Optimization of Non-Convex Economic Dispatch Problem Using Hybrid Approach Based on Bacterial Foraging and Genetic Algorithm

ABDUL SHAKOOR
Department of Electrical Engineering, University of Engineering and Technology, Taxila, PAKISTAN.

Abstract: Fulfillment of consumer demand is a foremost challenge for all electrical power utilities. An electrical power system consists of several generating units and each of these units owns a distinct operating set of operating parameters. A fundamental challenges lies in a fact that there may not be a correlation between operating costs of these machines and their generated output. Major reason for lack of the correlation includes the ramp-rate limits, transmission losses and manipulation due to valve-points in the generation units cost function, and thus, it becomes a non-linear optimization problem. In view of this fact, it creates a rigorous need to devise a robust solution to cater for such a non-linear optimization scenario. In this paper, bacterial foraging and genetic algorithms based hybrid technique is used to effectively tackle the economic dispatch problem. The presented technique incorporates two modifications in the original bacterial foraging algorithm including differential evolution inspired bacterial movement and genetic algorithm based bacterial reproduction. Where inspired bacterial movement involves modification in the directional movement for each bacterium in such a manner that every bacterium tries to improve its direction and position based on differential evolution. The proposed technique is applied to non-convex dynamic economic dispatch (DED) problem in order to obtain optimal solution within feasible functional limits while satisfying the load demand at the same time. The obtained results demonstrate that the proposed hybrid approach outperform the other techniques in term of optimal solution and significant reduction of computational time in the given scenarios.

Keywords: Economic Dispatch (ED), Dynamic Economic Dispatch (DED), Bacterial Foraging Algorithm (BFA), Genetic Algorithm (GA), Differential Evolution (DE).

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1. Introduction

Power networks are very complex systems formed by generation units, transmission and distribution networks. The main goal of all power utilities is to supply highly reliable power to the customer at lowest cost. At the same time, the boundaries and restrictions of the generating units should be also taken into account. This is known as "Economic Dispatch(ED)" problem [1]. Economic dispatch is useful to determine the best combination between the interconnected power plants, and the system load (demand) to minimize the fuel prices satisfying equality and inequality restrictions. Several techniques such as gradient search, lambda iteration, base point method, dynamic programming etc. are available for solving problems related to economic dispatch. The last one is widely used but there are problems regarding dimensionality. There exists significant non-linearity and lack of smoothness, due to multiple fuels and ramp rates, in the input-output characteristics of practical power plants. It is problematic to solve through both ordinary and classical ways. So, the wide variety of heuristic methods such as Bacterial Foraging Algorithm (BFA), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are general methods to solve these problems.

In past few years, hybrid techniques are observed to be more proficient to solve non-convex problems. They diminish the search space to locate optimal solution in a satisfactory computational time. Furthermore, they can facilitate number of constraints to solve both small and large scale problems with better quality of solution.

2. Literature Review

The bacterial foraging optimization algorithm was first proposed by K.M Passino to solve un-constrained optimization problems [2]. Now a days, the Swarm optimization techniques are drawn the attention of researchers considering the fact that they've information sharing and conveying mechanisms to remedy real world optimization problems .Amongst swarming based techniques, bacterial foraging is very promising with set of advantages related to regional minima, randomness, direction of movement, attraction/repelling, swarming and so on. The stand-alone bacterial foraging (BF) experiences poor convergence attributes for high dimensional issues. To handle the non-linear and multi-dimensional ED issue, this disadvantage ought to be treated with the reconciliation of other EA's. If Economic dispatch is taken in to account, there are few research papers published on BFA to solve the ED problem since 2008. Ahmed .Y. Saber, et al. [3], in order to solve economic dispatch problem, an adaptive methodology is introduced for the sake of improvement of searching skill ability of BFA, PSO has been offered. Ultimately, a standard test system from IEEE is used to demonstrate the ability of the proposed strategy and the effects are contrasted with different methods from recent literature. K. Vaisakh, et al. [4] presented a hybrid approach consisting on differential evolution, particle swarm optimization (DE-PSO) and BFA to treat DED problem of multiple generating units involving valve-point effects. The proposed method has been contrasted with others and seemed expert in two test cases comprising of five and ten units test models. I.A Farhat et al. [5] presented an improved bacterial foraging algorithm (IBFA) to remedy the ED problem on the grounds of the valve-point effects and transmission losses. To beat the poor convergence and dimensionality dilemma of BFA, the basic chemo-tactic step is tuned to have a dynamic behavior for enhancement of exploration and exploitation capabilities. Based upon the solution development, BFA can be more reliant and adaptive. The proposed algorithm is verified utilizing various test techniques. P.K Hota, et al. [6] proposed a modified bacterial foraging optimization algorithm (MBFOA) involving fuzzy logic methodology to obtain the best promising solution for economic and emission dispatch and validated on Taiwan power system of forty generating units. B.K. Panigrahi et al. [7] presented a bacterial foraging meta-heuristic algorithm for multi-purpose optimization. In this approach, the most recent bacterial locations are received by means of chemotaxis. Furthermore, Pareto optimal front (POF) is chosen through fuzzy logic sense based sorting. In order to verify the proficiency of proposed algorithm IEEE 30-bus 6-generator standard test system is considered and the outcome are contrasted with the other reported outcome. Rahmat-Allah Hooshmand, et al. [8] proposed a hybrid strategy based on Bacterial Foraging Algorithm and Nelder-Mead technique (BF-NM). Usefulness of the proposed technique is presented in comparison with several EA techniques. Total cost obtained as a result of the proposed technique proved the benefit of the method. Nicole Pandit, et al. [9] introduced a improved bacterial foraging algorithm (IBFA) where crossover operation and parameter automation system is used to improve computational efficiency. The performance of IBFA is compared with recently released methods and seems to be better. Ahmed Yousuf Saber, et al. [10] presented a modified particle swarm optimization (MPSO) involving advantages of bacterial foraging (BF) and PSO. The modified PSO has better exploration and exploitation capabilities to restrict regional minima. Finally, the results of present approached from literature are used to exhibit the effectiveness of the proposed technique. K. Vaisakh, et al. [11] offered BPSO-DE by the integration of BF with PSO and DE. The result gives the best foraging methodology search based on bacteria, that is then updated at every step of PSO. The solution produced as a result of BF and PSO is then regulated by the DE operator. Rasoul Azizipanah-Abarghooee, et al. [12] introduced a novel bacterial foraging (BF) approach, which involved initialization using opposition-based and a novel mutation operator. This operator is utilized in classical bacterial foraging (BF) to control the pre-mature convergence. In addition, long step size or short step size may be used for timely readiness of the bacteria involved in the chemo tactic step**.** Zhi Lu et al. [13] proposed a modified Bacterial foraging technique .In this procedure, a Lamarckian constraint coping with strategy established procedure is upgraded for upgrading of bacterial colony. Finally, IEEE 30 Bus system was incorporated for the testing of the proposed system. Results suggested that this proposed technique came up with the advantage of catering for the multi-purpose and non-convex features related to thermal generators taking both ED and EED issues. G. Wu et al.

[14] presented a bacterial foraging optimization algorithm (BFOA).

It performed a study of ED related to a hydropower system. Based upon the results that showed increased efficiency, it was concluded that the proposed system was better. Ehab E. Elattar et al [15]. Offered hybrid bacterial foraging and genetic algorithm. Proposed method is proven on 5, 10, 30 generation models for non-convex ED. The outcome are compared with the outcome acquired by means of different approaches.

The focus of this paper is to implement bacterial foraging and genetic algorithms based hybrid approach for non-convex economic dispatch problem considering the ramp rate limits and valve point loading effects. For the sake of validation of the research work, the results of the research are compared with many other techniques.

The paper organization as follows: Brief introduction and literature review in section-1. Mathematical model for non-convex economic dispatch problem is formulated in Section-2. Proposed hybrid algorithm is presented in section-3. Results and comparison with different techniques are in section-4. Section-5 concludes the whole work.

3. Non-convex Economic Dispatch Problem Formulation

In order to determine the optimal load of all the linked generating units, the economic dispatch problem is designed. The goal is to limit the cost function subject to the system constraint. In order to formulate the ED problem, N_G is defined as the number of committed units, P_D as the total load demand, P_{Gi} as active power generation for unit i, $F_i(P_{Gi})$ and F_r as Operational and total cost for unit i over the dispatch period.

$$Minimize: F_r = \sum_{i=1}^{N_G} F_i\left(P_{Gi}\right) \tag{1}$$

Subject to:
Load balance equation

$$\sum_{i=1}^{N_G} P_{Gi} - P_D = 0 \tag{2}$$

Generating unit capacity limits

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, i = 1, 2, \ldots, N_G \tag{3}$$

$P_{Gi}^{\min}$ and $P_{Gi}^{\max}$ are upper and lower operational limits for generator i.

Transmission Losses For energy systems: Mostly electrical energy is transmitted over long transmission lines, the values of the network losses must be monitored, as these affect the output of the generator. It is estimated that for practical systems the losses can be 5% to 10% of the total energy generation [16]. So the function is expressed in equation (1) must be minimized while satisfying the equilibrium equation (4) of the energy.

$$\sum_{i=1}^{N_G} P_{Gi} - P_D - P_L = 0 \tag{4}$$

P_L is the actual power loss of the system which is calculated by equation (5), known as George's formula [17].

$$P_L = \sum_{i=1}^{N_G} \sum_{J=1}^{N_G} P_{Gi} B_{ij} P_{Gj} \tag{5}$$

In order to obtain the most accurate losses, a constant and a linear and must be added to the equation (5) known as Kron loss formula [17] in equation (6).

$$P_L = \sum_{i=1}^{N_G} \sum_{J=1}^{N_G} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{N_G} B_{i0} P_{Gi} + B_{00} \tag{6}$$

The B-coefficients vary with the condition of the system operation. Although it is considered that they are constant parameters.

Valve Point Loading Effects: The actual input-output characteristics are highly non-convex due to opening and closing of fuel valve. In order to represent the valve points are included in the fuel cost function as follows:

$$F_i\left(P_{Gi}\right) = a_i + b_i * P_{Gi} + c_i * P^2{}_{Gi} + \left| e_i \sin\left(f_i\left(P_{Gi}^{\min} - P_{Gi}\right)\right)\right| \tag{7}$$

Where a_i, b_i and c_i are fuel cost coefficient of generator i. e_i, f_i are valve point loading effects, $P_{Gi}^{\min}$, $P_{Gi}^{\max}$ are upper and lower limits for generator i.

Ramp Rate Limits (RRL):

$$P_{it} - P_{i(t-1)} \le UR_i \tag{8}$$

$$P_{i(t-1)} - P_{it} \le DR_i \tag{9}$$

Where UR_i and DR_i are the ramp-up and ramp-down rate for the i^{th} generator. So, the limits of the capacity of the unit are modified as:

$$\max\left(P_{Gi}^{\min}, P_{i(t-1)} - DR_i\right) \le P_{Gi} \tag{10}$$

$$P_{Gi} \leq \min\left(P_{Gi}^{\max}, P_{i(t-1)} + UR_i\right) \quad (11)$$

4. Essential Background of Hybrid Techniques

4.1 Bacterial Foraging

Bacterial foraging algorithm (BFA) which is inspired by the foraging behavior of Escherichia coli (E. coli) was first proposed by K.M. Passino.

In the nature, the living organisms try to maximize ingested energy (E) due the measure of time (T) they spend seeking wild food assets. The foraging species also perform an optimization task to maximize the function E/T. This is important for the survival of the species. Foraging task involves the search of a food source, make the decision to enter and find wild food and determinate which is the best moment for seeking a better and a new food source. These tasks vary between one specie to another and affected by different internal aspects of the organisms such as food type, metabolic qualities. They are affected by external aspects like the weather and geography. Such tasks are also carried out at the same time with other tasks like seeking of safe shelter or territory. As indicated by ideal foraging theory, foraging can be planned as an optimization problem.

Commonly the animals that live in groups perform cooperative tasks. In this activity, the individuals share information with other group members. The information sharing can be possible through sound signals, chemical signals or body language. Through social foraging an individual may obtain higher rates of energy gain. Other advantages of grouping individuals are the ease of driving and the facility of protecting each other from predators. Some examples of social foraging are: Wolves, fishes, and ants. The food search strategy is the biggest part of the foraging and many foragers follow the same strategy used by predators. A bacterial foraging operates through locomotion, chemotexis and evolution process.

Locomotion is the nonstop rotation alternates between two modes: swimming and tumbling. During swimming, the counterclockwise rotation of the flagellum pushes the body forward. When it propels clockwise, the bacteria tumbles and moves in random direction. The displacement is small during tumbling.

Chemotexis is the movement of a bacterium in a direction corresponding to a gradient concentration of a particular substance. E. coli swim to head to nourished places. They have been observed to be attracted to serine or aspartate. On the other hand, they tumble to avoid unpleasant areas usually containing metal ions Nickel, Cobalt, amino acids and organic acids.The foraging behavior of E.coli is generally observed in chemotaxis (swimming or tumbling) in relation to the chemicals in the medium.In general, the concentration of desirable chemicals is directly proportional to the rate of swimming and indirectly proportional to tumbling [2].In an impartial domain where neither attractive nor dangerous substances exist, the bacteria movement alternates between swimming and tumbling. In homogenous environments, where both desirable and toxic substances exist, the bacteria will swim more and will tumble less. Note that the availability of food source will not inhibit the organisms to seek for food hence they will continue to look for nourishment. They will swim as long as the gradient concentration is favorable. If they come in contact with adverse substances, they will tumble but will still swim to climb back to the positive concentration gradient.

Evolution process in E. coli is occurred at a mutation rate of approximately 10-7 per gene per generation. The genes change through the process of conjugation where DNA attributed to fitness and fertility are passed on to the next generation. In other words, characteristics favorable to its survival are inherited by succeeding generations. When the environment is adverse or had sudden or slow changes, elimination, dispersion or both occurs. The population can be eliminated partially or totally. Dispersal drives the population to another part of the environment which can either be beneficial or disadvantageous. Either event has a two-sided impact on the chemotactic process.

4.2 Genetic Algorithm (GA)

Genetic algorithms are search strategies that utilize processes found in regular natural development. At every generation, another population is made by selecting an individual as per their physical fitness in the problem domain. Selection, crossover and mutation are the three fundamental operations employed in genetic algorithms. The selected solutions are modified through these operations and the most appropriate issue is selected to be passed on to succeeding generations. Genetic algorithms simultaneously consider multiple points on the search distance. They have been found to provide a rapid convergence to a near optimum solution in many cases of problems.

Differential development (DE) is also belong to the class of genetic algorithms (GAs) which utilize bio-inspired operations of selection, crossover, and mutation on a population to limit an objective function through the span of progressive generations. An initial mutant parameter vector is made through the selection of three random individuals from the population.DE utilizes real values rather than bit-string encoding, and arithmetic operations rather than logical operations in mutation compare to exemplary GAs. Let NP denote the number of individuals in the population. In order to generate the initial population, NP guess for the optimal values of the parameter vector by either choosing values between upper and lower limits or user defined. Every generation includes making of another population from the present population individuals {x_i | I = 1, . . . ,NP}, where i is population index.

5. Hybrid Bacterial Foraging, Genetic Algorithm, and Differential Evaluation (HBFA-DE-GA)

The Inspired movement for bacterium is accomplished using differential mutation as follow; an initial mutant parameter vector V_i is made by selecting the three individuals from the population, current member (x_i), and two random members x_{i1} and x_{i2} from population. Then v_i is generated as.

$$v_i = x_i + F.\left(x_{i1} - x_{i2}\right) \tag{12}$$

$$Where\ 0 < F < 1$$

Genetically inspired reproduction instead of simple bacterial reproduction is introduced as follows; bacteria are kept sorted according to their fitness and split into fittest 50% and worst 50% then fittest and worst are recombined using heuristic cross over operator [18] as:

$$Offspring = P1 + \ \left(P1 - P51\right) * \beta \tag{13}$$

Where β is random value (0-1) .P1 is fittest parent and P51 is worst parent.P2 and P52 is next pair for recombination vice versa. Offspring's than mutated using dynamic mutation operator [19] as.

$$x_j = \begin{cases} \bar{x}_j + \Delta\left(k, x_j^U - \bar{x}_j\right), \tau = 0 \\ \bar{x}_j + \Delta\left(k, \bar{x}_j - x_j^L\right), \tau = 1 \end{cases} \tag{14}$$

Where k is generation number. L and U are lower and upper limits for variablex_j, η is random number (0, 1), G is the highest number of generations, b is degree of dependency on iteration number.

$$\Delta(k, x_j) = x_j * \eta * (1 - k / G)^b \tag{15}$$

5.1 Economic Dispatch using Proposed BFA-DE-GA Algorithm

1. Initialization of parameters:
   - Number of bacteria (Nb)
   - Number of chemotexic steps(Nch)
   - Number of elimination dispersal steps(Ned)
   - Number of reproduction steps(Nre)
   - Probability of mutation(Pm)
   - Probability of crossover (Pc)
   - Scaling factor (SF)
   - Genetic algorithm iterations(GA iter)
   - Differential evolution iterations(DE iter)
2. Initialization of system parameters:
   - Population matrix (X)
   - Machines data matrix (H)
   - Load demand matrix(Ld)

Loop (iter: 1→T)

3. Elimination/ dispersal

Loop (l: 1→L)

4. Reproduction
   Loop (k: 1→K)
5. Chemotaxis
   Loop (j: 1→J)
6. Bacterium population
   Loop (i: 1→I)
   - Calculate the initial fitness of the i^{th} bacterium using fitness function using Eq. (16).

$$FITB = \frac{1}{FITB + Penalty\ Function} \tag{16}$$

   - Save as LAST_FITB
4. Differential Evolution inspired movement.
   Loop (DE iter: 1→Maximum DE iter)
   - Randomly select two bacteria from population
   - Apply differential evolution (DE) mutation using Eq. (12).
   - Calculate the fitness of the resultant bacterium using Eq. (16).
   - If resultant bacterium is better than the i^{th} bacterium then swim in the same direction.
   - Calculate the fitness of bacterium at new position using Eq. (16).
   - Save as FITB.

- If FITB <LAST_FITB, move bacterium into same direction.

End of Loop (DE iter)

End of Loop (j)

5. Genetic Reproduction:

Loop (GA iter: 1→Maximum GA iter)

- Sort bacteria in ascending order according to their fitness.
- Split bacteria in fittest 50% and worst 50%.
- Select one bacterium from fittest population list and one from worst population list.
- Apply Genetic cross-over and mutation between them using Eq. (13, 14).
- Calculate the fitness of the resultant bacterium using Eq. (16).
- If resultant bacterium is better than fittest member, replace worst with resultant.
- Else if, resultant bacterium is not better than fittest member, replace worst with fittest.

End of Loop (GA iter)

End of Loop (k)

6. Elimination-Dispersal:

- Eliminate bacteria according to Ped.
- Randomly disperse the bacteria in optimization domain to keep the bacteria size constant.

End of Loop (l)

End of Loop (iter)

Table 1: Parameters for hybrid BFA-DE-GA

Parameter	Value		
Number of bacteria	120		
Number of reproduction steps	4		
Elimination-dispersal steps	2		
Generation of GA	100		
Generation of DE	300		
Scaling factor for DE	0.8		
Crossover probability of DE	0.8		
Elimination/dispersal probability	0.25		
Adaptive parameters	5-Units	10-Units	30-Units
Number of chemotexic steps	50	100	200
Crossover probability	0.8	0.8	0.9
Mutation probability	0.1	0.15	0.15

The graphical illustration of Hybrid BFA-DE-GA is given in Figure 1.

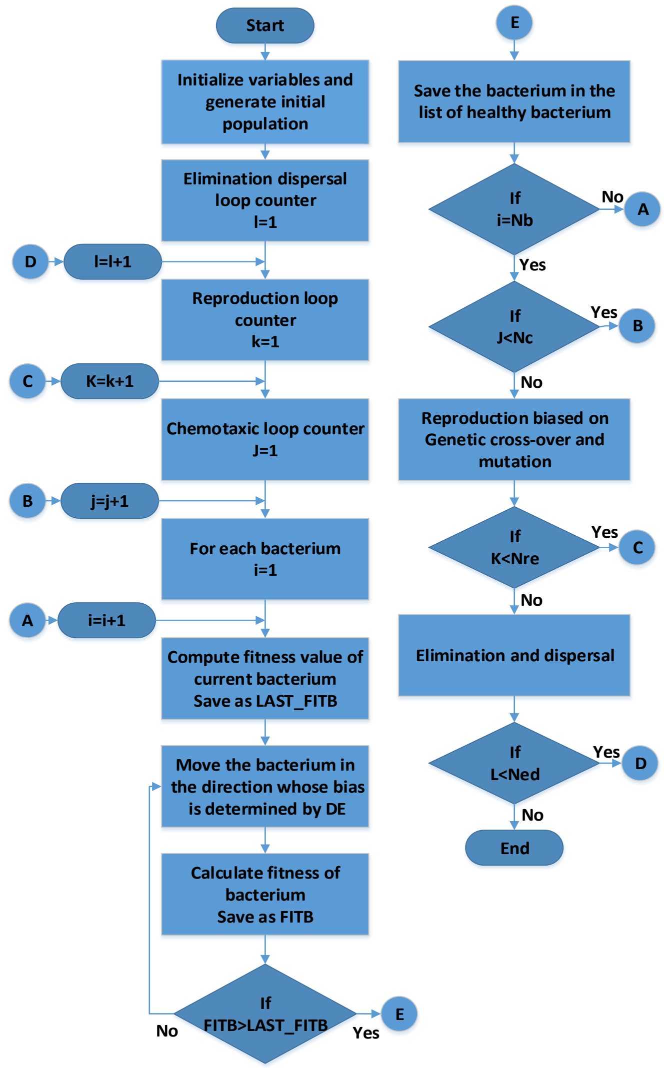

Figure 1: Hybrid BFA-DE-GA flow chart

6. Experimental Setup and Case Studies

In this research work hybrid BFA-DE-GA algorithm is implemented using Visual studio C++ and executed on an Intel ® Core ™ i5 CPU 2.50 GHz, 4GB RAM,PC. In order to check the consistency of algorithm 50 independent runs are conducted with random initial solutions for each run. Results are contrasted with different strategies reported in literature. The parameters used for various test cases have been shown in Table 1.

6.1 Non-convex Systems

Proposed algorithm is tested on standard IEEE test system compromise of 5, 10 and 30 generation units,the ramp rate limits and valve point loading effects are considered for all test cases.

6.1.1 Case-1: 5-Generation Units Test System

This case provides the solution for a 5 generation units test system by taking into account the transmission losses as well. Unit data and load demand pattern for case-1 is adapted from [18] and transmission loss coefficients from [19].

Table 2: Cost & computational time comparison for case-1.

Method	Cost($/24h)	Time(min)
CGNM [18]	47285.6	NA
GA [20]	44862.42	3.32
AIS [21]	44385.43	4.00
PSO [20]	44253.24	3.55
ABC [20]	44045.83	3.29
HBFA-DE-GA	44041.95	0.40

Table 2 shows the cost & computational time for 5-generation units test system. The proposed technique has achieved reduction in cost of $3243.65/day as compared with CGNM, $820.47/day as compared with GA, $343.48/day as compared to AIS, and $211.29/day as compared to PSO. However if compared to ABC $3.88/day. Proposed technique

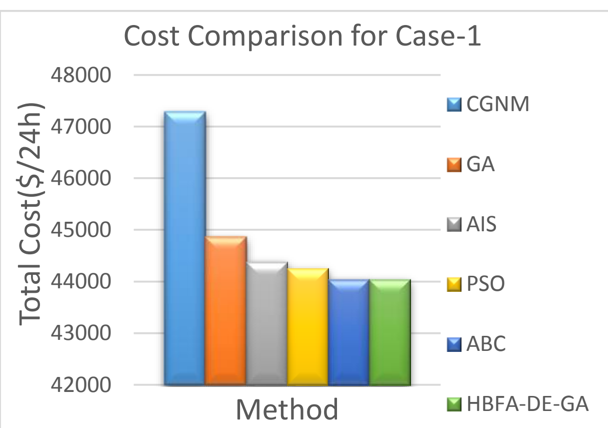

Figure 2: Cost Comparison for 5-units Test Case.

Figure 2 gives a graphical comparison of the optimal costs, the cost of proposed hybrid algorithm are far less than the existing AI techniques. The best scheduling for 5-units test case is given in Table 3. Figure-3 provides a distribution of the cost function for 50 independent runs for 5-unit test system.

Table 3: The best generation schedule of 5-unit system using Hybrid BF-DE-GA approach.

Hr.	P1	P2	P3	P4	P5	PL
1	10.02	20.04	30.02	124.50	229.41	3.99
2	34.97	20.02	30.00	124.91	229.51	4.41
3	64.96	30.76	30.00	124.94	229.52	5.19
4	75.00	26.75	30.22	174.94	229.55	6.45
5	75.00	20.51	30.33	209.83	229.55	7.21
6	75.00	31.41	70.32	209.83	229.57	8.13
7	64.75	20.01	110.30	209.81	229.51	8.38
8	74.99	36.00	112.75	209.82	229.53	9.10
9	75.00	66.00	119.68	209.84	229.55	10.07
10	66.61	95.98	112.66	209.78	229.52	10.55
11	75.00	103.97	112.74	209.82	229.52	11.04
12	74.97	124.68	112.68	209.82	229.58	11.72
13	64.03	98.54	112.66	209.82	229.52	10.56
14	49.62	98.55	112.66	209.83	229.52	10.17
15	19.62	92.26	112.63	209.21	229.50	9.21
16	10.01	75.79	112.67	159.21	229.52	7.20
17	10.02	87.77	112.52	124.86	229.53	6.68
18	40.00	108.67	112.68	125.01	229.52	7.89
19	70.00	125.00	113.25	125.32	229.55	9.13
20	74.99	122.08	112.66	175.31	229.50	10.55
21	45.00	92.94	112.61	209.81	229.52	9.88
22	15.00	96.01	112.54	159.81	229.48	7.84
23	10.00	96.34	72.56	124.77	229.49	6.16
24	10.05	70.86	32.66	124.90	229.51	4.98
Total Cost = 44041.952539($)						

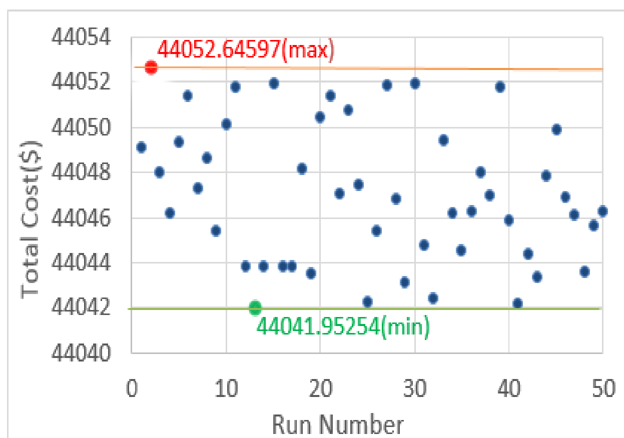

Figure-3 Distribution of the cost function for 50 independent runs for 5-unit test system.

6.1.2 Case Study 2: 10-Generation Units Test System without Network Losses

The ten-unit test system with non-smooth fuel cost function is used for DED problem. Unit data is taken from [18] and load demand pattern for case-2 is given in Table 3.

Table 4: Cost & computational time comparison for case-2.

Method	Cost ($/24h)	Time(min)
EP-SQP [22]	1031746.00	20.51
DGPSO [23]	1028835.00	15.39
PSO-SQP [24]	1027334.00	16.37
AIS [25]	1021980.00	19.01
HIGA [26]	1018473.38	3.53
HBFA-DE-GA	1018443.00	0.79

Table 4 shows that cost and computational time comparison for case-2.The cost $13303/day, $10392/day, $8891/day, $3537/day, and $30.38/day less than EP-SQP,DGPSO,PSO-SQP,AIS, and HIGA respectively. Computational time for 10-units test case is smallest as compared to all other Techniques.

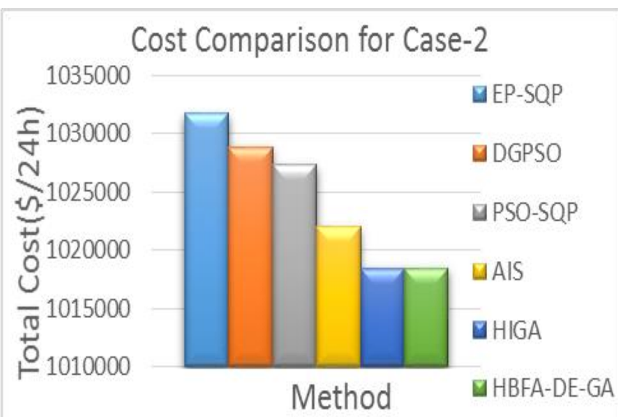

Figure 4: Cost Comparison for 10-units Test Case 2.

The graphical representation for optimal cost is shown in figure 4, evident that costs are reduced by significant amount. Distribution of cost function for 50 independent runs for case-2 is given in figure 5, which demonstrate that $ 1018443/day is minimum cost and $ 1020915.20/day is maximum cost. Best generation scheduling for case-2 at optimal cost of $ 1018443/day is given in Table 7.detail of power generation by each generator toward economical operation is also given in table 7.

Table 5: Hourly load demand for test cases.

Hours	5-Units	10-Units	30-Units
1	410	1036	3108
2	435	1110	3330
3	475	1258	3774
4	530	1406	4218
5	558	1480	4440
6	608	1628	4884
7	626	1702	5106
8	654	1776	5328
9	690	1924	5772
10	704	2072	6216
11	720	2146	6438
12	740	2220	6660
13	704	2072	6216
14	690	1924	5772
15	654	1776	5328
16	580	1554	4662
17	558	1480	4440
18	608	1628	4884
19	654	1776	5328
20	704	2072	6216
21	680	1924	5772
22	605	1628	4884
23	527	1332	3996
24	463	1184	3552

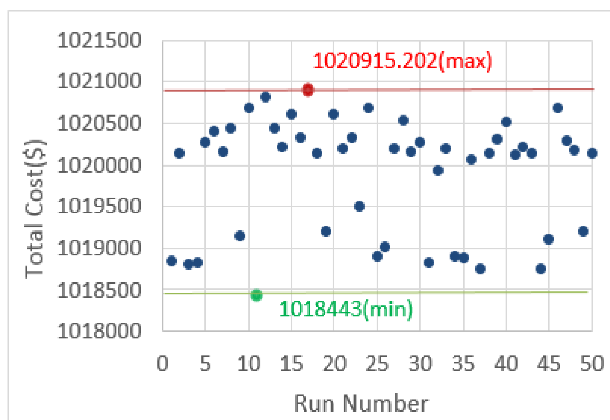

Figure 5 Distribution of the cost function for 50 independent runs for 10-unit test system.

6.1.3 Case Study 3: 30-Generation Units Test System

The data of the thirty-unit test system are obtained by tripling the ten-unit system of Case-2, and Non convexity of the test system is enhanced by varying the system parameters. Load demand pattern for case 3 can be found in Table 5.

Table 6: Cost and Computational Time Comparison for 30-units Test System.

Method	Cost($/24h)	Time(min)
IPSO [27]	3090570.00	NA
CE [28]	3086109.59	NA
ICPSO [29]	3064497.00	NA
HIGA [26]	3055435.068	NA
EAPSO [30]	3054961.00	NA
HGABF [15]	3050235.00	9.35
HBFA-DE-GA	3047263.00	4.52

Table 6 shows that when proposed technique applied to 30-generators test system gives very favorable results as compared to other AI techniques. A reduction of $43307/day is visible when proposed algorithms is compared to IPSO, $38846.59/day as compared to CE, $17234/day reduction when compared with ICPSO, $8172.068/day as compared to HIGA, $7698/day and $2972/day cost reduction as compared with EAPSO and HGABFA respectively.

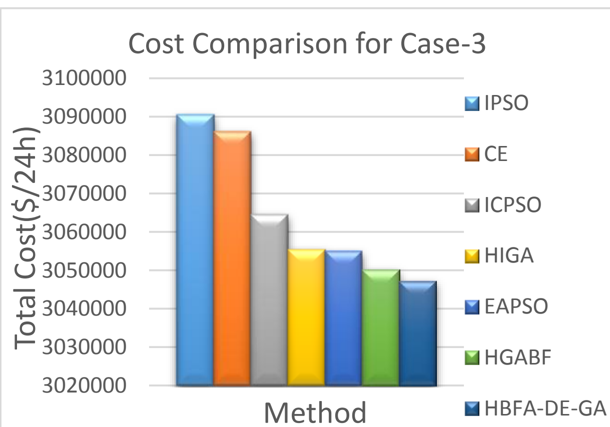

Figure 6: Cost compression for 30-units test case without losses.

The graphical representation of 30-generation test system is shown in figure-6, which evident that results obtained using proposed methods are much better than other reported methods. Distribution of cost function for 50 independent runs for case-3 is given in figure 7.

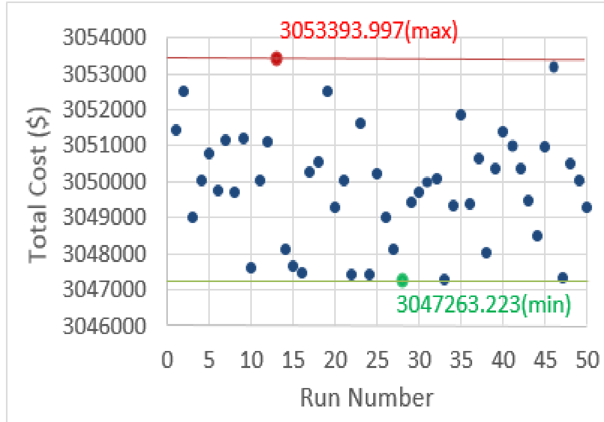

Figure 7: Distribution of the cost function for 50 independent runs for 30-unit test system.

7. Conclusion

A novel hybrid methodology is proposed in this paper, which is based upon HBF, GA and DE .for the solution of a non-convex DED problem is solved considering the valve point loading effects and the ramp rate limits. The proposed technique is tested on IEEE standard test systems in order to verify the proficiency. Finally proposed method is compared with the other evolutionary computational techniques for 5, 10 and 30 units.

For 5-units test system, results are compared with SA, GA, AIS, PSO and ABC.

For 10-units test system results are compared with EP-SQP, DGPSO, PSO, SQP, AIS and HIGA.

For 30-units test system results are compared with IPSO, CE, ICPSO, HIGA, EAPSO and HGABF.

The results assured that the proposed hybrid approach outperform the other techniques in term of cost and significant reduction of computational time in all the test cases.

Future work can involve the efforts to solve the economic dispatch problems with security restraints and the restricted operation areas. Moreover, RE resources like wind and solar plants can also be taken into consideration.

Table 7: Best scheduling of 10-generation units test system

Hour	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	PT
1	150.01	135.03	193.62	60.10	122.89	122.65	129.67	47.03	20.01	55	1036
2	226.63	135.01	191.41	60.02	122.88	122.45	129.60	47.00	20.01	55	1110
3	303.24	214.98	182.88	60.01	122.87	122.43	129.59	47.00	20.01	55	1258
4	379.87	222.26	196.88	60.01	172.73	122.63	129.58	47.02	20.01	55	1406
5	456.53	222.27	194.31	60.04	172.77	122.48	129.59	47.01	20.01	55	1480
6	456.52	222.27	274.30	60.05	222.60	140.64	129.60	47.01	20.02	55	1628
7	456.48	302.16	286.71	60.01	222.58	122.44	129.60	47.02	20.01	55	1702
8	456.53	309.55	303.19	109.99	222.60	122.51	129.59	47.00	20.04	55	1776
9	456.50	389.54	323.31	120.43	222.63	159.98	129.60	47.00	20.01	55	1924
10	456.49	460.00	320.86	170.42	222.64	159.99	129.60	47.00	50.00	55	2072
11	456.95	459.99	339.98	220.41	224.98	159.99	129.63	47.00	52.07	55	2146
12	456.49	459.97	339.99	267.34	222.60	159.99	129.59	76.99	52.06	55	2220
13	456.48	396.83	302.51	241.48	222.60	159.99	129.67	85.35	22.08	55	2072
14	456.48	396.80	294.21	191.49	172.70	122.40	129.60	85.31	20.02	55	1924
15	379.86	396.79	283.37	180.81	122.81	122.45	129.59	85.31	20.00	55	1776
16	303.25	316.80	317.75	130.81	73.01	122.47	129.59	85.31	20.01	55	1554
17	226.62	309.52	288.26	120.36	122.87	122.45	129.60	85.32	20.00	55	1480
18	303.27	309.55	309.55	120.41	172.76	122.47	129.64	85.32	20.03	55	1628
19	379.88	389.55	300.91	120.44	172.73	122.58	129.59	85.32	20.02	55	1776
20	456.57	460.00	312.49	170.43	222.60	159.98	129.59	85.32	20.01	55	2072
21	456.51	396.80	315.21	120.43	222.60	122.53	129.60	85.31	20.00	55	1924
22	379.88	316.81	275.72	70.48	172.76	122.44	129.67	85.24	20.02	55	1628
23	303.25	236.85	196.62	60.02	122.87	122.47	129.59	85.32	20.01	55	1332
24	226.70	222.28	189.25	60.11	73.21	122.48	129.62	85.32	20.03	55	1184
Total Cost = 1018142.725815($/24h)											

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