generator with valve-point effects and $P_j^{\min}$ is the minimum power generation limit of the jth generator (in MW).

2.2. Optimization Constraints

2.2.1. Power Balance Constraint. The total generated power should be equal to the sum of the total system demand (P_D) and the total transmission network loss (P_L):

$$\sum_{j=1}^{N_g} P_j = P_D + P_L. \tag{3}$$

The B coefficient method is widely utilized to calculate the total transmission network loss P_L. In such a way, P_L can be calculated as follows:

$$P_L = \sum_{j=1}^{N_g} \sum_{i=1}^{N_g} P_j B_{ji} P_i + \sum_{j=1}^{N_g} B_{0j} P_i + B_{00}, \tag{4}$$

where B_{ji}, B_{j0}, and B_{00} are the loss coefficients or B coefficients. It can be seen that $[\mathbf{B}_{ji}]$ is an $N_g \times N_g$ matrix.

2.2.2. Power Generation Limits. The power generation of each generator should be within its minimum and maximum limits:

$$P_j^{\min} \le P_j \le P_j^{\max}, \tag{5}$$

Input: particle index i immigration rate λ_k and emigration rates μ_k
Output: learning exemplar indices $\boldsymbol{\tau}_i = [\tau_i(1), \dots, \tau_i(d), \dots, \tau_i(D)]$
For $k = 1$ **to** D **Do** // for each dimension
  If rand $< \lambda_{\text{rank}(i)}$ **Then**
    Utilize a roulette wheel to select a particle index j with probability $\propto \mu_{\text{rank}(j)}$;
    $\tau_i(k) = j$; // learn from other particle
  Else
    $\tau_i(k) = i$; // learn from itself
  End If
End For
If $\tau_i(k) = i$ in all dimension **Then**
  Randomly select a particle index $l (l \neq i)$;
  Randomly select a dimension d;
  $\tau_i(d) = l$;
End If
Return $\boldsymbol{\tau}_i = [\tau_i(1), \dots, \tau_i(d), \dots, \tau_i(D)]$

ALGORITHM 1: (biogeography-based exemplar generation method).

Stage 1: Initialization
  For each particle $i = 1, 2, \dots, N$ **Do**
    Initialize position $\boldsymbol{x}_i$ and velocity $\boldsymbol{v}_i$**;**
    Evaluate the fitness $f(\boldsymbol{x}_i)$ and store the personal best position ***pbest***$_i$;
    Generate the learning exemplar indices $\boldsymbol{\tau}_i$ using Algorithm 1;
    Set the refreshing gap G;
  End For
Stage 2: Main loop
  For each particle $i = 1, 2, \dots, N$ **Do**
    If the stagnation number $stagnated(i) > G$ **Then**
      Generate the exemplar vector index $\boldsymbol{\tau}_i$ using Algorithm 1;
      Set $stagnated(i) = 0$;
    End If
    Update velocity $\boldsymbol{v}_i$ using Eq.16;
    Update position $\boldsymbol{x}_i$ using Eq.17;
    Evaluate the new position $f(\boldsymbol{x}_i)$**;**
    If $\boldsymbol{x}_i$ is better than ***pbest***$_i$ **Then**
      Set ***pbest***$_i = \boldsymbol{x}_i$, $stagnated(i) = 0$;
    Else
      $stagnated(i) = stagnated(i) + 1$;
    End If
  End For
Store swarm's ***gbest*** with the best ***pbest***$_i$
Stage 3: If the stop criterion is satisfied, the process is terminated. Otherwise, return to Stage 2.

ALGORITHM 2: (BLPSO).

where $P_j^{\min}$ and $P_j^{\max}$ are the minimum and maximum power generation limits of the jth generator.

2.2.3. Ramp-Rate Limits. The physical limitations of starting up and shutting down of generators impose ramp-rate limits, which are modeled as follows. The increase in generation is limited by

$$P_j - P_j^0 \leq \text{UR}_j. \tag{6}$$

Similarly, the decrease is limited by

$$P_j^0 - P_j \leq \text{DR}_j, \tag{7}$$

where P_j^0 is the previous output power and UR_j and DR_j are the up-ramp limit and the down-ramp limit of the jth generator, respectively.

Combining 6 and 7 with 5 results in the change of the effective operating or generation limits to

$$\max\left(P_j^{\min}, P_j^0 - DR_j\right) \leq P_j \leq \min\left(P_j^{\max}, P_j^0 + UR_j\right). \tag{8}$$

2.2.4. Prohibited Operating Zones. The prohibited operating zones (POZ) are due to steam valve operation or vibration

Initialize a set $I = \{1, 2, \ldots, D\}$
If $\sum_{j=1}^{Ng} P_{ij} \leq P_D + P_L$ **Then**
  Randomly select a component k from the set I;
  While $P_{ik} = P_i^{\max}$
    Exclude k from I, and let the new set be I';
    Randomly select a component k' from I';
    $k = k', I = I'$;
  End While
  Add an amount $w = |\sum_{j=1}^{Ng} P_{ij} \leq P_D - P_L|$ to P_{ik}, such as $P_{ik} = \min\,(P_{ik} + w, P_i^{\max})$;
Else If $\sum_{j=1}^{Ng} P_{ij} \leq P_D + P_L$
  Randomly select a component k from the set I;
  While $P_{ik} = P_i^{\min}$
    Exclude k from I, and let the new set be I';
    Randomly select a component k' from I';
    $k = k', I = I'$;
  End While
  Add an amount $w = |\sum_{j=1}^{Ng} P_{ij} \leq P_D - P_L|$ to P_{ik}, such as $P_{ik} = \max\,(P_{ik} + w, P_i^{\min})$;
End If

Algorithm 3: (the repair operator for power balance constraint).

in shaft bearing. The feasible operating zones of the jth generator can be described as follows:

$$P_j \in \begin{cases} P_j^{\min} \leq P_j \leq P_{j,1}^l, \\ P_{j,k-1}^u \leq P_j \leq P_{j,k}^l, \\ P_{j,n_j-1}^u \leq P_j \leq P_j^{\max}, \end{cases} \qquad k = 2, 3, \ldots, n_j, \; j = 1, 2, \ldots, N_g, \tag{9}$$

where n_j is the number of prohibited zones of the jth generator. $P_{j,k}^l$ and $P_{j,k}^u$ are the lower and upper power output of the kth prohibited zone of the jth generator, respectively.

Combining the equations from 2 to 9, the ED problem can be formulated as

$$\begin{aligned} \min \quad & F = \sum_{j=1}^{N_g} F_j(P_j) = \sum_{j=1}^{N_g} \left(a_j + b_j P_j + c_j P_j^2\right) + \left| e_j \sin\left(f_j\left(P_j^{\min} - P_j\right)\right)\right|, \\ \text{s.t.} \quad & \sum_{j=1}^{N_g} P_j = P_D + P_L, \\ \max \quad & \left(P_j^{\min}, P_j^0 - DR_j\right) \leq P_j \leq P_{j,1}^l, \\ & P_{j,k-1}^u \leq P_j \leq P_{j,k}^l, \\ & P_{j,k-1}^u \leq P_j \leq \min\left(P_j^{\max}, P_j^0 + UR_j\right), \\ & k = 2, 3, \ldots, n_j, \; j = 1, 2, \ldots, N_g. \end{aligned} \tag{10}$$

3. Particle Swarm Optimization and Its Three Variants

3.1. Particle Swarm Optimization. The PSO algorithm is a population-based metaheuristic algorithm which was firstly proposed by Eberhart and Kennedy [45]. It is based on the swarm intelligence theory, and the fundamental idea is that the optimal solution can be found through cooperation and information sharing among individuals in the swarm. In the past decade, PSO has gained increasing popularity due to its effectiveness in performing difficult optimization tasks.

In PSO, each individual is treated as a particle in the D-dimensional space, with a position vector $\mathbf{x}_i(t) = [x_{i1}(t), x_{i2}(t), \ldots, x_{iD}(t)]$ and a velocity vector $\mathbf{v}_i(t) = [v_{i1}(t), v_{i2}(t), \ldots, v_{iD}(t)]$. The particle updates its velocity and position according to the following equations:

$$\begin{aligned} v_{ij}(t+1) = {} & w v_{ij}(t) + c_1 r_1 \left(\text{pbest}_{ij}(t) - x_{ij}(t)\right) \\ & + c_2 r_2 \left(\text{gbest}_j(t) - x_{ij}(t)\right), \end{aligned} \tag{11}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t), \tag{12}$$

where $\text{pbest}_i(t) = [\text{pbest}_{i1}(t), \text{pbest}_{i2}(t), \ldots, \text{pbest}_{iD}(t)]$ is the personal best position of particle i; $\text{gbest}(t) = [\text{gbest}_1(t), \text{gbest}_2(t), \ldots, \text{gbest}_D(t)]$ is the position of the best particle in the population; w is the inertia weight; c_1 and c_2 are acceleration coefficients; and r_1 and r_2 are two random real numbers distributed uniformly within [0,1].

3.2. Comprehensive Learning Particle Swarm Optimization. Liang et al. [46] proposed a comprehensive learning PSO (CLPSO) which uses a novel comprehensive learning strategy whereby all other particle personal best positions are used to update a particle velocity. This strategy can preserve the diversity of the swarm to discourage premature convergence. CLPSO uses the following velocity updating equation:

$$v_{ij}(t+1) = w v_{ij}(t) + c r_1 \left(\text{pbest}_{\tau_i(j),j}(t) - x_{ij}(t)\right), \tag{13}$$

Table 1: Table of abbreviations.

Optimization algorithms	Abbreviation
Backtracking search algorithm	BSA
Biogeography-based optimization	BBO
Chaotic bat algorithm	CBA
Chaotic improved honey bee mating optimization	CIHBMO
Continuous quick group search optimizer	CQGSO
Differential evolution	DE
Enhanced Hopfield neural network	EHNN
Firefly algorithm	FA
Genetic algorithm-ant colony optimization	GAAPI
Group search optimizer	GSO
Honey bee mating optimization	HBMO
Hybrid chemical reaction optimization with differential evolution	HCRO-DE
Hybrid differential evolution with biogeography-based optimization	DE/BBO
Harmony search	HS
Hopfield modeling framework	HM
Hybrid harmony search	HHS
Hybrid differential evolution with biogeography-based optimization	DE/BBO
Hybrid differential evolution with particle swarm optimization	DEPSO
Immune algorithm	IA
Improved differential evolution	IDE
Improved orthogonal design particle swarm optimization-global version	IODPSO-L
Improved orthogonal design particle swarm optimization-local version	IODPSO-G
Improved random drift particle swarm optimization	IRDPSO
Modified artificial bee colony	MABC
Multiple tabu search	MTS
Multistrategy ensemble biogeography-based optimization	MsEBBO
New particle swarm optimization	New-PSO
New particle swarm optimization with local random search	NPSO-LRS
Oppositional invasive weed optimization	OIWO
Oppositional real-coded chemical reaction optimization	ORCCRO
Particle swarm optimization	PSO
Particle swarm optimization with chaotic sequences and crossover operator	CCPSO
Particle swarm optimization with time-varying acceleration coefficients	PSO-TVAC
Random drift particle swarm optimization	RDPSO
Self-tuning improved random drift particle swarm optimization	ST-IRDPSO
Simulated annealing	SA
Stochastic weight trade-off particle swarm optimization	SWT-PSO
Tabu search	TS

Table 2: Optimal generations and cost obtained by BLPSO for test system 1 (6-unit system, $P_D = 1263$ MW).

Unit	$P_j^{\min}$	$P_j^{\max}$	POZ	Generation
1	100	500	(210, 240); (350, 380)	447.0682
2	50	200	(90, 110); (140, 160)	173.5899
3	80	300	(150, 170); (210, 240)	263.2341
4	50	150	(80, 90); (110, 120)	142.6879
5	50	200	(90, 110); (140, 150)	162.5776
6	50	120	(75, 85); (100, 105)	86.5033
Cost (\$/hr)			15447.34	
Transmission loss (MW)			12.6619	

where $\text{pbest}_{\tau_i}(t) = [\text{pbest}_{\tau_i(1),1}(t), \text{pbest}_{\tau_i(2),2}(t), \ldots, \text{pbest}_{\tau_i(D),D}(t)]$ is the learning exemplar for particle i and $\tau_i = [\tau_i(1), \tau_i(2), \ldots, \tau_i(D)]$ is the learning exemplar indices for particle i, which is generated based on tournament selection procedure. The CLPSO does not introduce any complex operations to the original simple PSO framework, and the main difference from the original PSO is the velocity update equation.

3.3. Social Leaning Particle Swarm Optimization. Cheng and Jin [47] proposed a social learning PSO (SLPSO) inspired by learning mechanisms in social learning of animals. The SLPSO is performed on a sorted swarm, and particles learn from any better particles in the current swarm. The particles learn from different particles based on the following equations:

$$x_{ij}(t+1) = \begin{cases} x_{ij}(t) + \Delta x_{ij}(t) & \text{if } p_i(t) \le P_i^L, \\ x_{ij}(t), & \text{otherwise}, \end{cases} \tag{14}$$

$$\Delta x_{ij}(t+1) = r_1 \Delta x_{ij}(t) + r_2 \left(x_{kj}(t) - x_{ij}(t)\right) + r_3 \varepsilon \left(\bar{x}_j(t) - x_{ij}(t)\right), \tag{15}$$

where P_i^L is the learning probability for particle i, $p_i(t)$ is a randomly generated probability that satisfies $0 \le p_i(t) \le P_i^L \le 1$, $x_{kj}(t)$ is the demonstrator of particle i in the jth dimension, $\bar{x}_j(t) = \sum_{i=1}^{N} x_{ij}/N$ is the mean position of the all particles in the current swarm, and ε is the social influence factor. In addition, the SLPSO adopts dimension-dependent parameter control methods to determine the three parameters, that is, the swarm size N, P_i^L the learning probability, and the social influence factor ε.

3.4. Biogeography-Based Learning Particle Swarm Optimization. In this paper, a biogeography-based learning particle swarm optimization (BLPSO) which employs a new biogeography-based learning strategy (BLS) [48] is proposed for the ED problems.

Table 3: Comparison of fuel costs and statistical results for test system 1 (6-unit system, $P_D = 1263$ MW).

Algorithm	Minimum cost ($/h)	Mean cost ($/h)	Maximum cost ($/h)	Standard deviation	Time (s)
NPSO-LRS [54]	15,450	15,454	15,452	NA	NA
MTS [55]	15450.06	15451.17	15450.06	0.9287	1.29
TS [55]	5454.89	15472.56	15454.89	13.7195	20.55
SA [55]	15461.1	15488.98	15461.1	28.3678	50.36
GAAPI [56]	15449.78	15449.81	15449.85	NA	NA
HCRO-DE [42]	15443.075	15443.327	15443.916	0.067	4.17
DE [57]	15449.5826	15449.62	15449.6508	NA	3.634
MABC [31]	15449.8995	15449.8995	15449.8995	6.04E-08	0.62
CBA [58]	15450.2381	15454.76	15518.6588	2.965	0.704
RDPSO [26]	15449.89	15458.01	NA	13.647	0.707
IRDPSO [26]	15449.89	15456.55	NA	10.9865	0.676
ST-IRDPSO [26]	15449.89	15450.7	NA	1.416	0.727
CLPSO	15447.72	15449.83	15452.88	1.28	0.48
SLPSO	15447.34	15447.46	15447.62	0.08	0.84
BLPSO	15447.34	15447.45	15447.67	0.09	0.50

NA means the data are not available in the literature.

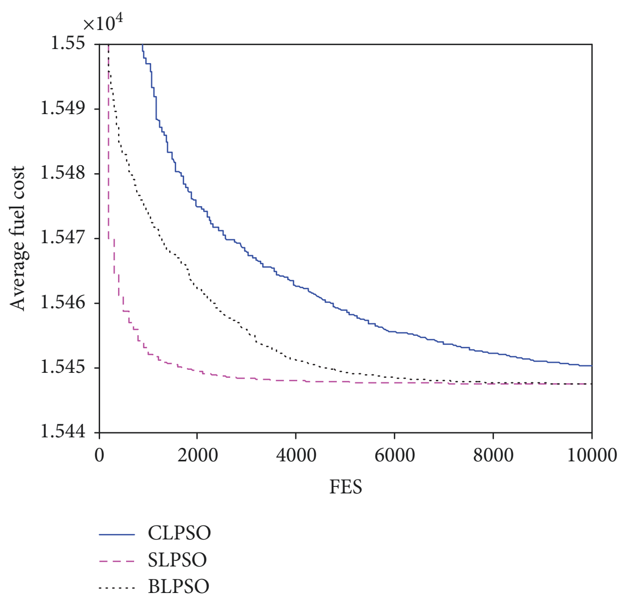

Figure 1: Convergence characteristics for test system 1.

3.4.1. Biogeography-Based Learning Strategy.

3.4.1. Biogeography-Based Learning Strategy. BLS is inspired from both from the comprehensive learning strategy of CLPSO [46] and biogeography-based optimization [49, 50]. It has two characteristics:

(1) Each particle updates itself by using the combination of its own personal best position and personal best positions of all other particles, which is similar to the comprehensive learning strategy of CLPSO. This updating method enables the diversity of the swarm to be preserved to discourage premature convergence.

Table 4: Optimal generations and cost obtained by BLPSO for test system 2 (15-unit system, $P_D = 2630$ MW).

Unit	$P_j^{\min}$	$P_j^{\max}$	Generation
1	150	455	455.0000
2	150	455	450.0000
3	20	130	130.0000
4	20	130	130.0000
5	150	470	200.0000
6	135	460	460.0000
7	135	465	430.0000
8	60	300	60.0000
9	25	162	35.1998
10	25	160	91.2383
11	20	80	80.0000
12	20	80	80.0000
13	25	85	25.0000
14	15	55	15.0000
15	15	55	15.0000
Cost ($/hr)		32587.33	
Transmission loss (MW)		12.6619	

(2) The migration operator of biogeography-based optimization is used to generate the learning exemplar for each particle, in which a ranking technique is employed to make particles learn more from particles with high-quality personal best positions. This can provide a more effecient balance between exploration and exploitation for the new PSO algorithm.

In BLS, each particle updates its velocity and position according to the following equations:

Table 5: Comparison of fuel costs and statistical results for test system 2 (15-unit system, $P_D = 2630$ MW).

Algorithm	Minimum cost ($/h)	Mean cost ($/h)	Maximum cost ($/h)	Standard deviation	Time (s)
CCPSO [60]	32704.4514	32704.4514	32704.4514	0	16.2
HBMO [59]	32637.6219	32663.19	32676.07	NA	2.8
CIHBMO [59]	32548.58588	32548.58588	32548.58588	NA	3.1
FA [15]	32,704.50	32,856.10	33,175.00	147.17	NA
MsEBBO [35]	32,692.40	32,692.40	32,692.40	0	NA
DEPSO [40]	32588.81	32588.99	32591.49	4.02	1.88 s
SWT-PSO [61]	32704.45	NA	NA	NA	NA
IA [62]	32,698.20	32,750.22	32,823.78	9.3	NA
IODPSO-G [63]	32,692.39	32,692.39	32,692.39	NA	NA
IODPSO-L [63]	32,692.39	32,692.39	32,692.39	NA	NA
CLPSO	32608.83	32649.9	32705.5	23.13	2.77
SLPSO	32674.25	32707.46	32758.69	14.67	4.93
BLPSO	32587.33	32607.17	32667.2	17.06	2.85

NA means the data are not available in the literature.

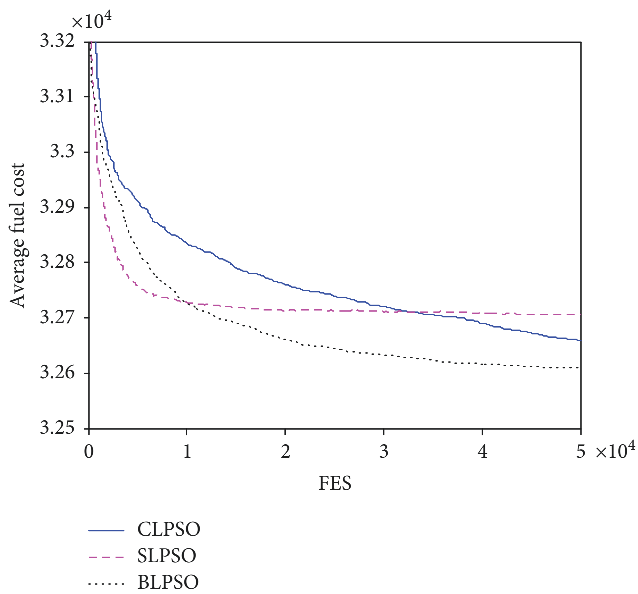

Figure 2: Convergence characteristics for test system 2.

$$v_{ij}(t+)1 = wv_{ij}(t) + cr_1\left(\text{pbest}_{\tau_i(j),j}(t) - x_{ij}(t)\right), \quad (16)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t), \quad (17)$$

where $\mathbf{pbest}_{\tau_i}(t) = [\text{pbest}_{\tau_i(1),1}(t), \text{pbest}_{\tau_i(2),2}(t), \ldots, \text{pbest}_{\tau_i(D),D(t)}]$ is the learning exemplar for particle i; $\boldsymbol{\tau}_i = [\tau_i(1), \tau_i(2), \ldots, \tau_i(D)]$ is the learning exemplar indices for particle i, which is generated by the biogeographic migration.

In the biogeographic migration, all particles are firstly sorted based on the value of their **pbest** from best to worst and assigned with ranking values. For a minimization problem, assume

$$f\left(\mathbf{pbest}_{s_1}\right) \le f\left(\mathbf{pbest}_{s_2}\right) \le \cdots \le f\left(\mathbf{pbest}_{s_N}\right), \quad (18)$$

Table 6: Optimal generations and cost obtained by the BLPSO for test system 3 (20-unit system, $P_D = 2500$ MW).

Unit	$P_j^{\min}$	$P_j^{\max}$	Generation
1	150	600	512.2358
2	50	200	169.7731
3	50	200	126.4272
4	50	200	102.6131
5	50	160	113.9049
6	20	100	73.6208
7	25	125	115.506
8	50	150	116.631
9	50	200	100.2842
10	30	150	105.5532
11	100	300	150.2329
12	150	500	293.3209
13	40	160	118.8701
14	20	130	30.6567
15	25	185	115.3421
16	20	80	36.2973
17	30	85	67.0567
18	30	120	87.9775
19	40	120	101.2398
20	30	100	54.4584
Cost ($/hr)		62456.58	
Transmission loss (MW)		92.0046	

where s_1 is the subscript of the particle with the best **pbest**, s_2 is the subscript of the particle with the second best **pbest**, and s_N is the subscript of the particle with the worst **pbest**; N is the population size. Then, the rankings of particles are assigned as below:

$$\text{rank}\ (\mathbf{x}_{sk}) = N - k, \quad k = 1, 2, \ldots, N. \quad (19)$$

Table 7: Comparison of fuel costs and statistical results for test system 3 (20-unit system, $P_D = 2500$ MW).

Algorithm	Minimum cost (\$/h)	Mean cost (\$/h)	Maximum cost (\$/h)	Standard deviation	Time (s)
EHNN [65]	62,610	NA	NA	NA	0.11
λ-iteration [64]	62456.6391	NA	NA	NA	33.757
HM [64]	62456.6341	NA	NA	NA	6.355
GSO [66]	62456.6332	62456.6336	62456.6353	NA	30.45
CQGSO [66]	62456.633	62456.6331	62456.63337	NA	11.13
BBO [22]	62456.7793	62456.7928	62456.7928	NA	NA
BSA [22]	62456.6925	62457.1517	62458.1272	NA	14.477
CBA [58]	62456.6328	62456.6348	62501.6714	0.3879	1.16
CLPSO	62456.44	62456.84	62457.10	0.17	2.68
SLPSO	62456.92	62457.38	62458.06	0.28	3.80
BLPSO	62456.58	62456.64	62456.65	0.01	2.75

NA means the data are not available in the literature.

Second, immigration and emigration rates are assigned for all particles. The immigration and emigration rates for all particles can be calculated as follows:

$$\lambda(\mathbf{x}_{s_k}) = \left(1 - \frac{N-k}{N}\right)^2,$$
$$\mu(\mathbf{x}_{s_k}) = \left(\frac{N-k}{N}\right)^2, \quad (20)$$
$$k = 1, 2, \ldots, N.$$

According to 20, the solution $\mathbf{x}_{s_1}$ with the best $\mathbf{pbest}_{s_1}$ will have the lowest immigration rate and highest emigration rate; and the solution $\mathbf{x}_{s_N}$ with the worst $\mathbf{pbest}_{s_N}$ will have the highest immigration rate and lowest emigration rate.

Third, the biogeography-based exemplar indices $\boldsymbol{\tau}_i = [\tau_i(1), \tau_i(2), \ldots, \tau_i(D)]$ for particle i can be generated based on the biogeography-based exemplar generation method, see Algorithm 1.

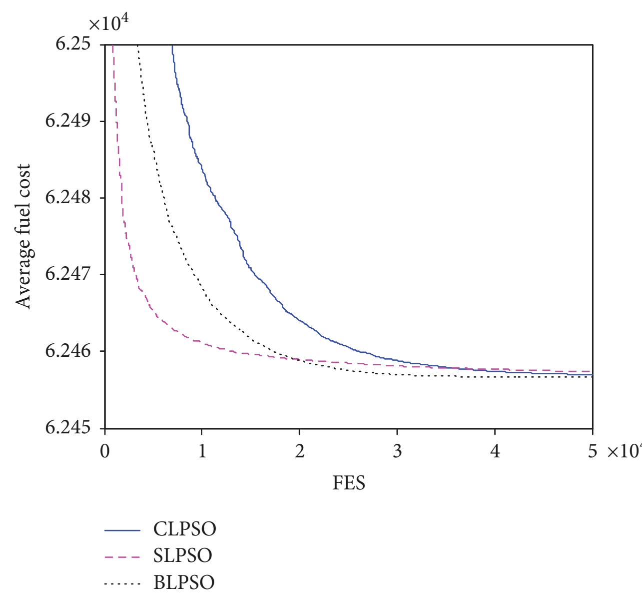

Figure 3: Convergence characteristics for test system 3.

3.4.2. Procedures of BLPSO. Using the BLS, the procedures of BLPSO can be outlined in Algorithm 2. It can be seen from Algorithm 2 that the structure of BLPSO is as simple as the classic PSO.

In addition, based on lines 10–13 in Algorithm 2, it can be seen that Algorithm 1 is executed to generate new learning exemplar indices $\boldsymbol{\tau}_i$ only when there is a stagnation for G generations, which is used to save computational cost of the BLPSO. In other words, if new learning exemplar indices $\boldsymbol{\tau}_i$ are generated for all particles in each generation, Algorithm 2 will be executed too frequently, and this may cost a large computational time, which is inappropriate for real-world ED problems.

3.4.3. Remarks

(1) Complexity Analysis. The computational costs of the original BLPSO algorithm involve the initialization (T_{ini}), biogeography-based exemplar generation method (T_{bio}), velocity and position update (T_{upd}), and evaluation (T_{eva}) for each particle. Assume D is the dimensionality of the optimization problem, N is the population size, and maxFES is maximum number of functional evaluations allowed for the algorithm. The complexity of initialization, velocity and position update, and evaluation are $O(D)$, $O(2D)$, and $O(D)$, respectively. The computational costs of biogeography-based exemplar generation method T_{bio} include population sorting $O(N \cdot \log(N))$, ranking assignment $O(N)$, immigration and emigration rate assignment $O(2N)$, and migration operator $O(N \cdot D)$. Therefore, $T_{\text{bio}} = O(N \cdot \log(N)) + O(N) + O(2N) + O(N \cdot D) = O(3N + N \cdot \log(N) + N \cdot D)$.

The total computational complexity of BLPSO is $T_{\text{BLPSO}} = T_{\text{ini}} + (T_{\text{eva}} + T_{\text{upd}} + (1/\text{G})T_{\text{bio}}) \cdot \text{maxFE} = O(D + (D + 2D + ((3N + N \cdot \log(N) + N \cdot D)/G)) \cdot \text{maxFES})$. In general, the population size N is often set to be proportional to the problem dimension D (i.e., $N = kD$) [47]. Thus, the complexity of BLPSO is $T_{\text{BLPSO}} = O(D + (D + 2D + ((3kD + kD \cdot \log(kD) + kD^2)/G)) \cdot \text{maxFES}) = O(D^2 \cdot \text{maxFES})$.

Table 8: Optimal generations and cost obtained by the BLPSO for test system 4 (38-unit system, $P_D = 6000$ MW).

Unit	$P_j^{\min}$	$P_j^{\max}$	Generation
1	220	550	426.5025
2	220	550	426.7865
3	200	500	429.5064
4	200	500	429.6401
5	200	500	429.7661
6	200	500	429.5265
7	200	500	429.7083
8	200	500	429.5542
9	114	500	114
10	114	500	114
11	114	500	119.7279
12	114	500	127.1661
13	110	500	110
14	90	365	90
15	82	365	82
16	120	325	120
17	65	315	159.6378
18	65	315	65
19	65	315	65
20	120	272	272
21	120	272	272
22	110	260	260
23	80	190	130.682
24	10	150	10
25	60	125	113.3391
26	55	110	88.0312
27	35	75	37.5497
28	20	70	20
29	20	70	20
30	20	70	20
31	20	70	20
32	20	60	20
33	25	60	25
34	18	60	18
35	8	60	8
36	25	60	25
37	20	38	21.7594
38	20	38	21.0902
Cost ($/hr)		9417208.19	

(2) Compared with Previous Hybrid PSO/BBO Algorithms. Several hybrid PSO/BBO algorithms have been proposed in the literature. For example, Guo et al. [51] presented a biogeography-based particle swarm optimization with fuzzy elitism (BPSO-FE) for constrained engineering problems. In this BPSO-FE algorithm, the whole population is split into several subgroups, and BBO is employed to search within each subgroup while PSO for the global search. Mo and Xu [52] applied the position updating strategy of PSO to increase the diversity of population in BBO and develop a biogeography particle swarm optimization algorithm (BPSO) to optimize the paths in path network. However, there are some differences between BLPSO and them. First, the hybrid strategies of BLPSO, BPSO-FE, and BPSO are different. In BLPSO, the biogeography-based migration is used to generate the learning exemplar for each particle; while in BPSO-FE and BPSO, the biogeography-based migration is used as search operator. Second, the application areas of BLPSO, BPSO-FE, and BPSO are different. BLPSO is presented for ED problems, while BPSO-FE and BPSO are proposed for classical engineering optimization problems and robot path planning, respectively.

4. Implementation of BLPSO for ED Problems

When solving the ED problems using BLPSO, the following three important issues should be considered: initialization of population, constraint handling, and stopping criterion.

4.1. Initialization of Population. In BLPSO, each individual of the population is a solution of an ED problem. If there are N_g units that must be operated to provide power to load, then the current position of the ith particle can be given by

$$X_i = \left[P_{i1}, P_{i2}, \dots, P_{ij}, \dots, P_{\mathrm{iN}_g}\right], \quad k = 1, 2, \dots, N, \tag{21}$$

where N is the population size, j is index of the generating unit, and P_{ij} is the generation power output of the jth generating unit in the ith particle.

4.2. Constraint Handling. One of the most important issues in solving ED problems is how to handle the quality and inequality constraints. There are four types of constraints in the ELD problems: power generation limits, ramp-rate limits, prohibited operating zone, and power balance constraint.

For power generation limit and ramp-rate limit constraints, the following strategy is employed:

$$P_{ij} = \begin{cases} \max\left(P_j^{\min}, P_j^0 - DR_j\right) & \textit{if } P_{ij} \le \max\left(P_j^{\min}, P_j^0 - DR_j\right), \\ \min\left(P_j^{\max}, P_j^0 + UR_j\right) & \textit{if } P_{ij} \ge \min\left(P_j^{\max}, P_j^0 + UR_j\right), \\ P_{ij}, & \text{otherwise.} \end{cases} \tag{22}$$

For prohibited operating zone constraints, if P_{ij} is located in the kth prohibited operating zone, that is, $P_{j,k}^l \le P_{ij} \le P_{j,k}^u$, it is truncated to the closest boundary of the kth prohibited operating zone as follows:

$$P_{ij} = \begin{cases} P_{j,k}^l & \text{if } P_{j,k}^l < P_{ij} \le \dfrac{\left(P_{j,k}^l + P_{j,k}^u\right)}{2}, \\ P_{j,k}^u & \text{if } \dfrac{\left(P_{j,k}^l + P_{j,k}^u\right)}{2} < P_{ij} < P_{j,k}^u, \end{cases} \tag{23}$$

Table 9: Comparison of fuel costs and statistical results for test system 4 (38-unit system, $P_D = 6000$ MW).

Algorithm	Minimum cost (\$/h)	Mean cost (\$/h)	Maximum cost (\$/h)	Standard deviation	Time (s)
New-PSO [67]	9516448.312	NA	NA	NA	NA
PSO-TVAC [67]	9500448.307	NA	NA	NA	NA
HS [68]	9,419,960	9,421,056	9,427,466	NA	10.02
HHSÂ [68]	9,417,325	9,417,336	9,417,466	NA	5.06
BBOÂ [41]	9417633.638	NA	NA	NA	NA
DE/BBO [41]	9417235.786	NA	NA	NA	NA
MsEBBO [35]	9417235.776	9417235.779	9417235.778	0.0032	NA
IDE [28]	9417235.786	9417235.786	9417235.786	6.00E-09	9.149
CLPSO	9418283.79	9419255.18	9420192.8	526.51	2.86
SLPSO	9418407.11	9419560.62	9425492.54	1312.2	3.53
BLPSO	9417208.19	9417234.16	9417235.9	5.23	2.89

NA means the data are not available in the literature.

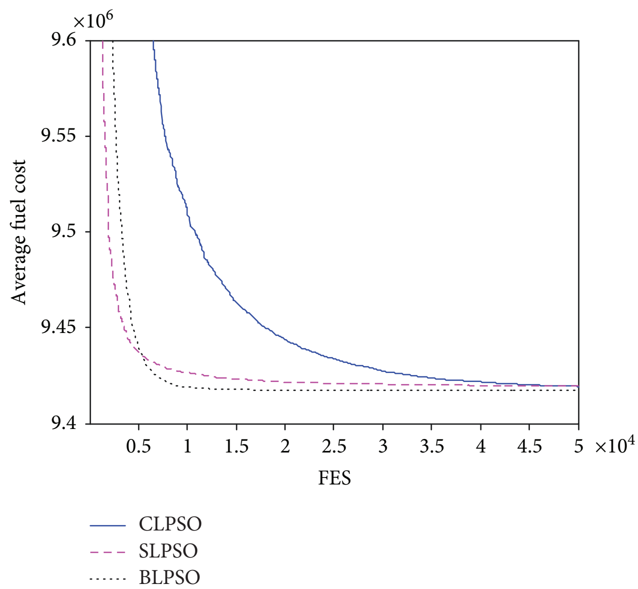

Figure 4: Convergence characteristics for test system 4.

where $P^l_{j,k}$ and $P^u_{j,k}$ denote the lower and the upper bounds of prohibited operation zone k of generator j, respectively.

For the power balance constraint, a repaired operator together with a common penalty is employed [28]. The repaired operator is shown in Algorithm 3, and the objective function becomes

$$\min \quad F = \sum_{j=1}^{N_g} F_j(P_j) + K\left|\sum_{j=1}^{N_g} P_j - P_D - P_L\right|, \tag{24}$$

where K is the penalty coefficient and the penalty term $|\sum_{j=1}^{N_g} P_j - P_D - P_L|$ is the measure of violation of the equality constraint.

4.3. Stopping Criterion. The BLPSO algorithm will be terminated if the maximum number of functional evaluations ma xFES is reached.

5. Results and Discussion

To test the effectiveness of the proposed BLPSO algorithm, five different test systems of varying computational difficulty levels have been solved using BLPSO. The results obtained by BLPSO are compared with two PSO algorithms, comprehensive learning PSO (CLPSO) [46] and social leaning PSO (SLPSO) [47]. The results are also compared with several techniques reported in the literature whose abbreviations are listed in Table 1.

To compare the performance of the BLPSO, 50 independent trial runs are made, and the statistical results including the minimum, mean, maximum fuel cost, and standard deviation, as well as average run time, are tabulated for each test system. The parameters of BLPSO are set as follows: population size $N = 40$, inertia weight w linearly decreases from 0.9 to 0.2, acceleration coefficient $c = 1.496$, and refreshing gap $G = 5$. The parameters of CLPSO and SLPSO are set as those recommended in their original papers. The maximum number of functional evaluations maxFES is set as 10,000; 50,000; 50,000; 50,000; and 200,000 for the five test systems, respectively. The programs are implemented in MATLAB language on a personal computer with a 3.2 GHz processor and 8 GB RAM.

5.1. Test System 1. This is a small system comprising 6 generators and meeting a load demand of 1263 MW and includes transmission loss, POZ, and ramp-rate limits. The system data are taken from [8, 53] and listed in Table S1. Table 2 presents the optimal generation values and fuel cost obtained by BLPSO. The obtained optimal cost is 15447.34 \$/hr. It can be seen that the generation values satisfy the generation limit constraints and do not fall in the POZs.

Table 3 shows the comparison of the statistical results of different algorithms. In the table, the results obtained by BLPSO are compared with CLPSO, SLPSO, NPSO-LRS [54], MTS [55], TS [55], SA [55], GAAPI [56], HCRO-DE [42], DE [57], MABC [31], CBA [58], RDPSO [26], IRDPSO [26], and ST-IRDPSO [26]. It can be seen that the minimum and mean fuel costs obtained by BLPSO are similar to SLPSO and less than all the other methods with the exceptions of

Table 10: Optimal generations and cost obtained by the CBA for test system 5 (110-unit system, $P_D = 5000$ MW).

Unit	Generation	Unit	Generation	Unit	Generation	Unit	Generation	Unit	Generation
1	2.4	23	68.9	45	660	67	70	89	82.7308
2	2.4	24	350	46	616.4766	68	70	90	89.7172
3	2.4	25	400	47	5.4	69	70	91	57.9161
4	2.4	26	400	48	5.4	70	360	92	100
5	2.4	27	500	49	8.4	71	400	93	440
6	4	28	500	50	8.4	72	400	94	500
7	4	29	200	51	8.4	73	105.0721	95	600
8	4	30	100	52	12	74	190.995	96	471.2608
9	4	31	10	53	12	75	90	97	3.6
10	64.6059	32	20	54	12	76	50	98	3.6
11	62.3474	33	80	55	12	77	160	99	4.4
12	36.3769	34	250	56	25.2	78	295.3172	100	4.4
13	56.6463	35	360	57	25.2	79	174.949	101	10
14	25	36	400	58	35	80	98.2904	102	10
15	25	37	40	59	35	81	10	103	20
16	25	38	70	60	45	82	12	104	20
17	155	39	100	61	45	83	20	105	40
18	155	40	120	62	45	84	200	106	40
19	155	41	156.791	63	185	85	325	107	50
20	155	42	220	64	185	86	440	108	30
21	68.9	43	440	65	185	87	13.9066	109	40
22	68.9	44	560	66	185	88	24.4992	110	20
Cost ($/hr)					197988.16				

HCRO-DE [42]. In addition, the smaller value of standard deviation indicates that BLPSO is consistent. It is also important to note that the BLPSO is very efficient according to the average computational time (0.50 s), which is less than most of other methods. Figure 1 presents the convergence characteristics obtained by CLPSO, SLPSO, and BLPSO. From Figure 1, SLPSO has the fastest convergence speed, and BLPSO has the second. Both BLPSO and SLPSO can converge to the optimal cost after about 6000 functional evaluations.

5.2. Test System 2. This test system consists of 15 generators meeting a load demand of 2630 MW and includes transmission loss, POZ, and ramp-rate limits. The system data are taken from [8, 59] and listed in Table S2. Table 4 presents the optimal generations and the costs obtained. The optimal cost obtained by BLPSO is 32587.33 $/hr, and the generations satisfy the generation limit constraints.

Table 5 shows the comparison of the statistical results of the BLPSO and other algorithms, including CLPSO, SLPSO, CCPSO [60], HBMO [59], CIHBMO [59], FA [15], MsEBBO [35], DEPSO [40], SWT-PSO [61], IA [62], IODPSO-G [63], and IODPSO-L [63]. The minimum and mean fuel costs obtained by BLPSO are the least of all methods with the exceptions of HBMO [59]. The average computation time of BLPSO (2.85 s) is also very small. The convergence characteristics obtained by CLPSO, SLPSO, and BLPSO are plotted in Figure 2. SLPSO has the fastest convergence speed in the beginning, but it is surpassed by BLPSO and CLPSO in the end. Only BLPSO can get the optimal cost in this case.

5.3. Test System 3. This test system consists of 20 generators supplying a demand of 2500 MW. Transmission losses are included in this system. The cost coefficient and B coefficient data are taken from [22, 64] and listed in Table S3. Table 6 presents the optimal generation values and fuel cost obtained by the BLPSO. The optimal obtained fuel cost is 62456.58 $/hr. It is seen that the all the generation limit constraints are satisfied.

Table 7 shows the comparison of the statistical results of different algorithms. In the table, the results obtained by BLPSO are compared with CLPSO, SLPSO, EHNN [65], λ-iteration [64], HM [64], GSO [66], CQGSO [66], BBO [22], BSA [22], and CBA [58]. It can be seen that the best fuel cost obtained by BLPSO is the least of all methods, and the mean fuel cost is the least of all methods with the sole exception of CBA [58]. In addition, the standard deviation and average computation time of BLPSO are both very small. Again, the BLPSO is efficient for this case. The convergence characteristics obtained by CLPSO, SLPSO, and BLPSO are plotted in Figure 3.

5.4. Test System 4. This test system consists of 38 generators, and the demand of this system is 6000 MW. The system data are taken from [28, 41] and listed in Table S4. Table 8 presents the optimal generation values and cost obtained by

Table 11: Comparison of fuel costs and statistical results for test system 5 (110-unit system, P_D = 15,000 MW).

Algorithm	Minimum cost ($/h)	Mean cost ($/h)	Maximum cost ($/h)	Standard deviation	Time (s)
SAB [71]	206912.9057	207764.73	NA	NA	NA
SAF [71]	207380.5164	207813.37	NA	NA	NA
SA [71]	198352.6413	201595.19	NA	NA	NA
ORCCRO [72]	198016.29	198016.32	198016.89	NA	0.15
BBO [72]	198241.166	198413.45	199,102.59	NA	115
DE/BBO [72]	198231.06	198326.66	198,828.57	NA	132
OIWO [69]	197989.14	197989.41	197989.93	NA	31
CLPSO	198137.7	198200.37	198257.56	27.88	23.43
SLPSO	198240.4	198351.62	198602.16	96	22.59
BLPSO	197988.16	197988.18	197988.19	0	22.81

NA means the data are not available in the literature.

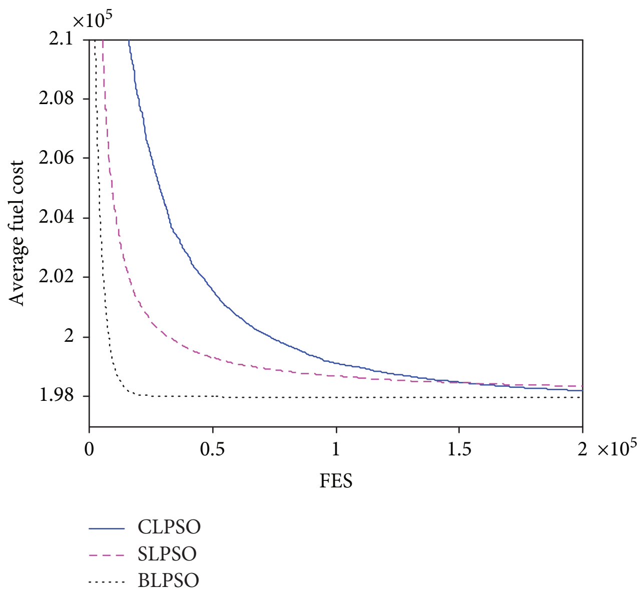

Figure 5: Convergence characteristics for test system 5.

BLPSO. The optimal cost is 9417208.19 $/hr. It is seen that the generations satisfy the generation limit constraints.

The results obtained by BLPSO are compared with those obtained by CLPSO, SLPSO, New-PSO [67], PSO-TVAC [67], HS [68], HHS [68], BBO [41], DE/BBO [41], MsEBBO [35], and IDE [28], as shown in Table 9. It can be seen that the minimum and mean fuel costs obtained by BLPSO are the least of all the methods. The average computation time of BLPSO is 2.89 s, smaller than all methods, with the exception of CLPSO. The convergence characteristics obtained by CLPSO, SLPSO, and BLPSO are plotted in Figure 4.

5.5. Test System 5. In order to study the performance of the BLPSO on high-dimensional ED problems, a large system with 110 generators is considered. The demand of this system is 15,000 MW, and the system data are taken from [69, 70] and listed in Table S5. Table 10 presents the optimal generation values and cost obtained by BLPSO. The optimal cost is 197988.16 $/hr.

Table 11 shows the comparison of the statistical results of BLPSO and other algorithms, including CLPSO, SLPSO, SAB [71], SAF [71], SA [71], ORCCRO [72], BBO [72], DE/BBO [72], and OIWO [69]. The minimum, mean, and maximum fuel costs obtained by BLPSO are the least of all the methods. Meanwhile, the smaller value of standard deviation indicates that BLPSO is consistent. The average computation time of BLPSO is also very small compared with other methods. The convergence characteristics obtained by CLPSO, SLPSO, and BLPSO are presented in Figure 5.

6. Conclusion

This paper has presented a biogeography-based learning particle swarm optimization (BLPSO) for solving the economic dispatch (ED) problems, which is nonlinear, nonconvex, and discontinuous in nature, with numerous equality and inequality constraints. In the BLPSO, a biogeography-based learning strategy is used to generate the learning exemplar for each particle, in which particles learn more from high-quality particles. The biogeography-based learning strategy can provide a more effective balance between exploration and exploitation for the BLPSO.

The BLPSO was applied to five test systems with various constraints such as power balance, POZs, and ramp-rate limits. Transmission losses have also been included in some systems. The experimental results show that the fuel costs obtained by BLPSO are either comparable or lower than those reported by other methods. The application to a 110-unit system shows that the BLPSO is also capable of handling high-dimensional ED problems.

In the future, we are planning to extend the BLPSO to solve other more complicated ED problems, such as dynamical ED problems and environmental ED problems. We are also interested in applying the BLPSO to other optimization problems in energy field such as solar photovoltaic modeling [73].

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Supplementary Materials

Table S1~Table S5 provides the system data of the five test systems studied in this paper. (1) Table S1: the system data of test system 1 (6-unit system). (2) Table S2: the system data of test system 2 (15-unit system). (3) Table S3: the system data of test system 3 (20-unit system). (4) Table S4: the system data of test system 4 (38-unit system). (5) Table S5: the system data of test system 5 (110-unit system). *(Supplementary Materials)*

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