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Research Article

SOLUTION OF ECONOMIC DISPATCH PROBLEM USING POLAR BEAR OPTIMIZATION ALGORITHM

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ABSTRACT

Polar Bear optimization (PBO) algorithm is a newly developed meta-heuristic optimization algorithm that is inspired by the hunting behavior of polar bears in nature. PBO is a population based algorithm that combines three distinct features of optimization strategies to create a unique solution namely local search, global search and dynamic population. In this paper PBO algorithm is applied to solve economic dispatch problem of electrical power for both convex and non-convex systems. The proposed technique is tested on four IEEE benchmarks systems and the results obtained are compared with other techniques available in literature. Comparison of results obtained proved its success in reducing cost and computation time as compared to other techniques.

Keywords: Polar Bear Optimization algorithm (PBO); Economic Dispatch of Electrical Power (EDEP); meta-heuristic; population based algorithms.

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1. INTRODUCTION

Economics has always been core feature in the planning of any venture. Power industry is no exception to this rule making the research of power system economics one of the leading and most researched fields. Power Industry is the backbone of any country's development, industry and economics. Efficient allocation of generation resources based on their fuel types, associated cost and operational constraints can ensure a country's safe and sustainable future at an economic expense.

Optimal dispatch of power by keeping in view the economic features of the involved systems that are governed by numerous constraints is a key power system operation and planning problem termed as Economic Dispatch. Existence of numerous constraints make Economic dispatch a multi-dimensional, non-linear, non-convex and multi-constrained problem. The mathematical complexity and the necessity of economic dispatch of units dictated by scarcity of resources, increasing demands and fluctuating fuel costs has inspired many researchers to tackle this problem and find an optimum dispatch of power. The core objective of this research is to find such a dispatch of units which results in minimum fuel cost incurred while neither of the constraints like power balance, generation capacity limit or prohibited operating zones are being violated.

Economic dispatch of electrical power under numerous constraints proved to be a very attractive avenue for the application and validation of optimization techniques. Initial attempts to solve this problem came for conventional strategies like Lagrangian relaxation [1], quadratic programming (QP) [2], branch and bound method [3], lambda iteration method (LI) [4], gradient method [5], linear programming (LP) [6], co-ordination equation [7] and dynamic programming (DP) [8]. The analysis of results achieved from conventional techniques indicated several short comings in these techniques. Conventional techniques were highly sensitive to initial point with tendency of getting stuck in local optimum and also suffered from curse of dimensionality. With the advancement in computation a new breed of optimization algorithms was developed that were either based on some stochastic principle, natural phenomenon or were inspired by the behavior of some living being in nature, these techniques were broadly categorized as evolutionary, heuristic and meta- heuristic techniques. Some of the well-known algorithms developed included Genetic Algorithm (GA) [9], Ant colony optimization (ACO) [10], Differential Evolution (DE) [11], Artificial bee colony (ABC) [12], particle swarm optimization (PSO) [13], Cuckoo Search (CS) [14], Firefly Algorithm (FFA) [15], Runner root algorithm (RRA) [16], Ant lion optimization (ALO) [17], Moth fly optimization (MFO) [18], Gravitation Search Algorithm (GSA) [19], Black Hole algorithm (BH) [20], Jaya Algorithm (JA) [21], Bat Search Algorithm (BSA) [22], Krill Heard algorithm (KH) [23], Whale optimization algorithm (WOA) [24], Dolphin Pod Optimization (DPO) [25], Artificial Neural Network (ANN) [26], Artificial Algae optimization (AAO) [27], Grey wolf optimization Algorithm (GWO) [28] etc. These numerical iterative techniques were mostly population based having large number of initial search agents and propelled themselves to optimal using proposed mathematical strategy which required intensive calculations and computational power. These algorithms either exhibited swarm behavior model or demonstrated a single individual model but both these models had a distinct two stage approach that was exploration of whole search space globally and exploitation of optimum region locally. Some of these optimization techniques or their hybrid variants have been used to solve economic dispatch problem. These advanced techniques had their advantages over the conventional techniques but also suffered from some disadvantages. Generally, these optimization strategies suffered from extensive computational burden because of large number of search agents, premature convergence, curse of dimensionality, large memory requirement and programming complexity. The proposed technique incorporates three distinct features of nature inspired algorithms into a single strategy. It enables global exploration while avoiding local stagnation through dynamic population growth and death mechanism and locates precise optimum by thorough exploitation of optimal local space. The dynamic birth and death mechanism ensures reduction in computational time and complexity all the while maintaining the inherent strengths of population based computational algorithms. In this paper polar bear optimization algorithm is used to solve economic dispatch problem of electrical power. Polar bear optimization (PBO) algorithm was presented by David Polap [29] et al. in 2017. In 2018 Marcin Wozniak et al. [30] demonstrated strength of PBO by attempting heat production optimization problem. PBO algorithm was able to achieve better results at a reduced number of calculations establishing it as an effective technique. These results motivated us to attempt our power system engineering problem using PBO.

2. RESEARCH METHODOLOGY

2.1 Problem Formulation

Economic dispatch is a constrained optimization problem that models the task of scheduling electrical power outputs from different generation units such that the total operational cost is minimized and all the respective constraints like generation limits, valve point effect and prohibited operating zones are satisfied. Economic dispatch problem also includes the calculation of transmission loses incurred by each generating unit at its respective power output. Mathematical the main objective of economic dispatch problem is minimization of operational cost of generation units that can be modeled as summed quadratic fuel cost equations as shown in eq. (1). Equation (1) is sum of uni-model convex equations but the inclusion of valve point effect introduces non-linearity in the objective expression making it non-convex and multi-model. This non-linear effect transforms the cost equation as (2).

$minimize$

$$Total\ Cost = \sum_{i=1}^{Nx} aP_i^2 + bP_i + c \qquad (1)$$

$$Total\ Cost = \sum_{i=1}^{Nx} aP_i^2 + bP_i + c + (e * abs(\sin(f * (P_{il} - P_i)))) \qquad (2)$$

Where a, b, c, e and f are cost coefficients, Nx is the maximum number of generation units available for scheduling, P_i is the i-th generating unit and $P_{il}$is the least power limit of i-th generating unit. These objective functions are subjected to following equality and inequality constraints.

Equality constraints include power generation balance shown in (3).

$$P_{generated} = P_{required} + P_{loss} \qquad (3)$$

Where $P_{generated}$ is the total power scheduled, $P_{required}$ is the power demand and P_{loss} is the transmission loss incurred at respective level of power scheduled.

Inequality constraints include generation limits represented by eq. (4) and prohibited operating zones represented by eq. (5).

$$P_{il} < P_i < P_{ih} \qquad (4)$$

$$\begin{cases} P_{il} < P_i < P_{i1} \\ P_{i2} < P_i < P_{i(n-1)} \\ P_{in} < P_i < P_{ih} \end{cases} \qquad (5)$$

Where $P_{il}$and $P_{ih}$are the lower and upper limits of i-th generation unit, $P_i$is the power scheduled on the i-th generation unit and $P_{i1}\, to\ P_{in}$represent the feasible operation regions of the i-th generation unit.

The transmission loses can be computed from loss coefficient matrix B using following equation (6).

$$P_{loss} = \sum_{i=1}^{Nx} \sum_{k=1}^{Nx} (P_i B_{ik} P_k) + \sum_{i=1}^{Nx} (B_{i0} P_i) + B_{00} \ (6)$$

2.2 Polar Bear Optimization Algorithm Theory and Modelling

Polar bear optimization algorithm was presented by David Polap [29] et al. in 2017. PBO is a nature inspired meta heuristic optimization algorithm which combines strong features of presently available population based heuristic techniques to develop a new technique which mimics the hunting capabilities of Polar bears in harsh arctic region. PBO algorithm is a population based algorithm having inherent higher local minima avoidance and efficient gradient free global optimum tracking capabilities. These unique features of PBO are in its amalgamation of three strategies of heuristic algorithms into a single algorithm. Each strategy mimics some important aspect of Polar Bear's hunting mechanism in arctic regions. The hunting mechanism of Polar Bears is modeled by following three stages.

- Global movement by ice floats
- Catching and encircling pray (local search)
- Dynamic population control

The mathematical modeling of PBO algorithm is explained as follows

2.2.1 Initializing Population

PBO algorithm starts its search with a random set of initial values and then propels itself to find optimum solution in search space using global and local search mechanism.
Each polar bear having n coordinates is represented as $\bar{x} = (x_0, x_1, \ldots\ldots, x_{n-1})$. At t-th iteration a set of i polar bears having j coordinates can be denoted by $(\overline{x_j}^i)^t$. The population is initialized randomly in the whole search space which models the arctic region.

2.2.2 Global Search on ice floats

Global search mechanism models Polar Bears nature to drift on arctic ice bergs in search of food when there is scarcity of food in immediate locality, to avoid extensive calculation during this process the floats are directed to move towards the current optimum solution available in population. This behavior is modeled using following equation:

$$(\overline{x_j}^t)^i = (\overline{x_j}^{t-1})^i + sign(\omega)\alpha + \gamma \qquad (7)$$

Where $(\overline{x_j}^t)^i$ is movement of i-th polar bear having j coordinates in t-th iteration towards the optimum, α is random number in range (0,1), ω is distance between the present bear and optimum bear and γ is random number in the range (0, ω).The distance is dealt in Euclidian metrics and is given as:

$$d((\bar{x})^{(i)}, (\bar{x})^{(j)}) = \sqrt{\sum_{k=0}^{n-1}((x_k)^{(i)} - (x_k)^{(j)})^2} \qquad (8)$$

2.2.3 Local Search and attacking prey

During local search, the bears encircle the prey and stab it with their teeth. The bears can approach their prey either through land or from under water making them a deadly predator. This behavior is effectively modeled using trifolium equations. To transform polar bears behavior into these equations two parameters are defined known as distance of vision 'a' selected randomly in range (0,0.3) and angle of tumbling Φ_o selected randomly in range $(0,\frac{\pi}{2})$. From these parameters, we compute radius of vision as:

$$r = 4\,\text{a}\cos(\Phi_o)\,sin\,(\Phi_o) \qquad (9)$$

This radius is used to compute movement in local search space for each spatial coordinate respectively as:

$$\begin{cases} x_0{}^{new} = x_0{}^{actual} \pm rcos(\Phi_1) \\ x_1{}^{new} = x_1{}^{actual} \pm [rsin(\Phi_1) + rcos(\Phi_2)] \\ x_2{}^{new} = x_2{}^{actual} \pm [rsin(\Phi_1) + rsin(\Phi_2) + rcos(\Phi_3)] \\ \dots \\ x_{n-2}{}^{new} = x_{n-2}{}^{actual} \pm [\sum_{k=1}^{n-2} rsin(\Phi_k) + rcos(\Phi_{n-1})] \\ x_{n-1}{}^{new} = x_{n-1}{}^{actual} \pm [\sum_{k=1}^{n-2} rsin(\Phi_k) + rsin(\Phi_{n-1})] \end{cases} \qquad (10)$$

Where $\Phi_1, \Phi_2 and\ \Phi_3$are selected at random in the range (0,π), for n coordinates of each solution wee compute the next local position by solving above equation by putting a + sign and comparing fitness if value deteriorates than the original the sign is replaced by – and process is repeated. This simplifies the two-dimensional movement along modified equation of the trifolium leaf.

2.2.4 Dynamic population control

To model the influence of harsh arctic weather and introduce randomness to the optimization strategy PBO algorithm initializes with 75% of population while the remaining 25% depends on population growth governed by reproduction of best or starvation of worst. To implement this strategy a new constant k is introduced having value in range (0,1). Depending on k we create or destroy individuals according to following rule:

$$\begin{cases} Death & if\ k < 0.25 \\ Reproduction & if\ k > 0.75 \end{cases} \qquad (11)$$

The individuals are destroyed depending on k until population in above 50% whereas the reproduced individual is given as:

$$({\bar{x}_j}^t)^{reproduced} = \frac{{\bar{x}_j}^{t(best)} + {\bar{x}_j}^{t(i)}}{2} \qquad (12)$$

Where ${\bar{x}_j}^{t(best)}$the best solution is up to current iteration and ${\bar{x}_j}^{t(i)}$is chosen randomly from among top 10% of best individuals up to current iteration.

2.2.5 Pseudo code of economic dispatch by PBO

1. Start
2. Initialize unit data (a, b, c, e, f& B matrix)
3. Initialize constraints (PD, Pmin, Pmax & POZ)
4. Initialize algorithm parameters (max_iterations (T)& max_bears(n))
5. Define fitness ($Fitness = \sum_{i=1}^{n} F_i\ (P_i) + \lambda|(\sum_{i=1}^{n} P_i - (P_D + P_{Loss}))|$
6. Initialize random population (75%n), $\bar{x}^t$
7. i=0, first iteration
8. **While** i<T do
9. **For** each polar bear $\bar{x}^t$ do
10. Generate all Φ randomly
11. Calculate r using equation (9) and ${\bar{x}_j}^{t(new)}$ using equation (10) using sign of plus
12. **If** fitness (${\bar{x}_j}^{t(new)}$) < fitness (${\bar{x}_j}^{t(actual)}$) then
13. Move bear ${\bar{x}_j}^{t(actual)}$=${\bar{x}_j}^{t(new)}$
14. **Else**, calculate new position ${\bar{x}_j}^{t(new)}$ using equation (10) by putting sign of minus
15. **If** fitness (${\bar{x}_j}^{t(new)}$) < fitness (${\bar{x}_j}^{t(actual)}$) then
16. Move bear ${\bar{x}_j}^{t(actual)}$=${\bar{x}_j}^{t(new)}$
17. Endif, end for
18. Sort population $\bar{x}^t$and randomly select a bear from top 10% population
19. Calculate new global position using equation (7)
20. **If** fitness (${\bar{x}_j}^{t(new)}$) < fitness (${\bar{x}_j}^{t(actual)}$) then
21. Move bear ${\bar{x}_j}^{t(actual)}$=${\bar{x}_j}^{t(new)}$
22. End if
23. Randomly select k in range (0,1)
24. If i<T-1 and k>0.75 then

25. Select two bears among top 10% of population and create a reproduced one using equation (12)
26. Else if bears>0.5n and k<0.25 then kill worst individual in population
27. End if
28. i++
29. Convergence in ith iteration =best bear so far
30. end while
31. Return the best bear in population, convergence curve
32. Stop

3. SIMULATION AND RESULT

The proposed PBO algorithm for economic load dispatch problem is simulated on 4 benchmark IEEE standard test systems and results are compared with other techniques available in literature to demonstrate its effectiveness. The simulations were performed on MATLAB 2016 software on Intel Core M-5Y10c@0.8GHz (4 CPU), 4GB RAM system.

3.1 Test System 1: 3-unit system including transmission loses

The three-unit test system at a load demand on 150MW including transmission loses was taken from [31]. 20 test runs were performed at a population of 50 and maximum iterations were kept at 100. The best result of 20 runs is shown in table 1 along with results of GWO [32], ALO [33], PSO [32] and LI [31] methods. It can be seen from table 1 that PBO algorithm achieved minimum fuel cost of 1597.433 Rs/h at a power loss of 2.3294 MW. The convergence curve is shown in fig 1 and comparison bar graph is shown in fig 2. The PBO algorithm takes 24 iterations to converge and average execution time per runtime was 0.521 seconds.

Table 1 Comparison of fuel cost for Test System 1 (150MW)

Method/ Technique	Unit Power (MW)			Fuel Cost (Rs/h)	Ploss (MW)	No of Iterations	Elapsed Time	Best Solution	Average Solution	Worst Solution
	P1	P2	P3							
LI	33.4401	64.0974	55.1011	1599.9	2.66	250	-	-	-	-
PSO	33.0858	64.4545	54.8325	1598.79	2.37	250	-	-	-	-
GWO	30.4998	64.6208	54.8994	1597.482	2.3444	250	4.7615	-	-	-
ALO	32.8101	64.595	54.9369	1597.482	2.342	250	2.2523	-	-	-
PBO	33.05371	64.07982	55.19585	1597.433	2.3294	100	0.521	1597.433	1597.81	1598.972

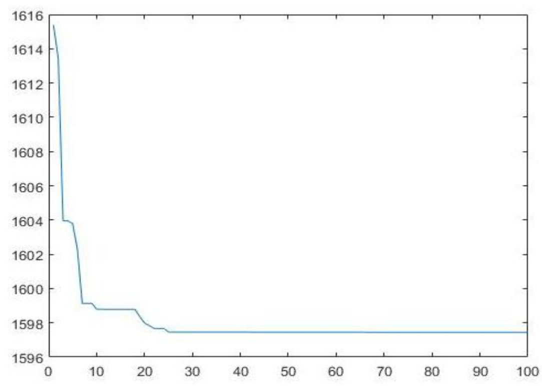

Fig. 1. Convergence Curve for Test System 1

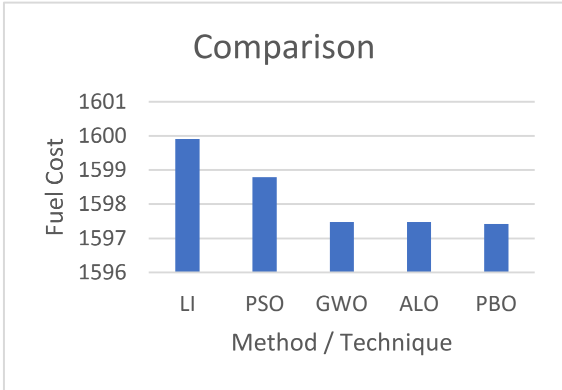

Fig. 2. Comparison Bar Graph Test System 1

3.2 Test System 2: 3 unit system under valve point effect

The three-unit test system under valve point effect [34] was tested for two cases at a load demand 850MW and 1050MW respectively. 20 test runs were performed for each case at a population of 50 and maximum iterations were kept at 100. The best result for 20 runs is shown in table 2 and table 3 for each case along with results of GWO [32], ALO [33], PSO [32], GA [32] , ABC [33] and LI [31] methods. It can be seen from table 2 & 3 that PBO algorithm achieved minimum fuel cost of 8252.309 Rs/h and 10122.84 Rs/h for each case respectively. For both cases the convergence curves and comparison bar graphs are shown in fig 3,4 and fig 5,6 respectively. The PBO algorithm takes 92 iterations to converge for case 1 and 69 iterations to converge for case 2 at an average execution time per runtime of 0.1124 seconds and 0.1121 seconds respectively.

Table 2 Comparison of fuel cost for Test System 2 Case 1

Method/ Technique	Unit Power (MW)			Fuel Cost (Rs/h)	Elapsed Time	Best Solution	Average Solution	Worst Solution
	P1	P2	P3					
LI	382.258	127.419	340.323	8575.68	-	-	-	-
GA	382.2552	127.4184	340.3202	8575.64	-	-	-	-
PSO	394.5243	200	255.4756	8280.81	-	-	-	-
ABC	300.266	149.733	400	8253.1	-	-	-	-
GWO	300.5116	149.8107	399.6777	8253.105	-	-	-	-
ALO	300.2673	149.733	399.9997	8253.105	-	-	-	-
PBO	300.1647	150.3856	399.3703	8252.309	0.1124	8252.309	8379.889	8526.368

3.3 Test System 3: 5 unit system

The 5 unit test system [35] under valve point effect excluding loses was tested at a load demand of 730 MW. 20 test runs were performed at a population level of 50 bears and total iterations were kept at 200. The best result for 20 runs is shown in table 4 along with results of LI [32], GA [32], PSO [32], APSO [33], EP [32], ABC [33], GWO [32] and ALO [33]. It can be seen from that PBO algorithm achieved minimum fuel cost of 2029.649 Rs/h. Convergence curve of best solution and comparison bar graph is shown in figures 7 and 8 respectively. The PBO algorithm takes 140 iterations to converge and average execution time per run is 0.3231 seconds.

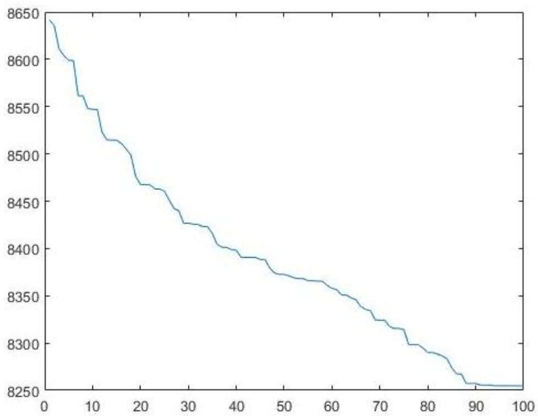

Fig.3. Convergence curve Test System 2 Case 1

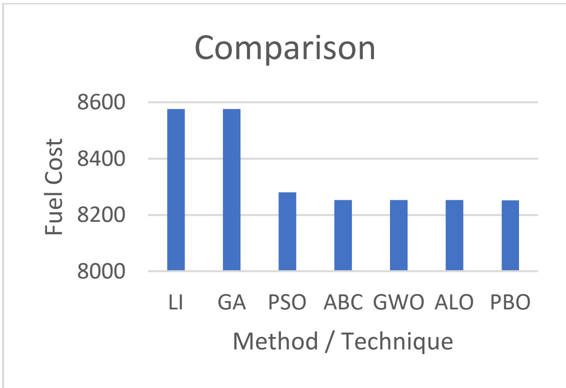

Fig.4. Comparison Bar Graph Test System 2 Case1

Table 3 Comparison of fuel cost for Test System 2 Case 2

Method/ Technique	Unit Power (MW)			Fuel Cost (Rs/h)	Elapsed Time	Best Solution	Average Solution	Worst Solution
	P1	P2	P3					
LI	487.5	162.5	400	10212.46	-	-	-	-
GA	487.498	162.499	400	10212.44	-	-	-	-
PSO	492.699	157.3	400	10123.73	-	-	-	-
ABC	492.6991	157.301	400	10123.73	-	-	-	-
GWO	492.8465	157.3927	399.7609	10123.72	-	10123.72	10123.73	10123.74
ALO	492.6994	158.1015	399.1991	10123.69	-	10123.69	10123.71	10123.73
PBO	492.7833	157.2734	399.887	10122.84	0.1121	10122.84	10243.94	10418.29

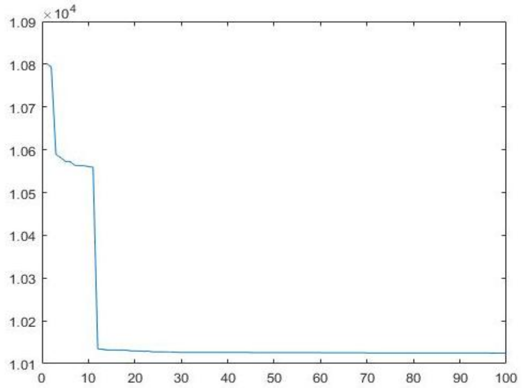

Fig.5. Convergence curve Test System 2 Case 2

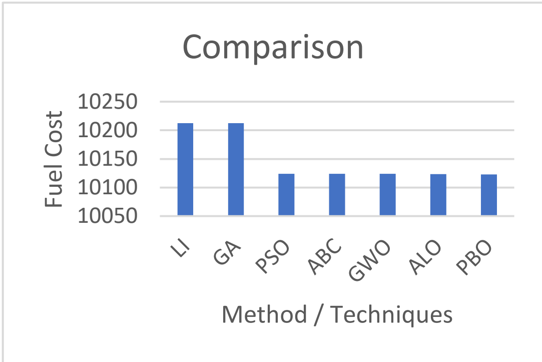

Fig.6. Comparison Bar Graph Test System 2 Case 2

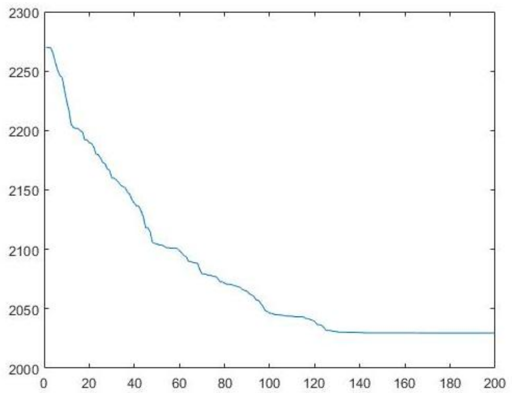

Fig.7. Convergence curve Test System 3

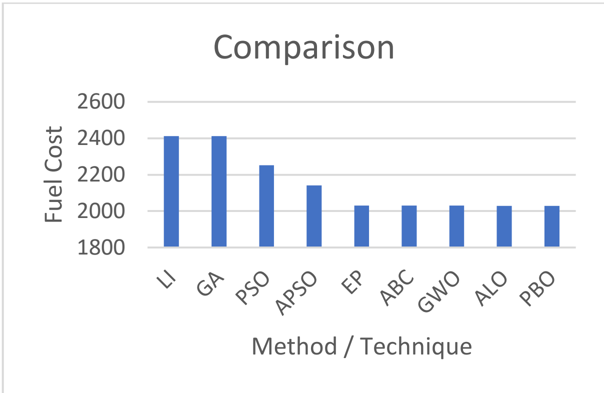

Fig.8. Comparison Bar Graph Test System 3

Table 4 Comparison of fuel cost for Test System 3

Method/ Technique	Unit Power (MW)					Fuel Cost (Rs/h)	Elapsed Time	Best Solution	Average Solution	Worst Solution
	P1	P2	P3	P4	P5					
LI	218.028	109.014	147.535	28.38	272.042	2412.709	-	-	-	-
GA	218.0184	109.0092	147.5229	28.37844	227.0275	2412.538	-	-	-	-
PSO	229.5195	125	175	75	125.4804	2252.572	-	-	-	-
APSO	225.3845	113.02	109.4146	73.11176	209.0692	2140.97	-	-	-	-
EP	229.803	101.5736	113.7999	75	209.8235	2030.673	-	-	-	-
ABC	229.5247	102.0669	113.4005	75	210.0079	2030.259	-	-	-	-
GWO	229.5534	102.3639	113.2209	74.9183	209.9434	2030.071	-	2030.071	2084.434	2161.497
ALO	229.5196	102.988	112.6765	75	209.8159	2029.667	-	2029.667	2055.172	2089.383
PBO	229.5277	102.9107	112.7185	74.99928	209.8338	2029.649	0.3231	2029.649	2157.763	2285.45

3.4 Test System 4: 6 unit system

The 6 unit test system [36] was tested at a load demand of 1263 MW including transmission loses under prohibited operating zone and generator limit constraints. 20 runs were performed at a maximum population size of 50 and the iterations were limited to 1000. The best result in 20 runs is shown in table 5 along with results of TS [36], CBA [37], PSO [38], MABC [39], Jaya [21], SPSO [40] and VSA [38]. It can be seen from table 5 that PBO algorithm achieved minimum fuel cost 15444.43 Rs / h at transmission loses of 12.4034MW. Convergence curve and comparison bar graph is shown in fig 9 and 10 respectively. The PBO algorithm converges in 624 iterations at an average execution time of 6.2178 seconds.

Table 5 Comparison of fuel cost Test System 4

Method/ Technique	Unit Power (MW)						Fuel Cost (Rs/h)	Ploss (MW)	Elapsed Time	Best Solution	Average Solution	Worst Solution
	P1	P2	P3	P4	P5	P6						
TS	459.0753	185.0675	264.2094	138.1222	154.4716	74.9	15454.89	12.9422	-	-	-	-
CBA	447.4187	172.8255	264.0759	139.2469	165.6526	86.7652	15450.238	12.9848	-	-	-	-
PSO	447.49	173.32	263.47	139.05	165.47	87.12	15450	12.95	-	-	-	-
MABC	447.5032	173.3177	263.4631	139.065	165.4735	87.1355	15449.899	12.958	-	-	-	-
Jaya	451.4248	176.0929	255.8996	150	174.2446	67.7409	15448.74	12.4028	-	-	-	-
VSA	446.03	181.09	263.45	133.96	176.65	74.53	15447	12.73	-	-	-	-
SPSO	473.66	140	240.06	149.97	173.78	97.91	15446.63	12.38	-	-	-	-
PBO	458.1617	171.6244	255.6233	139.6318	163.5335	86.82866	15444.43	12.4034	6.2178	15444.43	15465.09	15483.06

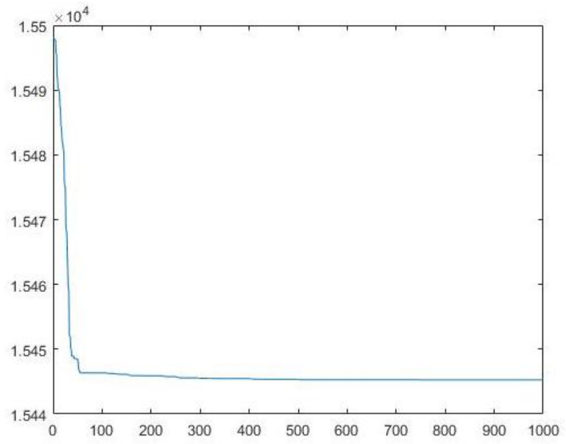

Fig.9. Convergence curve Test System 4

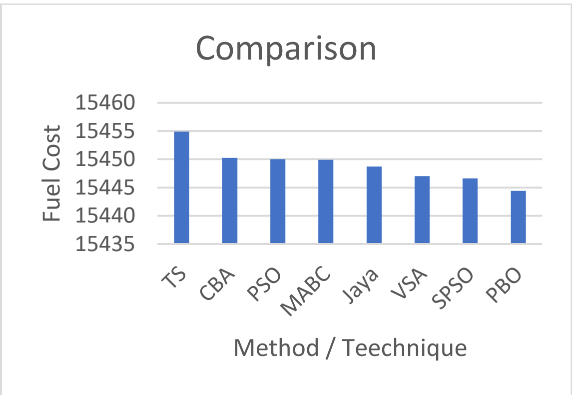

Fig.10. Comparison Bar Graph Test System 4

4. CONCLUSION

In this paper PBO algorithm was successfully used to solve economic dispatch problem of electrical power. The result achieved from PBO showed remarkable reduction in cost and execution times. Convergence curves of best solutions indicate smooth transition between global and local search. The significant reduction in execution times indicates the strength of algorithm to control its population and perform only necessary calculations avoiding unnecessary burden on computer. This successful implementation of PBO makes it a very promising candidate to solve more complex power system optimization problems available in literature. PBO can also be tested for multi objective optimization problems and economic dispatch problems that incorporate hybrid sources. All the presently tested systems were successfully solved by PBO and further improvement may be achieved by improving PBO algorithm or mixing it with different hybrid operators.

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