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A BBO-based algorithm for the non-convex economic/environmental dispatch

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ABSTRACT

The problem of power system optimization has become a deciding factor in electrical power system engineering practice with emphasis on cost and emission reduction. The economic emission dispatch (EED) problem has been addressed in this paper using a Biogeography-based optimization (BBO). The BBO is inspired by geographical distribution of species within islands. This optimization algorithm works on the basis of two concepts-migration and mutation. In this paper a non-uniform mutation operator has been employed. The proposed technique shows better diversified search process and hence finds solutions more accurately with high convergence rate. The BBO with new mutation operator is tested on ten unit system. The comparison which is based on efficiency, reliability and accuracy shows that proposed mutation operator is competitive to the present one.

Keywords*— Economic emission dispatch (EED); Biogeography based optimization; Mutation operator.*

I. Introduction

Electricity, like all energy forms or vectors generates environmental, economic and social impacts that are trying to limit. One of the challenges for the 21st century is that of production from clean, reliable, safe and renewable resources that can replace thermal and nuclear power plants. In this context, some states are introducing environmental policies to encourage electricity producers to reduce their greenhouse gas emissions and thus their direct or indirect contributions to climate change. For thermal energy, gas, oil and coal are fossil sources. It will come well on a day when their quantity will be restricted. In addition, the use of these fossil fuels leads to greater pollution, despite the measures taken (denitrification, desulphurization). To these harmful effects is added the rising cost of these different sources. It is in this axis that the content of our work lies, in order to reduce the emission of pollutant gas and the cost function of different sources simultaneously.

Several research considered the classic EED problem where the cost of production function of each thermal unit is approximated by a quadratic function [1-2]. While, modern systems are with units that have prohibited areas of operation (POZ) due to physical operation limitations. In addition, the practical problem of EED includes valve load effects (VPLE) in the cost function. These additional constraints make the problem with a high nonlinear and discontinuous objective function. For this reason, the traditional optimization techniques proposed in the literature, such as linear programming [3] Newton's methods [4] and lambda iteration [5] can not achieve the best solution.

In the past years, a number of approaches have been developed for solving this problem using classical methods like dynamic programming [6] and interior point [7] methods have been used to solve the static EED. Among metaheuristic-based optimization techniques, genetic algorithm [8], particle swarm optimization [9], simulated annealing [10-11], artificial bee colony (ABC) [12], tabu search [13], differential evolution [14] and bacterial foraging [15] have been suggested for solving the EED problem.

Recently, a new, easy-to-implement, robust evolutionary algorithm has been introduced known as Optimization based on biogeography (BBO) algorithm. This Optimization based on biogeography

(BBO) algorithm introduced by Simon [16], is one approach that has been used to find an optimal solution in numerical optimization problems. The BBO algorithm based on biogeography concept, is inspired by the principle of the movement of species, depends mainly on the topographical characteristics of the space considered called habitat and time.

II. PROBLEM FORMULATION

In this EED problem, two objective functions to be minimized simultaneously, which are the total emission and the total cost of the fuel in order to find the power production of the thermal power plants according to expected load demands. The description of objectives and constraints is as follows.

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A. Objective functions

The higher nonlinearity due to the VPLE shown in FIG. 1 which has been neglected in conventional methods, and which is caused by the sequential operation of thermal units with multi-steam intake valves, is considered constrained in this study. For this reason, a sinusoidal form will be included in the non-convex total cost function expressed in ($ / h), as shown in equation (1). The total emission in (ton / h) is described by equation (2) corresponding to the second objective.

$$C_T = \sum_{i=1}^{N} a_i + b_i P_i + c_i P_i^2 + \left| d_i \sin\left\{ e_i \left(P_i^{\min} - P_i \right) \right\} \right| \quad (1)$$

$$E_T = \sum_{i=1}^{N} \alpha_i + \beta_i P_i + \gamma_i P_i^2 + \eta_i \exp\left(\lambda_i P_i \right) \quad (2)$$

Where,

a_i, b_i, c_i, d_i and e_i are the cost coefficients of the *i*-th unit. While, α_i, β_i, γ_i, η_i and λ_i are the emission coefficients. P_i is the output power in MW at the the *i*-th unit.

In our study, the EED bi-objective problem is converted to a mono-objective optimization problem [17], as it is considered in several works. Using the price penalty factor (PPF) method, equation (3) describes the combined economic emission goal function F_T expressed as follows

$$F_T = \mu C_T + (1-\mu)\lambda E_T \quad (3)$$

Where, $\mu = rand(0,1)$. The generated value of optimal solution, which can be a candidate solution in the Pareto front, is obtained by minimizing the F_T function for each value of μ. λ is the average of the PPF of all thermal units. The PPF of the i-th unit is the ratio between its fuel cost and its emission for a maximum production capacity, described by equation (4).

$$PPF_i = \frac{C_{i_{\max}}}{E_{i_{\max}}} \quad (4)$$

B.Problem constraints

The resolution of the problem EED is obtained by minimizing the F_T function that is defined by equation (3) subject to the following constraints.

- Generation capacity

Depending on the unit design, the output active power of each unit must fall between its minimum and maximum limits respectively $P_i^{\min}$ and $P_i^{\max}$

$$P_i^{\min} \le P_i \le P_i^{\max}, \; i = 1, \ldots, N \quad (5)$$

- Power balance constraints

Respecting the balance of power constraints given by equation (6), the total electricity production must cover the total power required more total transmission losses P_L .

$$\sum_{i=1}^{N} P_i - P_D - P_L = 0 \quad (6)$$

Where P_L can be calculated using constant loss formula [18], as given below.

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \quad (7)$$

Where, B_{ij} , B_{oi} , B_{oo} are the loss parameters also called *B*-coefficients.

- POZ constraints

  The POZ constraints are described as follows.

$$P_i \in \begin{cases} P_i^{\min} \le P_i \le P_{i,1}^{down} \\ P_{i,k-1}^{up} \le P_i \le P_{i,k}^{down} & ,k = 2,...,z_i \\ P_{i,z_i}^{up} \le P_i \le P_i^{\max} \end{cases} \quad (8)$$

Where, $P_{i,k}^{down}$ and $P_{i,k}^{up}$ are down and up bounds of POZ number *k*. z_i is the number of POZ for the *i*-th unit due to the vibrations in the shaft or other machine faults.

This is explained in Figure 2 which illustrates the fuel cost function for a typical thermal unit with POZ constraints. Where, the machine has discontinuous input-output characteristics [19]. Equation (9) describes the minimum and maximum limits of power generation P_i of the i-th unit taking into account the production capacity and POZ constraints.

$$P_i \in \begin{cases} P_i^{\min} \le P_i \le \min\left(P_i^{\max}, P_{i,1}^{down}\right) \\ \max\left(P_i^{\min}, P_{i,k-1}^{up}\right) \le P_i \le \min\left(P_i^{\max}, P_{i,k}^{down}\right) & ,k = 2,...,z_i \\ \max\left(P_i^{\min}, P_{i,z_i}^{up}\right) \le P_i \le P_i^{\max} \end{cases} \quad (9)$$

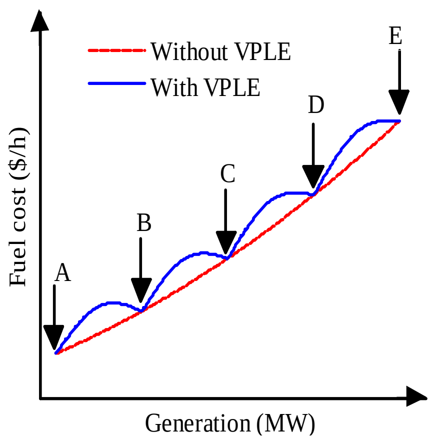

Figure 1. Fuel Cost Function with Five Valves (A, B, C, D, E)

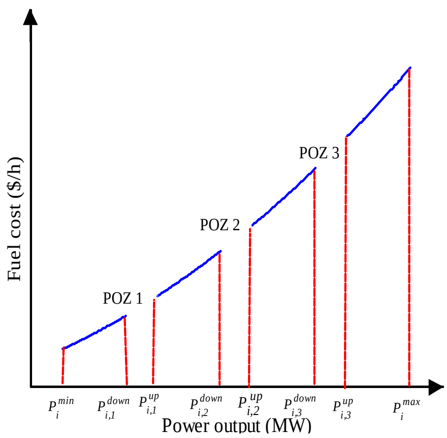

Figure 2. Cost function for a thermal unit with POZ constraints

III. PROPOSED ALGORITHM WITH MUTATION

Optimization based on biogeography (BBO) is a new algorithm inspired by the principle of the movement of species, introduced by Simon [16]. This algorithm depends mainly on the topographical characteristics of the space considered called habitat and time. Figure 3 explains immigration and species migration. It can be seen that the Smax habitat capacity is reached for one of zero immigration and the immigration rate λ is maximum when no species in the habitat and decreases the habitat will be more congested. Whereas the emigration rate μ is zero for the empty habitat. On the other hand, spices migrate when the habitat is congested to find other suitable residences. Therefore, the emigration rate of spices reaches its maximum value E when the number of spices in habitat S equals to Smax.

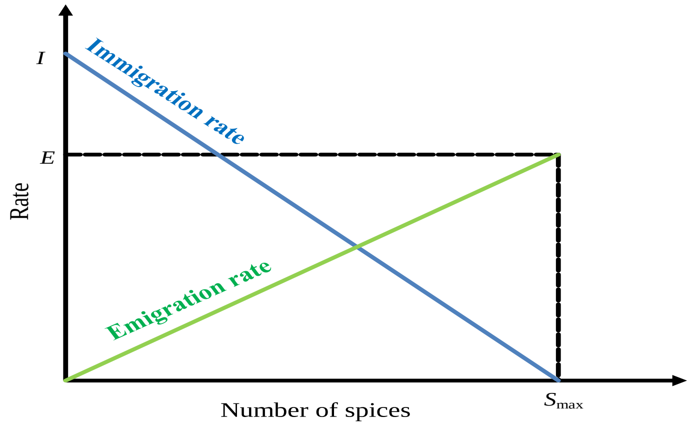

Figure 3. Migration rates vs. number of spices

A variable called Habitat Suitability Index (HSI) is assigned for each habitat. More than the rate of immigration decreases and the rate of emigration increases more HSI of the habitat increases, and vice versa since the habitats with high HSI which are well suited to the residence of the spices are more frequented. BBO is a population-based technique like GA. A detailed study in [20] for the similarities and dissimilarities between the characteristics of BBO and GA. In the BBO algorithm, individuals that are represented by chromosomes in GA, are represented by habitats. The fitness of each candidate habitat is its HSI. Habitats with high HSI correspond to the best solutions. Mutation and migration operators are the two main operators for BBO, as for GAs. Migration includes emigration and immigration.

A. *Migration operators*

To provide an improved solution to the optimization problem, immigration and emigration operators are used.

Let consider $N = S_{\max}$. Equations (10) and (11) respectively express the immigration and emigration rates of k

spices in the habitat as shown in Figure 3.

$$\lambda_k = I\left(1 - \frac{k}{N}\right) \tag{10}$$

$$\mu_k = \frac{Ek}{N} \tag{11}$$

Since each solution $X = (x_1, x_2, \ldots, x_n)$ is considered a habitat for this BBO algorithm and n is the number of decision variables. These variables are called Suitability Index variables(SIVs). By assigning each decision variable an SIV. A pre-specified probability Pmod is used to modify All solutions. All SIVs of the solution to be modified will migrate according to the immigration rate of the corresponding habitat. This standardized immigration rate is given by Equation (12). Once SIV is selected to migrate, the emigration rate is used to determine which of the other solutions must migrate its SIV to the solution to be changed.

$$\lambda_k \leftarrow \lambda^l + \frac{\left(\lambda^u - \lambda^l\right)\left(\lambda_k - \lambda^{\min}\right)}{\left(\lambda^{\max} - \lambda^{\min}\right)} \qquad (12)$$

Where, $\lambda^{\min}$ and $\lambda^{\max}$ are minimum and maximum bounds of the immigration rate, respectively. λ^l and λ^u are lower and upper limits of the normalized immigration rate, respectively.

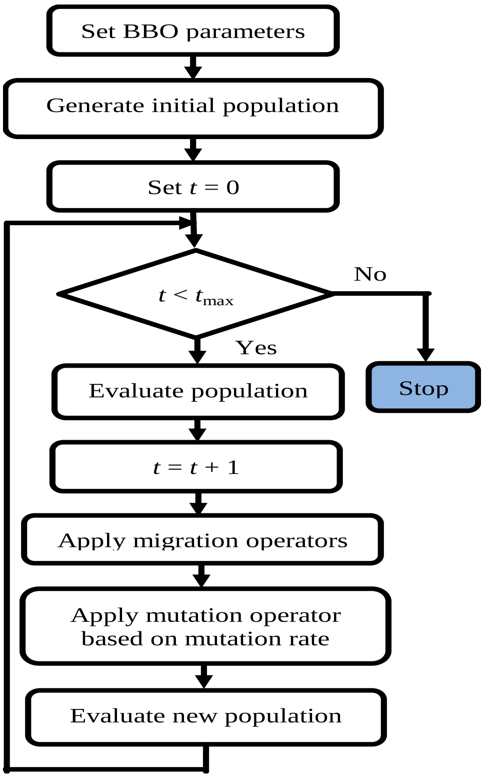

Figure 4. Flowchart of the proposed optimization algorithm

B. *Mutation operator*

In the sudden immigration of a large number of species from a neighboring habitat, the HSI of each habitat can undergo drastic changes due to climate change, natural disasters, diseases. This random change is modeled by a mutation operator in the BBO algorithm. After application of the migration operators, the SVI of the number of habitats of the population obtained will be modified using a mutation operator according to the mutation rate [21]. This mutation is applied in order to obtain the diversity of the population at the next iteration, like in GA. Regarding the most BBO-based optimization techniques, the mutation rates for each H habitat depend on the probability that P of this habitat contains S species. As shown in reference [16], Ps is updated. for each time step Δt as follows.

$$\begin{aligned} P_S(t+\Delta t) &= P_S(t)(1-\lambda_S\Delta t-\mu_S\Delta t) \\ &\quad + P_{S-1}\lambda_{S-1}\Delta t + P_{S+1}\mu_{S+1}\Delta t \end{aligned} \qquad (13)$$

For $\Delta t \to 0$, equation (13) can provide the following expression.

$$\dot{P}_S = \begin{cases} -(\lambda_S+\mu_S)P_S + \mu_{S+1}P_{S+1}; & S=0 \\ -(\lambda_S+\mu_S)P_S + \lambda_{S-1}P_{S-1} + \mu_{S+1}P_{S+1}; & 1 \le S \le S_{\max}-1 \\ -(\lambda_S+\mu_S)P_S + \lambda_{S-1}P_{S-1}; & S = S_{\max} \end{cases} \qquad (14)$$

The mutation rate can be described as follows.

$$m_s = m_{\max}\left(1-\frac{P_s}{P_{\max}}\right) \quad (15)$$

Where $m_{\max} \in [0,1]$ is a pre-specified parameter. $P_{\max} = \max\{P_1, P_2, \ldots, P_N\}$.

In our study, the non-uniform mutation operator has been employed. So, at the *t*-th iteration, each SIV will be transformed to other SIV' with a probability as follows.

$$SIV' = \begin{cases} SIV + \Delta(t, b - SIV), \text{ if } \tau=0 \\ SIV - \Delta(t, SIV - a), \text{ if } \tau=1 \end{cases} \quad (16)$$

$$\Delta(t,y) = y\left(1 - r^{\left(1-\frac{t}{t_{\max}}\right)^{\beta}}\right) \quad (17)$$

Where τ is a binary number, *r* is a random number and t_{max} is the maximum number of iteration. *a* and *b* are lower and upper bounds of the corresponding SIV. β represents the dependency degree on the iteration number.The flowchart of the proposed BBO algorithm with mutation operator is given in Fig. 4.

IV. Implementation of the Proposed Algorithm

Having been applied for the first time to solve one of the main power system problems which is the EED problem, the BBO will be tested in this section on ten unit power system. In order to demonstrate the effectiveness of the proposed optimization technique, a comparison with BBO algorithm and more than ten metaheuristic-based techniques used for solving the power dispatch problem is presented. Results have been obtained using MATLAB R2009a installed on a PC with i7-4510U CPU @ 2.60 GHz, 64 bit.

A. EED problem for the ten-unit system without POZs

To further demonstrate the applicability of this method for real power network, a large test system is also used that is the forty-unit system with VPLE. The EED problem is performed for this system with total power demand P_D of 2000 MW. Fuel cost coefficients, emission coefficients and operating limits of generators are taken from [18]. For validation, the proposed algorithm has been compared with other techniques that are recently used in the literature to solve the EED problem for the ten-unit system. The fitness function given in equation (3) has been minimized for $\lambda = 1.38501\,\$/\text{ton}$. Convergence characteristics of fuel cost and emission functions using BBO algorithm are depicted in Fig. 5 and front Pareto Solutions in Fig.6.

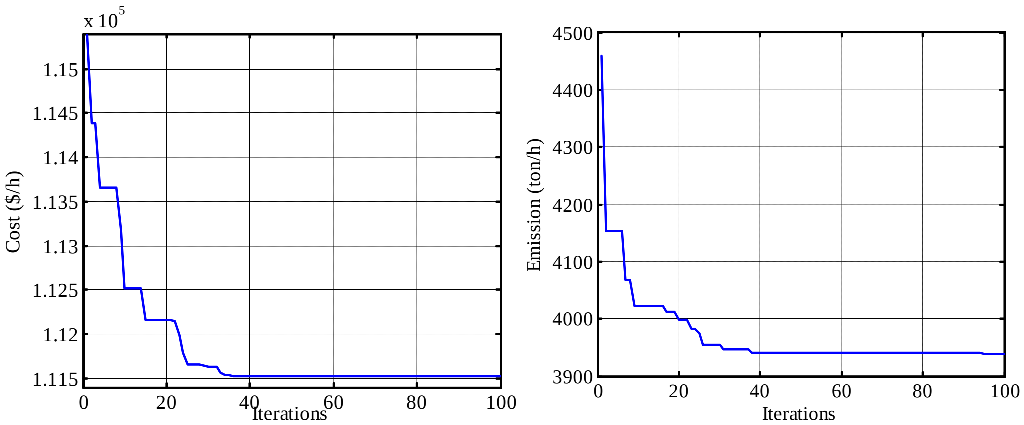

Figure 5.Convergence of the proposed algorithm of the Ten unit system without POZ

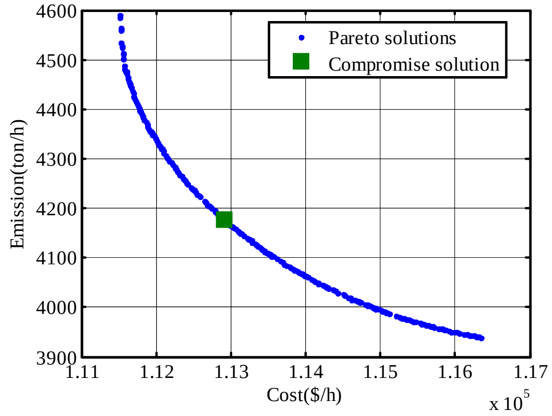

Figure 6.Pareto Solutions of the Ten unit system without POZ

Best solution for minimum cost, minimum emission and best compromise solution extracted from the Pareto front are tabulated in Table 1. Results for the proposed algorithm BBO and several techniques proposed in the literature [22-28] such as NSGAII and MOPSO-based methods, are compared in Table 2. It is clear that the proposed BBO provides the cheapest generation cost and the lowest emission that are around 112906 $/h and 4176 ton/h as a compromise solution respectively.

B. EED problem for the ten-unit system with POZs

In this case, the ten-unit system is used to prove the feasibility of BBO for solving the EED problem including all operating constraints such as VPLE and POZ constraints. The problem becomes with high nonlinearity and more complicated. The B-loss matrix of the ten-unit system is given below.

$$B = 10^{-4}\begin{bmatrix} 0.49 & 0.14 & 0.15 & 0.15 & 0.16 & 0.17 & 0.17 & 0.18 & 0.19 & 0.20 \\ 0.14 & 0.45 & 0.16 & 0.16 & 0.17 & 0.15 & 0.15 & 0.16 & 0.18 & 0.18 \\ 0.15 & 0.16 & 0.39 & 0.10 & 0.12 & 0.12 & 0.14 & 0.14 & 0.16 & 0.16 \\ 0.15 & 0.16 & 0.10 & 0.40 & 0.14 & 0.10 & 0.11 & 0.12 & 0.14 & 0.15 \\ 0.16 & 0.17 & 0.12 & 0.14 & 0.35 & 0.11 & 0.13 & 0.13 & 0.15 & 0.16 \\ 0.17 & 0.15 & 0.12 & 0.10 & 0.11 & 0.36 & 0.12 & 0.12 & 0.14 & 0.15 \\ 0.17 & 0.15 & 0.14 & 0.11 & 0.13 & 0.12 & 0.38 & 0.16 & 0.16 & 0.18 \\ 0.18 & 0.16 & 0.14 & 0.12 & 0.13 & 0.12 & 0.16 & 0.40 & 0.15 & 0.16 \\ 0.19 & 0.18 & 0.16 & 0.14 & 0.15 & 0.14 & 0.16 & 0.15 & 0.42 & 0.19 \\ 0.20 & 0.18 & 0.16 & 0.15 & 0.16 & 0.15 & 0.18 & 0.16 & 0.19 & 0.44 \end{bmatrix} \quad (18)$$

Total cost and emission functions will be minimized individually and simultaneously according to the power demand PD in MW. Unit data are taken from [18]. Generation schedule in MW using BBO algorithm for front Pareto Solutions of fuel cost and emission function with POZ constraints is shown in Fig 7. In addition, it can be seen that when total cost in $/h is minimized, the total emission in ton/h is at its maximum value and vice versa.

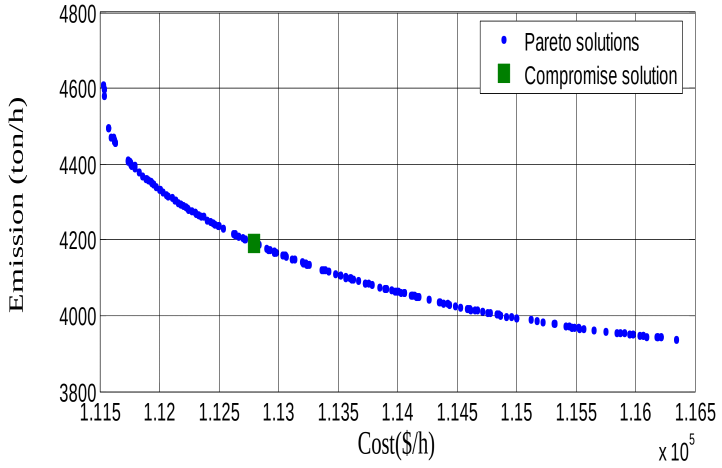

Figure 7.Pareto Solutions of the Ten unit system with POZ

TABLE 1. OPTIMUM GENERATION IN MW FOR PD = 10500 MW USING BBO ALGORITHM.

	Minimum cost	Minimum Emission	Compromise Solution
P1	54.3119	54.9189	54.9958
P2	79.6698	75.6915	79.6828
P3	116.0014	78.9341	88.1911
P4	100.1478	79.6363	85.0721
P5	83.6505	158.4241	128.3153
P6	76.2487	239.9714	148.1736
P7	299.7389	294.7465	297.4553
P8	339.0521	300.5536	321.0205
P9	468.500	397.6924	441.6506
P10	469.6871	401.2364	440.0315
Cost ($/h)	111534	116348	112794
Emission (ton/h)	4608	3937	4190
Losses (MW)	87.0085	81.8051	84.5885

TABLE 2. COMPARISON WITH OTHER META-HEURISTIC TECHNIQUES (TEN-UNIT SYSTEM, 2000 MW).

	Minimum cost			Minimum Emission			Compromise Solution		
	With CBBO	*With MOPSO*	*With NSGAII*	*With CBBO*	*With MOPSO*	*With NSGAII*	*With CBBO*	*With MOPSO*	*With NSGAII*
P1	54.8956	54.9999	54.7824	54.8214	54.9455	54.9126	54.8799	54.9704	54.9875
P2	79.9981	74.1543	79.6555	73.0994	79.8454	75.8895	78.8306	78.7160	77.6534
P3	109.6777	99.3913	87.7777	87.2102	81.8472	76.0226	87.7033	86.8131	80.0651
P4	102.8462	103.4706	97.9282	81.5546	84.1212	81.4785	83.5823	85.0392	84.3108
P5	87.1997	92.6824	97.7244	160.0000	159.9553	160.0000	133.3311	133.0219	139.1104
P6	74.6702	89.0310	106.6724	238.7611	231.0996	238.0721	149.2570	152.7218	163.6017
P7	298.5086	299.8666	289.6461	292.5171	280.8557	273.3706	295.6187	297.7803	288.3222
P8	339.5090	334.2644	333.4564	294.3314	302.8003	314.0412	318.8995	319.2379	325.0241
P9	469.8485	469.9252	469.1623	397.3514	406.5345	415.6467	441.1648	437.2097	444.0404

P10	469.8811	468.9854	469.7723	402.0187	399.8273	392.4622	441.2869	438.8710	426.9918
Cost ($/h)	111519	111590	111706	116347	116014	116282	112906	112985	113360
Emission (ton/h)	4590	4514	4432	3939	3946	3946	4176	4165	4129
Losses (MW)	87.0347	86.7711	86.5778	81.6653	81.8320	81.8962	84.5541	84.3814	84.1072

Shaded columns correspond to the results provided by the proposed algorithm.

V. CONCLUSION

Economic emission dispatch (EED) is a difficult optimization problem in the operation of the electrical system. The quality of its optimal solution is influenced by the operating constraints, such as the prohibited operating zones and the load effects of the valve. In this context, this study presented an optimization based on Cauchy biogeography (BBO) to solve the EED problem. All the above constraints have been considered. In addition, the power balance constraint was considered. The validation of the proposed optimization algorithm has been verified on ten unit test system. The results of comparison with more than ten metaheuristic techniques used recently in the literature show that the proposed algorithm gives the best optimal solutions. Therefore, according to the results, BBO can be presented as an algorithm capable of EED problem.

REFERENCES

[1] C.L. Chen & C.L. Wang, Branch-and-bound scheduling for thermal generating units, *International Journal of Industrial Mathematics*, 4(3), 163-170, 2012.

[2] A.J. Wood & B.F. Wollenberg, Power Generation, Operation and Control, 1994, *Wiley*, New York-USA.

[3] *C.W. Gar, J.G. Aganagic, B. Tony Meding Jose & S. Reeves, Experience with mixed integer linear programming based approach on short term hydrothermal scheduling, IEEE Transaction on Power Systems,16(4), 743-749, 2001.*

[4] C.E. Lin, S.T. Chen & C.L. Huang, A direct Newton-Raphson economic dispatch, IEEE Transactions on Power Systems, 7(3), 1149-1154, 1992.

[5] J.B. Park, K.S. Lee, J.R. Shin & K.Y. Lee, A particle swarm optimization for economic dispatch with nonsmooth cost functions, IEEE Transaction on Power Systems, 20, 34-42, 2005.

[6] Liang Z, Glover JD. A zoom feature for a dynamic programming solution to economic dispatch including transmission losses. IEEE Trans Power Syst 1992;7:544-550.

[7] Torres G, Quintana V. On a nonlinear multiple centrality corrections interior-point method for optimal power flow. IEEE Trans Power Syst 2001;16(2):222-228.

[8] Ganjefar S, Tofighi M. Dynamic economic dispatch solution using an improved genetic algorithm with non-stationary penalty functions. Eur Trans Electr Power 2011;21(3):1480-1492.

[9] Tlijani K, Guesmi T, Hadj Abdallah H. Extended dynamic economic environmental dispatch using multiObjective particle swarm optimization. Int J Electr Eng Inf 2016;8(1):117-131.

[10] Panigrahi CK, Chattopadhyay PK, Chakrabarti RN, Basu M. Simulated annealing technique for dynamic economic dispatch. Electr Power Compon Syst 2006;34(5):577-586.

[11] Ziane I, Benhamida F, Graa A. Simulated annealing algorithm for combined economic and emission power dispatch using max/max price penalty factor. Neural Comput Applic 2016:1-9. DOI 10.1007/s00521-016-2335-3.

[12] Sen T, Mathur HD. A new approach to solve economic dispatch problem using a hybrid ACO–ABC–HS optimization algorithm. Electr Power Energy Syst 2016;78:735-744.

[13] Lin WM, Cheng FS, Tsay MT. An improved Tabu search for economic dispatch with multiple minima. IEEE Trans Power Syst 2002;17(1):108-112.

[14] Jiang X, Zhou J, Wangc H, Zhang Y. Dynamic environmental economic dispatch using multiobjective differential evolution algorithm with expanded double selection and adaptive random restart. Electr Power Energy Syst 2013;49: 399-407.

[15] Vaisakh K, Praveena P, Naga Sujatha K. Solution of dynamic economic emission dispatch problem by hybrid bacterial foraging algorithm. Int J Comput Sci Electron Eng 2014;2(1):58-64.

[16] Simon D (2008) Biogeography-based optimization. IEEE Trans Evol Comput 12:702–713.

[17] Pandit N, Tripathi A, Tapaswi S, Pandit M. An improved bacterial foraging algorithm for combined static/dynamic. Appl Soft Comput 2012;12:3500-3513.

[18] M. Basu. Economic environmental dispatch using multi-objective differential evolution. Applied Soft Computing 11 (2011) 2845–2853.

[19] Ahrari A, Atai AA. Grenade explosion method-A novel tool for optimization of multimodal functions. Appl Soft Comput 2010;10:1132-1140.

[20] Zhang GH, Gao L, Shi Y (2010) A novel variable neighborhood genetic algorithm for multi-objective flexible job-shop scheduling problems. Adv Mater Res 118–120:369–373

[21] Zhang GH, Gao L, Shi Y (2011) An effective genetic algorithm for the flexible job-shop scheduling problem. Experts System with Applications 38(4):3563–3573

[22] Labbi Y, Ben Attous D, Mahdad B. Artificial bee colony optimization for economic dispatch with valve point effect. Front Energy 2014;8(4):449-458.

[23] Sinha N, Chakrabarti R, Chattopadhyay PK. Evolutionary programming techniques for economic load dispatch. IEEE Trans Evol Comput 2003;7(1):83-94.

[24] Sharma R, Samantaray P, Mohanty DP, Rout PK. Environmental economic load dispatch using multi-objective differential evolution algorithm. International Conference on Energy, Automation, and Signal (ICEAS), India, 28-30 december 2011.

[25] Amjady N, Nasiri-Rad H. Solution of nonconvex and nonsmooth economic dispatch by a new adaptive real coded genetic algorithm. Expert Syst Appl 2010;37(7):5239-5245.

[26] Pothiya S, Ngamroo I, Kongprawechnon W. Ant colony optimization for economic dispatch problem with non-smooth cost functions. Electr Power Energy Syst 2010;32(5):478-487.

[27] Yang XS, Hosseini SSS, Gandomi AH.Firefly algorithm for solving non-convex economic dispatch problems with valve loading effect. Appl Soft Comput J 2012;12(3):1180-1186.

[28] Basu M. Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II. Electr Power Energy Syst 2008;30:140-149.