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ARTICLE

AN IMPROVED BIOGEOGRAPHY-BASED OPTIMIZATION FOR ECONOMIC/ENVIRONMENTAL DISPATCH

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ABSTRACT

Scientific researches and technological developments, although they seek to solve the problems related to the reduction of the cost of generation and the emissions, are in the course of finding the best solutions. It is in this context that our paper is located and which focuses on the problem of dynamic economic environmental dispatch (DEED) using a Biogeography-based optimization (BBO). Ramp rate limits, Prohibited of operation zones (POZs) and effects of loading valve points are taken into account. The proposed technique integrates the Cauchy operator and the explosion method in the original BBO algorithm, to avoid the random search mechanism. The BBO is inspired by geographical distribution of species within islands. However, this optimization algorithm works on the basis of two concepts-migration and mutation. In this paper a non-uniform mutation operator and a Shannon's entropy based-method have been employed. The proposed technique shows a better diversified search process and therefore more precisely finds solutions with a high rate of convergence. This algorithm with new mutation operator is validated on forty-unit test system. The results showed that the proposed technique provides better compared optimal solutions with over ten meta heuristics techniques.

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KEY WORDS
Dynamic economic emission dispatch (DEED, Biogeography based optimization, Cauchy operator, Shannon's entropy

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INTRODUCTION

The dynamic economic environmental dispatch problem is to minimize two competing objective functions, total fuel cost and emission, while satisfying several equality and inequality constraints. In this paper, an improved of the original biogeography-based optimization is proposed and adapted for solving dynamic economic environmental dispatch problem. In order to enhance the performance of the original biogeography-based optimization, we will introduce the Cauchy operator and the extended entropy weighted reference approach.

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.

With the economic dispatch, sending emissions has become a major issue in market conditions. It aims to reduce the harmful emissions caused by power plants to fossil fuels such as CO, CO_2, NO_x and SO_2 [1-2]. This paper focuses specifically on this axis of electrical power systems to reduce carbon emissions for the thermal plants with equality and integrality constraints.

Thus, the combination of the above problems in one problem called economic emission dispatch (EED) problem became inevitable. However, due to the dynamic nature of the today network loads, it is required to schedule the thermal unit outputs in real time according to the variation of power demands during a certain time period [3]. To solve this modified EED problem known as dynamic economic emission dispatch (DEED), several mathematical formulations have been suggested in the literature [3-9]. In the most references, the DEED problem is considered as dynamic optimization problem having the same objectives as EED over a time period of one day, subdivided into definite time intervals of one hour with respect to the constraints imposed by generator ramp-rate limits (RRL) [3]. Therefore, the operational decision at an hour may be influenced by that taken at a previous hour.

Other constraints such as Prohibited Operation zone (POZ) and Valve Point Loading Effects (VPLE) have been taken into account in some works [10-12].However, incorporating VPLE in the fuel cost function makes it with ripples and the problem will be with multiple minima. On the other hand, POZ constraints due to physical operation limitation such as vibrations in the shaft bearing [13-14] create discontinuities in the objective functions. Therefore, the DEED becomes highly nonlinear problem with non-convex and discontinuous fitness functions.

Goal of this article is to propose a new approach to introduce a Cauchy operator in the classical Biogeography-Based Optimization for Economic/Environmental Dispatch problem. This methodology use a new optimization technique incorporating an Extended entropy-weighted reference approach to obtain convergence in the overall solution in a computation time, that there is a persistent requirement to solve a DEED problem.

A considerable amount of research works have been suggested for solving this kind of problems. Classical methods like dynamic programming [15], linear programming [16], lambda iteration [17] and interior point

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[18] methods have been used to solve the static EED. However, several criticisms have been addressed to these techniques because they require an initialization step and are iterative. That can cause the convergence of the search process into local optima. Moreover, they may fail to solve the dynamic case including above constraints.

Among meta heuristic-based optimization techniques, genetic algorithm [3-19], particle swarm optimization [11], simulated annealing [20-21], artificial bee colony (ABC) [14], tabu search [22], differential evolution [6] and bacterial foraging [7] have been suggested for solving the EED problem.

Although these techniques have proved superior to traditional methods, they are criticized in later studies [23]. Their effectiveness is sensitive to the form of the problem constraints and the number of units. Several studies prove that the BBO algorithm works better or just as well as other biologically inspired algorithms. References [24 and 25] contain a presentation of the BBO's main idea, its definitions and steps, and the validation of its good performance by Simon.

The performances of the BBO are improved in the reference [26] by the insertion of other distinguishing features of the heuristic algorithms. An oppositional BBO (BBOL) has been proposed and proved mathematically, where there is a highest probability of approaching the solution of the problem [27]. Regarding [28] Chen and Ma have explored the performance of six BBO migration models by extending the number of species in equilibrium theory of biogeography and proved that the sine migration model outperforms other models.

To evaluate the BBO's performance, it is also compared to other algorithms that each has a structure and a technical aspect of optimization. It is the quality of research that differs between them. The Cauchy operator is integrated in this study to improve globally and locally the optimization technique and to ensure convergence in a shorter calculation time. This integration has been used in some optimization techniques to improve overall search capability [29].

Finally, a multi-attribute decision-making method (MADM) based on Shannon's entropy is proposed in this study to classify the non-dominated solutions obtained, since EED is a bi-objective optimization problem with functions contradictory. Thus, the results with any optimization algorithm will be a set of non-dominated solutions called the Pareto front. However, providing an optimal Pareto solution for decision makers (DMs) is a persistent requirement. The concept of Shannon's entropy is used in several scientific domains [30] and single-sensor fault location [31].

Thus, a new method exploiting the advantages of BBO with mutation and Cauchy operator has been proposed in this study, for solving the DEED problem with respect to the all above constraints. This optimization symbolized by CBBO integrates the mutation and Cauchy operator into the BBO technique. On the other hand, new decision making method based on Shannon's entropy, called extended entropy-weighted reference (EEWR) approach, is developed and incorporated in the CBBO algorithm to select the suitable solution among all non-dominated solution provided by the optimization algorithm. Unlike other techniques such as those based on graph theory [32] and Z-transformation [33]. The EEWR is characterized by uncomplicated mathematics [34].

The main contributions of this work are summarized on the one hand by the application of a new optimization technique called CBBO to program the energy production of the thermal units according to the expected load variations, and on the other hand by The use of a EEWR-based technique proposed for decision-making as a first attempt to resolve the DEED problem using the CBBO algorithm. In addition, the consideration of all the above constraints simultaneously in the DEED problem. While noting that the RRL constraints have been taken into account during the transition between the last hour of the day and the next day for the first hour.

Mathematic formulation

In the literature, the dynamic economic emission dispatch (DEED) problem was considered as a multi-objective optimization problem (MOP). It aims to minimize simultaneously the total emission and total fuel cost by finding the power generation of thermal plants according to the predicted load demands. The resolution of the DEED problem can be accomplished by solving the static EED (SEED) problem over a certain period of time subdivided into smaller time intervals. In the present work, DEED problem objectives and constraints are described as follows.

Objective functions

Thermal units with multi-steam admission valves that work sequentially to cover ever-increasing generation, make the total fuel cost with higher order nonlinearity due to the VPLE, as illustrated in [Fig. 1]. Unfortunately, neglecting the VPLE, which is required when using classical methods, causes some inaccuracy in the solution of the DEED problem. Taking into account the VPLE constraints, a sinusoidal form is included in the total non-smooth cost function expressed in ($/h), as given in equation (1). The second objective corresponding to the total emission in (ton/h) is described by equation (2).

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

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

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^t is the output power in MW at the t-th interval. T is the number of hours. In this study, $T = 24$.

In several works the bi-objective DEED problem is converted into a mono-objective optimization problem [23]. In this study, the price penalty factor (PPF)-based method is adopted. Thus the combined economic-emission objective function FT can be described by equation (3).

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

where, $\mu = rand(0,1)$. For each generated value of µ, the function FTis minimized to obtain the optimum solution that can be a candidate solution to be in the Pareto front. The parameter ☐ is the average of the PPF of all thermal units. As shown in equation (4), the PPF of the i-th unit is the ratio between its fuel cost, $C_{i_{\max}}$, and its emission, $E_{i_{\max}}$, for maximum generation capacity.

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

Problem constraints

The DEED problem is solved by minimizing the function FT defined by equation (3) with respect to the following constraints.

- Generation capacity

Due to the unit design, the real power output of each unit i should be within its minimum limit $P_i^{\min}$ and maximum limit $P_i^{\max}$.

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

- Power balance constraints

At each time period t, the total power generation must cover the total demand power P_D^t plus the total transmission losses P_L^t. Thus, the power balance constraints can be described by the following equation.

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

where P_L^t can be calculated using the constant-loss formula [3] given by equation (7).

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

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

- Generating unit RRL

In practice, the power generation of each unit i during two consecutive time periods islimited by its RRLs defined by equations (8) and (9).

$$P_i^{t-1} - P_i^t \le R_i^{down} \quad (8)$$

$$P_i^t - P_i^{t-1} \le R_i^{up} \quad (9)$$

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where, P_i^{t-1} is the previous output real power of the i-th machine. R_i^{down} and R_i^{up} are the down-ramp and up-ramp limits of the i-th unit in (MW/time period).

As one of the contributions of this work, the RRL constraints are taken into account during the transition between the last hour of the day until the next day for the first hour. Two constraints are embedded in the problem formulation and they are described by equations (10) and(11).

$$P_i^{24} - P_i^{1} \leq R_i^{down} \quad (10)$$

$$P_i^{1} - P_i^{24} \leq R_i^{up} \quad (11)$$

- POZ constraints

The POZ constraints are described as follows.

$$P_i^t \in \begin{cases} P_i^{\min} \leq P_i^t \leq P_{i,1}^{down} \\ P_{i,k-1}^{up} \leq P_i^t \leq P_{i,k}^{down} & ,k = 2,\ldots, z_i \\ P_{i,z_i}^{up} \leq P_i^t \leq P_i^{\max} \end{cases} \quad (12)$$

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.

Therefore, the machine has discontinuous input–output characteristics [19]. [Fig. 2] shows the fuel cost function for a typical thermal unit with POZ constraints.

By considering the generation capacity, RRL and POZ constraints, the minimum and maximum limits of the power generation P_i^t of the i-th unit for the period tare modified as follows.

$$P_i^t \in \begin{cases} \max\left(P_i^{\min}, P_i^{t-1} - R_i^{down}\right) \leq P_i^t \leq \min\left(P_i^{\max}, P_i^{t-1} + R_i^{up}, P_{i,1}^{down}\right) \\ \max\left(P_i^{\min}, P_i^{t-1} - R_i^{down}, P_{i,k-1}^{up}\right) \leq P_i^t \leq \min\left(P_i^{\max}, P_i^{t-1} + R_i^{up}, P_{i,k}^{down}\right) \\ \max\left(P_i^{\min}, P_i^{t-1} - R_i^{down}, P_{i,z_i}^{up}\right) \leq P_i^t \leq \min\left(P_i^{\max}, P_i^{t-1} + R_i^{up}\right) \end{cases} \quad (13)$$

where $k = 2,\ldots, z_i$

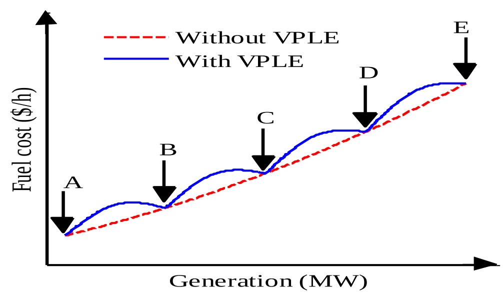

Fig. 1: Fuel Cost Function with Five Valves (A, B, C, D, E).

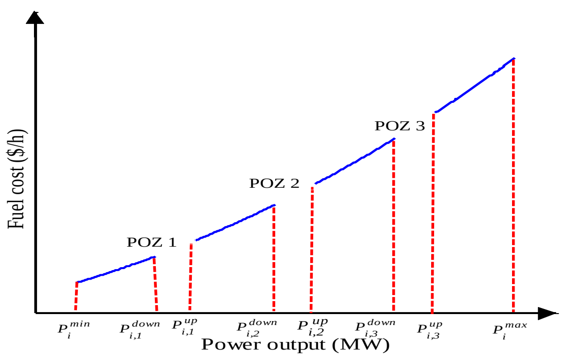

Fig. 2: Cost function for a thermal unit with POZ constraints

Cauchy biogeography-based optimization

The classical BBO algorithm with Migration and Mutation operator, is well detailed in the references [24-25-26]. [Fig. 3] illustrates the flowchart of this proposed BBO algorithm. In this work, the Cauchy operator is used in the lightening phase to improve the local and global exploration capabilities of the optimization algorithm and to obtain convergence in the overall solution in a computation time. Using a Cauchy operator in optimization technique has been integrated to certain algorithms to improve overall performance. [23] This is illustrated in [Fig. 4].

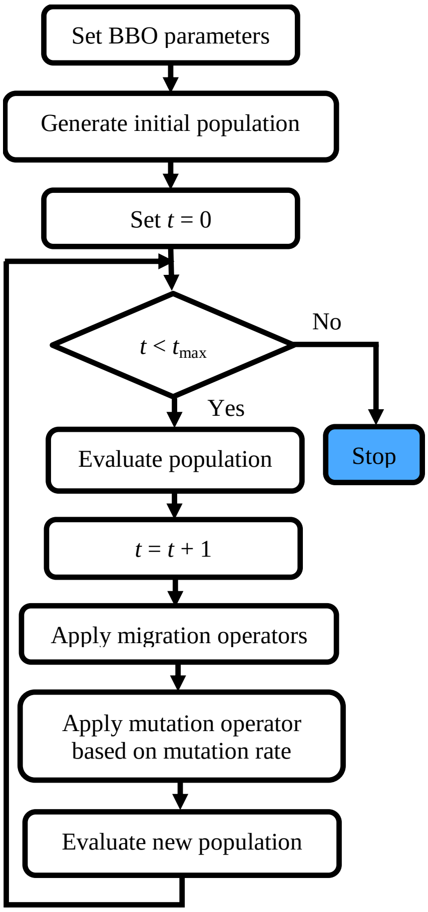

Fig. 3: Flowchart of the proposed optimization algorithm

Thereafter, the new solution is obtained using the equation (14).

$$x_j^i = x_j^i CAUCHY(0,1) \qquad (14)$$

where,

$$CAUCHY(0,1) = \frac{1}{\pi\left(1+(x_j^i)^2\right)} \qquad (15)$$

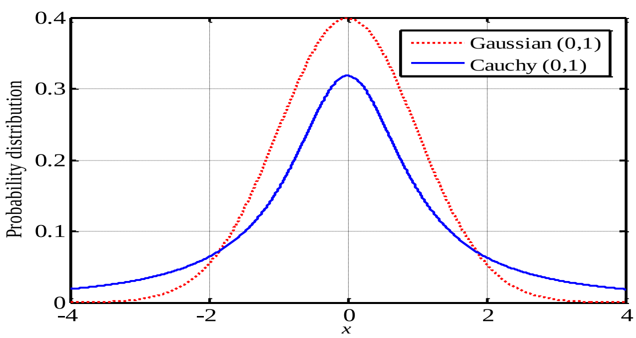

Fig. 4: Standard Cauchy and Gaussian distributions

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Extended entropy-weighted reference approach

The DEED is a bi-objective optimization problem with contradictory functions. Thus, results with any optimization algorithm will be a set of non-dominated solutions called Pareto front. However providing adequate candidate Pareto-optimal solution for the decision makers (DM) is a persistent requirement.
In this study, a Shannon's entropy-based multi-attribute decision-making (MADM) method is proposed to rank the obtained non-dominated solutions. The concept of Shannon's entropy is used in several scientific domains such as for materials selection [30] and single-sensor fault location [31]. This concept can be adopted for MOPs with n objective functions and m non-dominated solutions as follows.

Step 1: Construct the decision matrix $X = \left(x_{ij}\right)_{m\times n}$. Where x_{ij} called performance index is the value of the j-th function for the i-th solution.

Step 2: Normalize matrix X in order to have performance indices comparable and dimensionless [30].

$$x_{ij}^{*} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}^{2}} \quad (16)$$

Step 3: Calculate entropy h_j as follows.

$$E_j = -E_0 \sum_{i=1}^{m} x_{ij}^{*} \ln x_{ij}^{*},\ j = 1,\dots,n \quad (17)$$

Where, $E_0 = \frac{1}{\ln(m)}$ and $\ln x_{ij}^{*}$ is considered 0 for $x_{ij}^{*} = 0$.

Step 4: Compute the weight of each objective j.

$$w_j = \frac{1-E_j}{\sum_{j=1}^{n}\left(1-E_j\right)} \quad (18)$$

On the other hand, the decision maker can assign a degree of importance s_j for each objective function j called subjective weight. Thus, weights should be modified as follows.

$$w_j^{*} = \frac{s_j w_j}{\sum_{j=1}^{n} s_j w_j} \quad (19)$$

Step 5: Determine the i-th co-ordinate reference point (CRP) per objective function. It is defined as the highest performance index for maximization and the lowest performance for minimization [31]. However the DEED is minimization problem. Thus, the CRP can be found as follows.

$$r_j = \min_i x_{ij}^{*} \quad (20)$$

Step 6: Calculate the deviation of each performance index from the CRP for each objective function. Then, determine the maximum deviation for each alternative respecting all objective functions using the following equation. Each non-dominated solution is considered as alternative.

$$z_i = \max_j \left| w_j^{*} r_j - w_j^{*} x_{ij}^{*} \right| \quad (21)$$

Step 7: Classify all alternatives according their maximum deviations. Then, select the alternative with rank one as the optimal alternative.

MATERIALS AND METHODS

Optimization based on biogeography (BBO), is a new algorithm inspired by the principle of displacement of species that depends mainly on the topographical characteristics of the space considered habitat and time. Similarly at the GA, BBO is a population-based technique. The similarities and differences between the characteristics of GA and BBO were examined in [25]. Individuals represented by chromosomes in GA are represented by habitats in BBO. Like GA, BBO has two main operators that are mutation and migration operators. Migration includes emigration and immigration, which are used to provide an improved solution to the optimization problem. All solutions will be modified with a predefined probability. At an iteration t, the flow chart of the migration operator is described in [Fig. 3]. In the BBO algorithm, the random change is modeled by the mutation operator. As in GA, the mutation is applied to ensure population diversity at the next iteration. The flowchart of the proposed BBO algorithm with mutation operator is given in [Fig. 3]. In order to improve the global and local exploration capabilities of the optimization algorithm and to ensure convergence in the overall solution in a short computation time, the Cauchy operator is integrated. Since DEED is a dual objective optimization problem with conflicting functions. Thus, the results obtained with any optimization algorithm will constitute a set of non-dominated solutions called the Pareto front. However, providing a Pareto-optimal candidate solution suitable for decision makers (DS) is a persistent requirement. In this study, a multi-attribute decision-making (MADM) method based on Shannon's entropy is proposed to rank the obtained non-dominated solutions.

RESULTS

Implemented of the proposed algorithm

Having been applied for the first time to solve the DEED problem, the CBBO will be tested in this section on forty-unit test system. In order to demonstrate the effectiveness of the proposed optimization technique, a comparison with CBBO algorithm and more than ten meta heuristic-based techniques used for solving the power dispatch problem is presented. For fair comparison, CBBO and BBO algorithms have been implemented with same parameters. Results have been obtained using MATLAB R2009a installed on a PC with i7-4510U CPU @ 2.60 GHz, 64 bit.

Simulation results for forty-unit system

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 DEED problem is performed for this system with total power demand PD of 10500 MW. Fuel cost coefficients, emission coefficients and operating limits of generators are taken from [31]. For validation, the proposed algorithm has been compared with other techniques that are recently used in the literature to solve the DEED problem for the forty-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 CBBO algorithm are depicted in [Fig. 5].

Best solution for minimum cost, minimum emission and best compromise solution extracted from the Pareto front using the EEWR method are tabulated in [Table 1]. Results for the proposed algorithm CBBO and several techniques proposed in the literature [31-37] such as ABC, differential evolution (DE), GA, FA, PSO-based methods, etc. are compared in [Table 2]. It is clear that the proposed CBBO provides the cheapest generation cost and the lowest emission that are around 121274.7 $/h and 176298.75 ton/h, respectively.

DISCUSSION

In order to investigate the importance of the proposed algorithm is tested on a large system. This test system consists of forty units. The fuel cost and emission rate coefficients of the system are taken from [33]. Total load demand of the system is 10500(MW). Concerning the function fuel cost, the best fuel cost achieved is 121274.7 ($ / h), the corresponding emission is 129911.09 (ton/h). While for the minimum emission, the best emission achieved is 176298.75 (ton/h), the corresponding fuel cost increased to 386005.6 ($/h). The convergence characteristic of the emission cost and the total fuel cost is shown in [Fig. 5].

In comparison with the other works, we can say first of all concerning the fuel cost function that all the results found for the other methods are between 121410.1038 ($ / h) given by Amjady & Nasiri in [43] applying the adaptive real coded genetic algorithm, and 124963.5028 ($ / hr) given by Sharma et al in [42] using multi-objective differential evolution algorithm, while the best cost achieved is 121274.7 ($ / h) corresponds to our approach. Similarly for the function emission, the best value achieved is 176298.75 (ton / h) which represents a brave result compared to the value 176680 (ton / h) quoted by Basu M using multi-objective differential evolution [3], and also more acceptable compared to the result achieved by Sharma et al in [42] which has the value 176691.9677 (ton / h).

The best results of the proposed algorithm for emission and fuel cost compared with other methods are illustrated in [Table 2] shows clearly the efficiency of the proposed algorithm.

In other words, the comparison of the optimization solution values obtained by different methods, lets us say that the Cauchy Biogeography-Based Optimization CBBO) provides better results. For the total fuel cost function, this result has led to a difference of 135.4038 ($ / hr) corresponds to a reduction of 0.11% compared to the lowest average reaching 121410.1038 ($ / hr) given by Amjady & Nasiri in [43]. While for the emission function, this result offers a difference of 381.25 (ton / h), corresponding to a reduction of 0.21% compared to that found by Basu M using multi-objective differential evolution, and reaching 176680 (ton/h).

Finally, The best optimization results found proves the robustness of this proposed algorithm and explains the employment interest of cauchy operator and extended entropy weighted reference approach, which facilitate the calculation of the fitness function in a large research space and the convergence towards the optimal solutions and therefore the reach of the best distribution of solutions on the Pareto-optimal front.

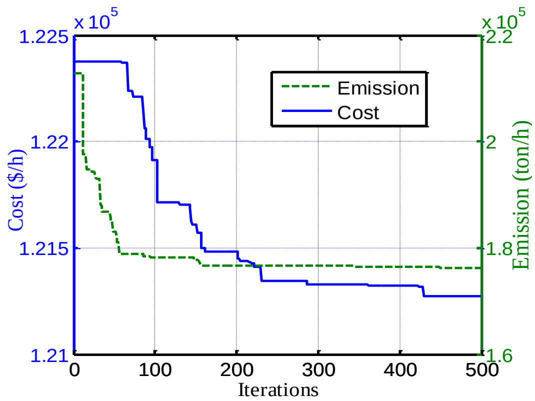

Fig. 5: Convergence characteristics for the forty-unit system

Table 1: Optimum generation in MW for PD = 10500 MW using CBBO algorithm

Unit	Best cost	Best emission	Compromise solution	Unit	Best cost	Best emission	Compromise solution
1	113.8290	118.8684	119.8063	22	524.1471	432.0455	432.2057
2	113.2299	119.5250	115.6567	23	524.3811	437.9027	433.2583
3	98.0011	120.0000	119.2039	24	524.2323	433.8896	433.5362
4	186.3411	171.0041	178.3300	25	521.8417	437.0916	501.0573
5	87.0371	99.6506	96.0204	26	536.4294	440.2194	437.0645
6	138.6373	126.4088	134.3184	27	10.0000	28.2081	14.1721
7	271.3121	293.3165	299.4197	28	10.4862	28.3884	11.7179
8	288.1500	298.0365	296.6266	29	10.0000	28.3276	16.2792
9	284.2195	296.4214	287.9952	30	92.5794	98.9027	100.0000
10	127.1966	136.1537	129.7703	31	200.0000	171.4707	187.0198
11	166.6426	298.0555	284.9993	32	200.0000	171.9558	187.8337
12	94.2546	300.0000	242.3292	33	200.0000	169.5057	169.5994
13	125.0000	435.5130	394.3331	34	196.6399	200.0000	200.0000
14	392.2697	428.8594	393.9470	35	165.3106	200.0000	200.0000
15	304.9252	424.3950	392.6474	36	200.2927	200.0000	200.0000
16	390.9502	418.5687	393.7188	37	119.6147	102.1179	109.8768
17	490.4709	438.3276	485.8105	38	115.0000	103.8253	106.2503
18	489.4177	441.5894	488.9333	39	119.6390	102.6590	105.2231
19	513.9565	437.8936	431.9575	40	520.6428	444.5290	423.5281
20	511.1485	433.7515	436.0734	TC ($/h)	121274.7	129911.09	125949.3
21	521.7736	432.6224	509.4806	TE(ton/h)	386005.6	176298.75	206914.8

TC: Total cost ($/h) and TE: Total emission (ton/h)

Table 2: Comparison with other meta-heuristic techniques (forty-unit system, 10500 MW)

Method	Minimum cost ($/h)	Minimum emission (ton/h)
CBBO	121274.7	176298.75
DE (Basu, 2011) in reference [3]	121840	176680
ABC (Labbi et al., 2014) in reference [40]	121479.6	NA
CEP (Sinha et al., 2003) in reference [41]	122679.71	NA
MODE (Sharma et al., 2011) in reference [42]	121836.98	129956.09
NSGAII (Sharma et al., 2011) in reference [42]	124963.5028	176691.9677
ARCGA (Amjady&Nasiri, 2010) in reference [43]	121410.1038	NA
APSO (Amjady&Nasiri, 2010) in reference [43]	121663.52	NA
TS (Pothiya et al., 2010) in reference [44]	122288.38	NA
FA (Yang et al., 2012) in reference [45]	121415.05	NA

CONCLUSION

In this study, a flexible and efficient improved biogeography-based optimization has been successfully adapted and applied for solving dynamic economic environmental dispatch problem satisfying several equality and inequality constraints. Dynamic economic environmental dispatch (DEED) 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 (CBBO) to solve the DEED problem. All the above constraints have been considered. In addition, the power balance constraint was considered. The proposed optimization technique integrates the grenade explosion method and the Cauchy operator into the classic BBO algorithm to avoid random search in the different stages of the BBO. To provide an adequate compromise solution for decision makers, an approach based on an extended entropy weighting reference was proposed. The validation of the proposed optimization algorithm has been verified on forty-unit test system. The results of comparison with more than ten meta heuristic techniques used recently in the literature show that the proposed algorithm gives the best optimal solutions. Therefore, according to the results, CBBO can be presented as an algorithm capable of DEED problem. In the future direction, one of the most effective approaches to reducing carbon emissions is the integration of renewable energy sources into electricity grids. Currently, wind energy sources are the fastest growing sources of all renewable sources. So the reproduction of this work to solve the DEED problem incorporating wind farms.

CONFLICT OF INTEREST

There is no conflict of interest.

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