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Real Coded Biogeography-Based Optimization for Environmental Constrained Dynamic Optimal Power Flow

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Abstract – The optimization is an important role in wide geographical distribution of electrical power market, finding the optimum solution for the operation and design of power systems has become a necessity with the increasing cost of raw materials, depleting energy resources and the ever growing demand for electrical energy. In this paper, the real coded biogeography based optimization is proposed to minimize the operating cost with optimal setting of equality and inequality constraints of thermal power system. The proposed technique aims to improve the real coded searing ability, unravel the prematurity of solution and enhance the population assortment of the biogeography based optimization algorithm by using adaptive Gaussian mutation. This algorithm is demonstrated on the standard IEEE-30 bus system and the comparative results are made with existing population based methods.

Keywords: Biogeography based optimization, Diversity, Dynamic optimal power flow, Real coded, Searching ability

1. Introduction

In competitive electrical power market, electrical energy must be offered at a least cost with high quality, which is very difficult task for market operator in deregulated power system. Optimal power flow (OPF) is the tool for solving these complicated problems. The main objective of optimal power flow is to obtain optimal operating schedule for each generator which minimizes the cost of production and satisfies the system equality and inequality constraints. The earlier researches are done in different methods of optimal power flow. The methods are Linear Programming in [1], Nonlinear Programming in [2], Quadratically convergent in [3], Newton approach in [4], Interior Point Method in [5, 6] and P-Q decomposition in [7].

In deregulated power system, multiple transactions are done every hour and hence loads are varied. Optimal power flow is carried out dynamically based on load variation. Dynamic optimal power flow (DOPF) is discussed in [8]. Thermal power plants are major part of power generation in electric power sector, where power is generated by burning of fossil fuels. It releases polluted gases in the environment. In the concern of environmental awareness, pollution should be minimized which is achieved by combining cost and emission dispatch in a single objective function. Emission constrained economic dispatch is discussed in [9].

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Earlier conventional based optimal power flows have excellent convergence characteristics, but they could not perform well when deal with systems having non-differentiable objective functions and practical constraints with some theoretical assumptions. So researchers concentrate towards evolutionary algorithms like as Genetic Algorithm [10, 11], Enhanced Genetic Algorithm [12], Evolutionary Programming [13], Tabu Search [14], Simulated Annealing [15], Particle Swarm Optimization [16], Differential Evolution [17], Modified Differential Evolution [18], Modified Shuffle Frog Leaping Algorithm [19], and Artificial Bee Colony Algorithm [20]. Non – Reliability is the disadvantage of these optimization techniques.

In [21], Biogeography-based Optimization (BBO) algorithm was employed by Bhattacharya and Chattopadhyay for solving OPF problems. This approach is briefly discussed in next section. The probability based random mutation is applied in the BBO algorithm, so that the population are diverted at the end of the solution. This is the main drawbacks of the algorithm. It could be avoided by using Gaussian mutation in real coded biogeography based optimization (RCBBO). In this paper, RCBBO algorithm is discussed, which is applied to dynamic optimal power flow problem. The results are compared with existing methods.

2. Biogeography Based Optimization

The Biogeography-based Optimization (BBO) technique, which is proposed by Dan Simon [22] is a comprehensive algorithm for solving optimization problems and is based on the study of geographical distribution of species.

The nature's way of distributing species is known as Biogeography, and is analogous to general problem solutions. The BBO technique has two main operators, they are migration and mutation.

2.1 Migration operator

Migration is the process that probabilistically modifies each individual in the habitat by sharing information with other individual solution. Geographical areas with high Habitat Suitability Index (HSI) are said to be well suitable for biological species. Suitability Index Variables (SIVs) are the variables that characterize the habitat of the species. Geographical areas with high HSI tends to have a large number of species, high emigration rate and low immigration rate. Therefore, habitats with high HSI tends to be more static in their species distribution compared to low HSI habitats. A habitat with high HSI is analogous to a good solution and a habitat with low HSI is analogous to a poor solution. The sharing of features of individuals in the habitat is done based on the migration rate. The immigration rate, λ_k and the emigration rate, μ_k are functions of the number of species in the habitat. When there are no species in a habitat, the immigration rate of the habitat is maximal. The immigration rate, λ_k can be formulated as:

$$\lambda_k = I\left(1-\frac{k}{n}\right) \tag{1}$$

Where I is maximum possible immigration rate, k is number of species of k^{th} individual and n is maximum number of species. The emigration rate, μ_k can be formulated as:

$$\mu_k = E\left(\frac{k}{n}\right) \tag{2}$$

Where E is maximum possible emigration rate.

2.2 Mutation operator

The process of mutation tends to increase diversity among the individuals in the habitat to get better solution. Due to natural events, HSI of habitat is changed drastically. It causes a species count differ from its equilibrium value. Each species count is associated with probability (P_i). Individual's solution is mutated with other solution if the probability is very low. So mutation rate of individual solution is calculated by using species count probability.

$$M_i = M_{\max} * \left(\frac{1-P_i}{P_{\max}}\right) \tag{3}$$

Where M_i is the mutation rate, M_{max} is the maximum mutation rate which is user defined parameter, and P_{max} is the maximum probability of species count.

In BBO, mutation characteristic function is given by:

$$X_i^{'} = X_i + rand(0,1) \times (X_i^{\max} - X_i^{\min}) \tag{4}$$

where X_i is the decision variable; $X_i^{\max}$ and $X_i^{\min}$ are the lower and upper limits of the decision variable, respectively.

The advantages of BBO are that using of probabilistic migration can create the better solutions from the poor ones by sharing more information. For the meantime, it would not loss good solutions at the progress. The main drawback of BBO technique is that the migration operator fails to improve the exploration ability and the diversity of the population.

3. Real Coded Biogeography-Based Optimization

Real Coded Biogeography-based Optimization (RCBBO) is an extension of BBO where individuals are directly encrypted by a floating point for the continuous optimization problems.

In BBO, individuals are represented by a D–dimensional integer vector, whereas in RCBBO individuals are represented by a D–dimensional real parameter vector. In Real Coded Biogeography Based Optimization technique, the assortment of the population is improved and its searching ability is enhanced by integrating the mutation operator with BBO technique. Mutation operator is intended to expose liabilities belonging to the matching fault class. Real coded biogeography based optimization is discussed in [24], where Gaussian mutation is used probabilistically based to modify the original BBO technique.

In this paper, Gaussian mutation operator is applied to improve the worst half of the individuals in the population. Adaptive mutation probability is used to prevent premature convergence and produce a smooth convergence. This method of mutation can be easily used for real-coded variables which have been widely used in Evolutionary Programming (EP) and it is able to carry out local search as well as global search.

The Gaussian mutation characteristic function is given by:

$$X_i^{'} = X_i + N(\mu, \sigma_i^2) \tag{5}$$

where $N(\mu, \sigma_i^2)$ represents the Gaussian random variable with mean μ and variance σ^2. The values of mean and variance are considerd 0 and 1, respectively [24].

Generally, a probability-based mutation operation is known to improve the convergence characteristics. Therefore, adaptive Gaussian mutation is applied in the present work to improve the solution of worst half set of habitats in the population.

In Eq. (5), μ = 0, and σ_i is found using the following Eq. [27]:

$$\sigma_i = \beta * \sum_{i=1}^{n}\left(\frac{F_i}{f_{\min}}\right) * \left(X_i^{\max} - X_i^{\min}\right) \tag{6}$$

where β is the scaling factor or mutation probability, F_i is the fittness value of ith individual, and f_{min} is the minimum fitness value of the habitat set in the population.

Adaptive mutation probability is given by

$$\beta = \beta_{\max} - \frac{\beta_{\max} - \beta_{\min}}{T_{\max}} \times T \tag{7}$$

where $\beta_{\max} = 1$, $\beta_{\min} = 0.005$, T_{max} is the maximum iteration, and T is the current iteration. The main difference between Evolutionary Programming (EP) and Real Coded Biogeography-based Optimization (RCBBO) is that it makes use of migration operator, which utilizes the information of population effectively and the adaptive mutation balances the exploitation and exploration ability of the RCBBO technique.

4. Problem Formulation

Generally, an OPF problem is a large-scale, highly constrained nonlinear optimization problem. It may be defined as

$$\min f(x,u) \tag{8}$$

subject to

$$g(x,u) = 0 \tag{9}$$

$$h(x,u) \le 0 \tag{10}$$

where f is the objective function to be minimized, x and u are the vectors of dependent and independent control variables, respectively, g is the equality constraint, and h is the operating constraint.

The vector of dependent variables can be represented as:

$$x^T = \left[P_{G1}, V_{L1} \ldots V_{LNpq}, Q_{G1} \ldots Q_{GNg}, S_{L1} \ldots S_{LNl}\right] \tag{11}$$

where P_{G1} denotes the slack bus power, V_L denotes the load bus voltage, Q_G denotes the reactive power output of the generator, S_L denotes the transmission line flow, N_g is the number of voltage-controlled buses, N_{pq} the number of load buses, and N_l is the number of transmission lines.

The vector of independent control variables can be represented as:

$$u^T = \left[P_{G2} \ldots P_{GNg}, V_{G1} \ldots V_{GNg}, T_1 \ldots T_{Nt}, Q_{C1} \ldots Q_{CN_C}\right] \tag{12}$$

where N_t and N_C are the number of tap-changing transformers and shunt VAR compensators, respectively; P_G is the active power output of generators; V_G is the voltage at the voltage-controlled bus; T is the tap setting of the tap-changing transformer; and Q_C is the output of shunt compensating devices.

4.1 Objective function

This paper discusses about two different objective functions and combined both functions into single objective function to prove the effectiveness of the proposed technique based on RCBBO. The objective functions are discussed below:

4.1.1 Minimization of fuel cost

This objective function aims to minimize the total fuel cost for the operation and planning of power systems under varying loads. The objective function is formulated as:

$$FC = \sum_{i=1}^{Ng} f_i\left(P_{Gi}\right) \tag{13}$$

Where FC is the total fuel cost, N_g is the number of generators. The fuel cost function for the operation of Power Systems can be expressed as:

$$f_i\left(P_{Gi}\right) = a_i + b_i\left(P_{Gi}\right) + c_i\left(P_{Gi}^2\right) \tag{14}$$

Where P_{Gi} is the real power output of an i^{th} generator and a_i, b_i and c_i are the fuel cost coefficients.

4.1.2 Minimization of environmental pollution

The main goal of this objective function is to minimize the environmental pollution caused by the operation of thermal power systems. The objective function is formulated as:

$$Em = \sum_{i=1}^{Ng} E_i\left(P_{Gi}\right) \tag{15}$$

Where *Em* is the total emission generation. The emission function can be expressed as:

$$E_i\left(P_{Gi}\right) = \alpha_i + \beta_i\left(P_{Gi}\right) + \gamma_i\left(P_{Gi}^2\right) \tag{16}$$

Where α_i, β_i and γ_I are the emission coefficients of the i^{th} unit.

4.1.3 Minimization of total cost

The objective functions are combined and formulated into a single optimization problem by introducing the Price Penalty Factor 'h' as follows:

$$MinimizeTC = FC + h * Em \quad (17)$$

The procedure of price penalty factor calculation is discussed in [25].

4.2. Constraints

4.2.1 Equality constraints

The equality constraints are the power flow equations given by:

$$P_{Gi} - P_{Di} - \sum_{j=1}^{NB} |V_i||V_j||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (18)$$

$$Q_{Gi} - Q_{Di} - \sum_{j=1}^{NB} |V_i||V_j||Y_{ij}|\sin(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (19)$$

Where P_{Gi} & Q_{Gi} are the injected active and reactive power at ith bus, P_{Di} & Q_{Di} is the demanded active and reactive power at ith bus, Y_{ij} is the admittance between bus i and j, θ_{ij} is the load angle between bus i and j, δ_i is the phase angle of voltage at ith bus and NB is the total number of buses.

4.2.2 Inequality constraints

These constraints are the set of continuous and discrete constraints that represent the system operational and security limits as follows:

(a) ***Generator constraints***: the generator active and reactive power outputs are restricted by their upper and lower limits.

$$P_{Gi,\min} \le P_{Gi} \le P_{Gi,\max}; i = 1, 2, ..., N_g \quad (20)$$

$$Q_{Gi,\min} \le Q_{Gi} \le Q_{Gi,\max}; i = 1, 2, ..., N_g \quad (21)$$

Where $P_{Gi,min}$ & $P_{Gi,max}$ are the minimum and maximum value of real power generation at ith generator bus, $Q_{Gi,min}$ & $Q_{Gi,max}$ are the minimum and maximum value of reactive power generation at ith generator bus.

(b) ***Security constraints***: these include the limits on the load bus voltage and transmission line flow limits:

$$V_{i,\min} \le V_i \le V_{i,\max}, i = 1, 2, ..., N_{pq} \quad (22)$$

Where $V_{i,\min}$ & $V_{i,\max}$ are the minimum and maximum value of magnitude of voltage at ith load bus and N_{pq} is the number of load bus.

The power flow limit on transmission line is restricted by

$$MVA_k \le MVA_k^{\max} \quad (23)$$

Where $MVA_k^{\max}$ is the maximum rating of kth transmission line.

The most common method for handling the inequality constraints is to make use of a penalty function. The original constrained optimization problem is transformed to an unconstrained one by penalizing the inequality constraints.

Finally, the dynamic optimal power flow objective function is combined with constraints as

$$Min\ F = TC + \sum_{i\in Ng} \lambda_{Pg}(P_{Gi} - P_{Gi}^{\lim})^2 + \sum_{i\in Ng} \lambda_{Qg}(Q_{Gi} - Q_{Gi}^{\lim})^2 + \sum_{i\in Npq} \lambda_V (V_i - V_i^{\lim})^2 + \sum_{i\in NL} \lambda_{Pf}(MVA_i^{\max} - MVA_i)^2$$

Where λ_{Pg} , λ_{Qg} , λ_V & λ_{Pf} are the penalty factors.

If $P_{Gi} > P_{Gi,\max}$ then $P_{Gi}^{\lim} = P_{Gi,\max}$ otherwise
If $P_{Gi} < P_{Gi,\min}$ then $P_{Gi}^{\lim} = P_{Gi,\min}$,
If $Q_{Gi} > Q_{Gi,\max}$ then $Q_{Gi}^{\lim} = Q_{Gi,\max}$ otherwise
If $Q_{Gi} < Q_{Gi,\min}$ then $Q_{Gi}^{\lim} = Q_{Gi,\min}$ &
If $V_i > V_{i,\max}$ then $V_i^{\lim} = V_{i,\max}$ otherwise
If $V_i < V_{i,\min}$ then $V_i^{\lim} = V_{i,\min}$

4.3 Algorithm

The steps for solving the OPF problem using RCBBO is as follows:

Step 1: Initialization

Habitat modification probability (P_{mod}), minimum and maximum values of adaptive mutation probability (β_{min} and β_{max}), maximum immigration and emigration rates for each island, maximum species count (P), and maximum iterations are initialized.

Step 2: Generate SIVs for the habitat randomly within the feasible region.

Individuals (control variables) in the habitats are initialized as:

$$X_{ij} = X_j^{\min} + rand(0,1) \times (X_j^{\max} - X_j^{\min}) \quad (24)$$

where i = 1, 2… P, and j = 1, 2… N_{var}; N_{var} is the number of control variables; $X_j^{\max}$ and $X_j^{\min}$ are the lower and upper limits of jth control variable.

Step 3: Perform load flow analysis using Newton-Raphson method and determine the dependent variables. Compute the fitness value (HSI) for each habitat set.

Step 4: Based on the HSI value, elite habitats are identified.

Step 5: Iterative algorithm for optimization:

(i) Perform migration operation on SIVs of each non-elite habitat selected for migration.

(ii) Calculate immigration and emigration rates for each habitat set, using Eqs. (1) and (2).

(iii) Update the habitat set after migration operation.
(iv) Recalculate the HSI value of modified habitat set; feasibility of the solution is verified and habitat set sorted based on new HSI value.
(iv) Perform mutation operation on the worst half set of population by Gaussian adaptive mutation using Eqs. (5-7)
(v) Compute the fitness value (HSI) for each habitat set after mutation operation and verify the feasibility of the solution.
(vi) Sort the habitat set based on new HSI value.
(vii) Stop the iteration counter if the maximum number of iterations is reached.

Step 6: Finally SIVs should satisfy the objective function as well as constraints of the problem.

5. Simulation Results

The proposed Real Coded Biogeography-based algorithm for solving dynamic OPF problem has been applied to the IEEE 30-bus test system. The numerical results are presented in this section. The results obtained by the proposed approach are compared with the results found by alternative population-based algorithms reported in the literature recently. Power flow calculations by Newton-Raphson method were performed using the software package MATPOWER 4.1 [26].

The IEEE-30 bus system has six generators at buses 1, 2, 5, 8, 11 and 13, and four tap changing transformers. The total system demand is 283.4MW for the active power, and 126.2 MVAR for the reactive power at 100 MVA base. Bus 1 is taken as the slack bus. The fuel cost and emission co-efficients for IEEE-30 bus is given in appendix.

The optimal control parameters for the algorithm are chosen from number of simulation results. They are: habitat size=50, habitat modification probability = 1, immigration probability = 1, step size for numerical integration = 1, maximum immigration and emigration rate = 1, mutation probability = 0.005 and maximum number of iterations = 200. The results show the corresponding objective functions for 50 independent trails.

In the subsequent paragraphs, we discuss the results obtained by the proposed RCBBO algorithm and existing BBO algorithm [22] with regard to each objective function of the OPF problem for standard system demand. The optimal settings of control parameters are given in Table 1. The bolded values represent the optimal value of respective objective functions.

The robustness of the proposed RCBBO algorithm is compared with different optimization techniques, for the objective function of minimization of fuel cost is presented in Table 2. The first two rows mentioned in the table are obtained by our own implementation of algorithms. Best fuel cost obtained by the proposed RCBBO was 799.0908$/h, which is lesser than minimum fuel cost obtained using BBO algorithm and solution reported in [12, 16-21]. Convergence characteristics of optimization methods, considered in this work are depicted in Fig. 1, which indicates premature convergence in BBO and smooth convergence in RCBBO.

The robustness of the RCBBO algorithm is compared with BBO algorithm for the objective function of minimization of emission, in Table 3. Convergence characteristics of proposed RCBBO algorithm and BBO algorithm for this objective function are depicted in Fig. 2.

Simulation results obtained by proposed RCBBO and BBO algorithm for minimization of total cost are presented

Table 1. Simulation results for minimization of fuel cost and emission

Parameter	Best fuel cost		Best emission	
	RCBBO	BBO	RCBBO	BBO
P_{G1}(MW)	177.1632	177.4098	111.7876	111.3816
P_{G2}(MW)	48.7043	48.7610	46.5052	45.8533
P_{G5}(MW)	21.3087	21.2656	35.8822	37.0000
P_{G8}(MW)	20.9014	21.0000	30.9833	31.0000
P_{G11}(MW)	11.9608	11.9878	29.9979	30.0000
P_{G13}(MW)	12.0000	12.0000	32.8148	32.9690
V_{G1}(p.u)	1.1000	1.0875	1.1000	1.0792
V_{G2}(p.u)	1.0872	1.0637	1.0893	1.0672
V_{G5}(p.u)	1.0609	1.0280	1.0677	1.0291
V_{G8}(p.u)	1.0679	1.0380	1.0786	1.0487
V_{G11}(p.u)	1.1000	1.1000	1.0989	1.0973
V_{G13}(p.u)	1.1000	1.1000	1.1000	1.0820
T_{6-9}	1.0712	1.0000	1.0510	1.0000
T_{6-10}	0.9000	1.0000	0.9192	1.0000
T_{4-12}	0.9995	1.0000	0.9915	1.0000
T_{28-27}	0.9711	0.9913	0.9846	1.0000
Q_{C10}(MVAR)	5.0000	5.0000	4.8701	4.0000
Q_{C12}(MVAR)	5.0000	1.0000	4.9789	5.0000
Q_{C15}(MVAR)	4.9463	3.0000	4.9492	5.0000
Q_{C17}(MVAR)	5.0000	5.0000	4.9981	5.0000
Q_{C20}(MVAR)	4.3900	5.0000	4.7471	4.0000
Q_{C21}(MVAR)	5.0000	5.0000	5.0000	5.0000
Q_{C23}(MVAR)	2.7637	2.7731	2.8051	3.0000
Q_{C24}(MVAR)	5.0000	5.0000	5.0000	5.0000
Q_{C29}(MVAR)	2.5122	3.8239	3.0984	4.0000
Fuel cost ($/h)	**799.0908**	**800.4022**	852.5789	856.2308
Emission(Kg/h)	419.1108	420.1382	**331.6470**	**332.2085**
Power loss(MW)	8.6384	9.0242	4.5710	4.8039

Table 2. Comparison of results for minimization of fuel cost

Methods	Fuel cost (Kg/h)		
	Best	Mean	Worst
RCBBO	799.0908	799.5392	800.0281
BBO	800.4022	801.8500	802.5698
ABC [20]	800.6600	800.8715	801.8674
BBO [21]	799.1116	799.1985	799.2042
PSO [16]	800.41	NA	NA
DE [17]	799.2891	NA	NA
EGA [12]	799.56	NA	NA
MDE [18]	802.376	802.382	802.404
MSFLA [19]	802.287	802.4138	802.5087

Table 3. Comparison of results for minimization of emission

Method	Emission(Kg/h)		
	Best	Mean	Worst
RCBBO	331.6470	332.3868	332.8725
BBO	332.2085	332.7410	332.2545

Table 4. Comparison of results for minimization of total cost

Method	Price penalty factor	Fuel cost ($/h)	Emission (Kg/h)	Total cost ($/h)
RCBBO	2.0534	828.852	336.378	1519.556
BBO	2.0534	829.405	336.936	1521.256
PSO [27]	2.3384	835.5655	337.2407	1624

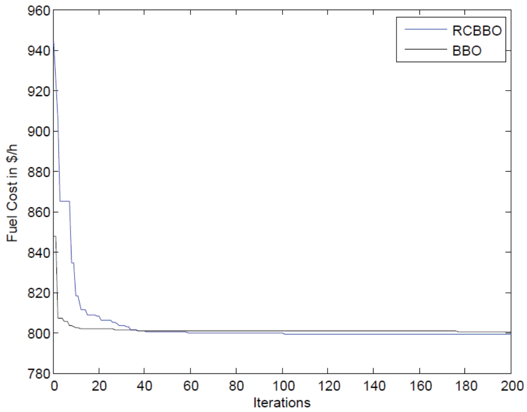

Fig. 1. Convergence characteristics for objective function - minimization of fuel cost

in Table 4. Best total cost obtained by the proposed RCBBO was 1519.556$/h, which is lesser than minimum total cost obtained using BBO algorithm and solution reported in [27].

For 24 hours load pattern, solution for dynamic optimal power flow is obtained by proposed RCBBO and BBO, are presented in Tables 5 and Table 6 respectively. The price penalty factor for the system demand of 283.4MW is 2.0534 and 1.7916, for all other demands. Total cost obtained for 24 hours by the proposed RCBBO is 23168.753$, which is 20$ lesser than total cost obtained using BBO algorithm. From the results, RCBBO based DOPF is perceived which provides higher lead to terms of accuracy and reliability.

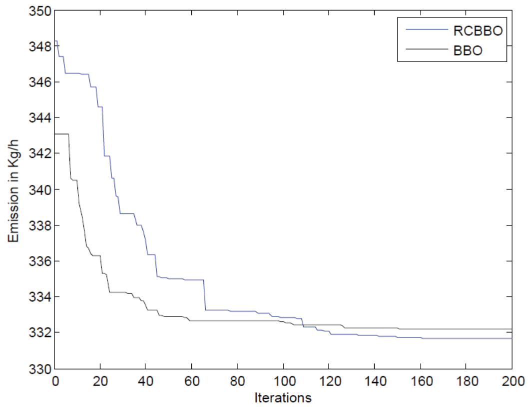

Fig. 2. Convergence characteristics for objective function - minimization of emission

Table 5. Result obtained for DOPF using RCBBO method

Hour	Power Demand (MW)	Injected active power (MW)						Power Loss (MW)	Fuel Cost ($/h)	Emission (Kg/h)	Total Cost ($/h)
		Pg1	Pg2	Pg3	Pg4	Pg5	Pg6				
1	166	85.364	29.000	18.000	12.000	12.000	12.000	2.364	421.172	176.147	736.763
2	196	96.482	34.042	20.557	17.224	15.406	15.334	3.044	517.177	207.089	888.204
3	229	107.521	39.727	23.567	22.551	19.651	19.722	3.740	628.847	248.857	1074.705
4	267	120.391	46.494	27.138	28.604	24.622	24.667	4.917	765.521	308.268	1317.823
5	283.4	124.336	49.161	29.134	31.428	27.188	27.470	5.317	828.852	336.378	1519.556
6	272	122.200	47.297	27.669	29.487	25.099	25.305	5.057	783.885	316.982	1351.799
7	246	113.258	42.698	25.140	25.298	21.857	21.976	4.227	688.956	273.929	1179.734
8	213	102.052	36.906	22.134	19.909	17.623	17.689	3.312	573.862	227.350	981.189
9	192	96.189	31.000	20.681	17.000	15.000	15.000	2.869	504.463	202.337	866.974
10	161	83.783	27.668	17.329	11.449	11.009	12.000	2.238	405.761	171.573	713.155
11	147	77.367	24.000	15.580	10.000	10.000	12.000	1.947	365.445	159.329	650.902
12	160	83.600	28.000	16.717	11.000	11.000	12.000	2.317	402.696	170.927	708.933
13	170	87.050	30.000	18.000	13.000	12.141	12.209	2.399	433.136	179.987	755.605
14	185	92.517	32.010	19.597	15.388	14.127	14.078	2.717	481.223	194.811	830.252
15	208	100.406	36.000	22.000	19.000	17.213	16.677	3.296	557.337	221.227	953.693
16	232	108.406	40.294	23.927	23.026	20.046	20.118	3.817	639.429	253.058	1092.815
17	246	113.216	42.774	25.176	25.223	21.868	22.082	4.338	689.436	274.052	1180.436
18	241	111.535	42.000	25.000	24.133	21.155	21.555	4.379	672.379	266.645	1150.108
19	236	109.739	40.972	24.276	23.841	20.559	20.681	4.069	654.031	259.021	1118.100
20	225	106.060	39.006	23.236	21.762	19.290	19.284	3.638	615.167	243.216	1050.919
21	204	98.675	35.242	21.206	18.495	16.522	17.039	3.178	544.307	216.069	931.422
22	182	89.766	32.462	19.601	14.687	13.601	14.585	2.702	472.646	191.440	815.636
23	161	83.892	27.696	17.271	11.439	10.868	12.001	2.167	405.409	171.573	712.804
24	131	65.331	20.000	15.000	10.000	10.000	12.000	1.331	323.164	147.387	587.226
Total cost for 24 hours											23168.753

Table 6. Result obtained for DOPF using BBO method

Hour	Power Demand (MW)	Injected active power (MW)						Power Loss (MW)	Fuel Cost ($/h)	Emission (Kg/h)	Total Cost ($/h)
		Pg1	Pg2	Pg3	Pg4	Pg5	Pg6				
1	166	85.811	28.549	17.768	12.158	12.181	12.001	2.468	421.562	176.176	737.204
2	196	96.143	34.000	20.604	17.000	16.000	15.392	3.140	517.977	206.979	888.806
3	229	107.492	39.000	24.000	22.138	20.000	20.398	4.028	630.812	248.833	1076.629
4	267	120.313	46.000	27.493	28.997	24.224	25.000	5.027	766.392	308.295	1318.741
5	283.4	124.632	49.237	29.000	31.441	27.000	27.656	5.565	829.405	336.936	1521.256
6	272	122.649	46.790	27.638	30.000	25.000	25.000	5.078	783.541	317.260	1351.953
7	246	113.250	42.647	25.000	25.286	22.250	22.178	4.611	690.586	274.367	1182.151
8	213	102.067	38.000	22.210	20.000	17.252	17.000	3.529	573.768	228.087	982.415
9	192	94.811	33.335	20.275	16.662	14.952	15.051	3.085	504.806	202.570	867.737
10	161	83.305	28.000	17.000	12.000	11.000	12.000	2.305	406.242	171.525	713.550
11	147	76.500	24.026	16.209	10.000	10.180	12.000	1.915	365.788	159.199	651.014
12	160	83.464	27.104	17.660	12.011	10.153	12.000	2.393	403.371	170.861	709.490
13	170	87.300	28.454	17.903	13.940	12.001	12.906	2.504	434.491	179.635	756.331
14	185	93.538	31.000	19.000	16.000	14.000	14.288	2.825	481.517	194.965	830.822
15	208	100.213	36.187	21.848	19.202	17.041	16.997	3.488	558.090	221.388	954.735
16	232	108.721	40.000	24.000	23.000	20.000	20.281	4.002	640.058	253.310	1093.894
18	241	111.440	41.895	24.874	24.521	21.271	21.474	4.474	672.805	266.749	1150.720
19	236	109.347	42.000	24.444	23.000	20.525	21.000	4.316	654.984	259.353	1119.649
20	225	106.876	39.154	23.000	21.000	19.000	19.779	3.809	615.067	243.719	1051.722
21	204	98.749	35.435	21.000	18.901	17.000	16.241	3.325	544.561	216.381	932.235
22	182	90.801	32.000	19.400	15.000	13.606	14.000	2.806	472.333	191.737	815.854
23	161	84.274	28.000	17.000	11.000	11.000	12.000	2.274	405.347	171.841	713.221
24	131	65.428	20.000	15.000	10.000	10.000	12.000	1.428	323.405	147.440	587.562
Total cost for 24 hours											23188.472

6. Conclusion

In this paper, real coded biogeography based optimization algorithm is developed and successfully applied to solve the environmental constrained dynamic optimal power flow problems. This approach is tested and examined with combined multi- objective functions including the generator constraints and security constraints to show its effectiveness using the IEEE 30-bus system. The results obtained from the RCBBO approach are compared with those reported in the recent literature. The superiority and solution quality of the proposed method are found better than other techniques. According to the results obtained, the RCBBO algorithm has a simple framework and quick convergence characteristic and, therefore, can be used to solve the OPF problem in large-scale power systems with several thousands of buses utilizing the strength of parallel computing.

Appendix

Fuel cost and emission co-efficients

Bus.No.	a	b	c	α	β	γ
1	0	2.00	0.00375	22.983	-1.1000	0.0126
2	0	1.75	0.01750	22.313	-0.1000	0.0200
5	0	1.00	0.06250	25.505	-0.1000	0.0270
8	0	3.25	0.00834	24.900	-0.0050	0.0291
11	0	3.00	0.02500	24.700	-0.0400	0.0290
13	0	3.00	0.02500	25.300	-0.0055	0.0271

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