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Article

Economic Dispatch Using Modified Bat Algorithm

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Abstract: Economic dispatch is an important non-linear optimization task in power systems. In this process, the total power demand is distributed amongst the generating units such that each unit satisfies its generation limit constraints and the cost of power production is minimized. This paper presents an over view of three optimization algorithms namely real coded genetic algorithm, particle swarm optimization and a relatively new optimization technique called bat algorithm. This study will further propose modifications to the original bat. Simulations are carried out for two test cases. First is a six-generator power system with a simplified convex objective function. The second test case is a five-generator system with a non-convex objective function. Finally the results of the modified algorithm are compared with the results of genetic algorithm, particle swarm and the original bat algorithm. The results demonstrate the improvement in the Bat Algorithm.

Keywords: economic dispatch; genetic algorithm (GA); particle swarm optimization (PSO); bat algorithm (BA); modified bat algorithm (MBA); non-convex optimization

1. Introduction

Economic load dispatch (ELD) is an optimization problem for scheduling generator outputs to satisfy the total load demand at the least possible operating cost. ELD problem is often formulated as a quadratic equation [1]. The ELD problem is in reality a nonconvex optimization problem [2]. These arise from ramp rate limits due to the physical limitations of the generating unit, effect of steam valve operation and prohibited operating zones of the generators due to vibration if the shaft bearing.

The conventional method of solving the ELD problem is by applying nonlinear programming techniques. These techniques minimize a convex objective function over a convex set thus insuring a single minimum. The problems can then be minimized using gradient or Newton based search techniques. However as nonconvex problems generally have multiple minima these techniques may be trapped at local minima. Dynamic programming is one way solving this problem, but it also has limitations due to the "curse of dimensionality" [3].

Metaheuristic optimization is another way of solving nonconvex optimization problems [4]. These algorithms are usually based on processes witnessed in physics or biology. Metaheuristic techniques are ideal for nonconvex ELD problem as they do not suffer from restriction of continuity, differentiability and convexity. Many metaheuristic techniques such as simulated annealing (SA), tabu search (TS), genetic algorithm (GA), particle swarm optimization (PSO) and bat algorithm (BA) have been successfully implemented to solve ELD problem [5,6].

Many variants of GA have previously been used with good results to solve nonconvex ELD problems [7–9]. The main advantage GA has over other algorithms is that it can use a chromosome coding technique tailored to the specific problem. The two main disadvantages of GA over other techniques are firstly, there is no guarantee of convergence to the global optimum solution and secondly, the execution time is very long.

PSO and many of its variants have also been extensively used for solving nonconvex ELD problems [10–13]. PSO has numerous advantages over other algorithms. It is very easy to preform and has only a few adjustable parameters. It is also very efficient in global search (exploration). The main disadvantages of PSO are it is slow convergence at refined search stage (exploitation) and its weak local search ability.

BA like PSO and GA is a relatively new population based metaheuristic approach [14,15]. This algorithm mimics the echolocation ability of micro bat which they use it for navigating and hunting. The position of the bat provides the possible solution of the problem. Fitness of the solution is specified by the best position of a bat to its prey. A big advantage BA has over other algorithms is that it has a number of tunable parameters giving a greater control over the optimization process. BA and its variants have also been used to solve the ELD problem [16–18]. It has proven efficient in for lower dimensional optimization problem but ineffective for high dimensional problems because of fast initial convergence [19].

This paper proposes two modifications to the original BA. The first modification is inspired from anti predatory PSO in which the particles moves not only towards the best solution but also away worst position experienced by itself and the global worst solution. The intention behind this modification is increasing the exploration capacity of the algorithm. The second modification is the introduction of a nonlinear weight for the velocity called inertia weight factor (IWF). The purpose of IWF is to provide balance between global and local exploration and better convergence rate.

For the purpose of comparison GA and PSO are also implemented and the results are compared with the modified bat algorithm (MBA). Verification of the modified algorithm has been carried out by simulating two test cases. For the verification of the results, Lambda Iteration method has been used for the convex optimization problem.

2. Problem Formulation

2.1. Problem Objectives

The objective of the economic dispatch problem is minimization of operating cost. The generator cost curves are represented by a quadratic function with a sine component. The sine component denotes the effect of steam valve operation. The fuel cost $F_c(P_G)$ ($/h) can be expressed as [10].

$$F_c(P_G) \ = \sum_{i=1}^{Ng} a_i P_i^2 + b_i P_i + c_i + \left| d_i \sin\left[e_i * (P_i^{min} - P_i) \right] \right| \quad (1)$$

where Ng is the number of generating units. a_i, b_i, c_i, d_i and e_i are the cost coefficients of the ith generating unit. P_i is the real power output of the ith generator.

2.2. Problem Constraints

Power balance constraint. Generation should cover the total demand and the active power losses that occur in the transmission system.

$$\sum_{j=1}^{Ng} P_i = P_d + P_{loss} \quad (2)$$

where P_d is the total demand load and P_{loss} is the total transmission losses computed using quadratic approximation.

$$P_{loss} = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} P_i B_{ij} P_j \quad (3)$$

where B_{ij} is the loss coefficient matrix. In this paper it is assumed constant.

Power generation limits. Each unit should generate power within its minimum and maximum limits.

$$P_i^{min} \leq \ P_i \leq P_i^{max} \quad (4)$$

The objective and constraints can be mathematically formulated as follows.

$$\min\ [F_c(P_i)] \quad (5)$$

$$Subject\ to\colon \begin{cases} g_j(P_i) \leq \ 0\ j = 1, \dots, J \\ h_k(P_i) = \ 0\ k = 1, \dots, K \end{cases} \quad (6)$$

where J and K are the number of inequality and equality constraints respectively. In this paper, the power balance constraint has been handled using the penalty function. This paper uses a penalty function that adds a penalty to the fitness function if the constrains are violated. This turns a constrained optimization problem into an unconstrained optimization problem. Mathematically it can be denoted as

$$\min[\varphi(P_i)] = \ F_c(P_i) + p * G[\ h_k(P_i)] \quad (7)$$

$$Subject\ to\colon g_j(P_i) \leq \ 0\ j = 1, \dots, J \quad (8)$$

$$G[\, h_k(x)] = \varepsilon^2 + \ \omega^2 \tag{9}$$

where p is the penalty factor for the violation of the constraints. ε and ω are equality and inequality constraint violation penalties respectively and are calculated using the following formulas.

$$\varepsilon = \left| P_d + P_{loss} - \sum_{j=1}^{Ng} P_i \right| \tag{10}$$

And

$$\omega = \begin{cases} |P_i^{min} - P_i| & P_i^{min} > P_i \\ 0 & P\,_i^{min} < P_i < P_i^{max} \\ |P_i - P_i^{max}| & P_i^{max} < P_i \end{cases} \tag{11}$$

3. Bat Algorithm

Bat algorithm is a population based metaheuristic optimization technique like PSO and GA. It was developed by Xin-She Yang in 2010 [14,15]. The algorithm mimics the echolocation behavior most prominent in bats. Bats send out streams of high-pitched sounds usually short and loud. These signals then bounce off nearby objects and send back echoes. The time delay between the emission and echo helps a bat navigate and hunt. This delay is used to interpret how far away an object is. Bats use frequencies ranging from 200 to 500 kHz. In the algorithm pulse rate ranges from 0 to 1 where 0 means no emissions and 1 means maximum emissions.

At the start the populations is initialized randomly. The positions of the bats are updated using the following equations.

$$Q_i^{(t)} = \ Q_{min} + (Q_{max} - Q_{min}) * \mathrm{u}(0,1) \tag{12}$$

$$v_i^{(t+1)} = \ v_i^{(t)} + \left(x_i^{(t)} - x_{Gbest}\right) * Q_i^{(t)} \tag{13}$$

$$x_i^{(t+1)} = \ x_i^{(t)} + v_i^{(t)} \tag{14}$$

where Q_i is the pulse frequency subject to $Q_i \in \ [Q_{min}, Q_{max}]$. $\mathrm{u}(0,1)$ is a uniform random number ranging from 0 to 1. v_i is the velocity of the bat and x_i denotes the current position of the bat. x_{Gbest} is the best position found by the swarm. The next step is to use random walk for local search. The following equation is used for this purpose.

$$x^{(t)} = \ x_{Gbest} + \varphi A_i^{(t)} \mathrm{N}(0, \sigma) \tag{15}$$

where φ is a scaling factor that limits the step size of the random walk, A_i is the loudness and $\mathrm{N}(0, \sigma)$ is a normal random number with mean 0 and standard deviation σ. As bats near their target they increase the pulse rate and decrease the amplitude. Mathematically this can be achieved using the equations.

$$A_i^{(t+1)} = \varsigma A_i^{(t)} \tag{16}$$

$$r_i^{(t)} = r_i^{(0)}[1 - e^{-\zeta\epsilon}] \tag{17}$$

where ς and ζ are constants. The ς parameter, like in simulated annealing, controls the rate of convergence of the algorithm.

4. Modifications

This paper proposes two modifications to the original bat algorithm.

4.1. Add Bad Experience Component

A new variant to the classical PSO was introduced by Selvakumar and Thanushkodi by splitting the correction component into two components [10]. These components were called the good and bad experience components. A particle tries to achieve a better position while trying to avoid the bad positions it has encountered. This paper proposes to add bad experience component to the velocity update equation. This modification is intended for enhancing the exploration capability of the algorithm. The modified equation is can be mathematically written as:

$$v_i^{(t+1)} = v_i^{(t)} + Q_i^{(t)}\left[C_1\left(x_i^{(t)} - x_{Gbest}\right) + C_2\left(x_i^{(t)} - x_{i,best}\right) + C_3\left(x_{Gworst} - x_i^{(t)}\right) + C_4\left(x_{i,worst} - x_i^{(t)}\right)\right] \quad (18)$$

where x_{Gbest} and x_{Gworst} are the global best and worst positions. $x_{i,best}$ and $x_{i,worst}$ are the personal best and worst positions. C_1 and C_2 are parameters that accelerate the particle towards the global best and personal best positions respectively. C_3 and C_4 are constants that accelerate the particle away the swarm worst and personal worst positions respectively.

4.2. Nonlinear Inertia Weight

A variant of the bat algorithm called improved bat algorithm (IBA) has recently been presented by Jamil [20]. He proposed adding an inertia weight coefficient to the velocity component in the velocity update equation. The paper proposes the weight component decrease linearly from its maximum value to its minimum value. The purpose of the weight is to provide balance between global and local exploration and better convergence rate. This paper proposes using a nonlinear weight. The reason for using nonlinear weight is to have to ability to control the transition between the global and local exploitation so that it can be tailored for a specific problem. In this paper the following three equations have been derived to get a better control over the transition between global and local exploitation.

$$W^{(t)} = 1 - \frac{1}{1 + e^{\frac{B-t}{A}}} * (W_{max} - W_{min}) + W_{min} \quad (19)$$

where W_{max} and W_{min} are maximum and minimum bounds of inertia weight coefficient. t_{max} is maximum allowed iterations. The constants calculated using the following equations.

$$A = \frac{t_{max} - 1}{G} \quad (20)$$

$$B = \frac{t_{max} + 1}{\left(1 + 10^{\left(1 - \frac{2*H}{t_{max}}\right)}\right)} \quad (21)$$

The constants G and H are tunable parameters that can be adjusted for a particular problem. The constant H controls the transition from global to local search. Constsnt G controls the speed of the transition. H The equations derived in (20) and (21) make it easier to tune the parameters A and B for the optimization problem. The value of H is set between 0 and t_{max} and the value of G is set between 1 and 30. Figure 1 shows the effect of tuning variable G while H is kept constant at 250. Figure 2 shows the effect of tuning H while keeping G constant at 10. In both graphs the upper and lower bounds for inertia weight are 1 and 0 respectively.

The final form of the modified velocity update equation is given below.

$$v_i^{(t+1)} = v_i^{(t)} * W^{(t)} + Q_i^{(t)}[C_1(x_i^{(t)} - x_{Gbest}) + C_2(x_i^{(t)} - x_{i,best}) + C_3(x_{Gworst} - x_i^{(t)}) + C_4(x_{i,worst} - x_i^{(t)})] \quad (22)$$

The following flowcharts detail the bat algorithm and the modified bat algorithm.

5. Experiments and Results

5.1. Test Case 1—Six-Generator Test System with System Losses

The modified bat algorithm was applied to a six-generator test system. For the first test case, the values of parameters d and e have been set to zero to simplify the problem into a convex optimization problem. Two simulations were carried out for a total demand of 700 MW and 800 MW. For all the experiments the maximum allowable error tolerance was set to 0.01 MW. The data for the test system is given in Tables 1–3.

Table 1. Generator active power limits.

Generator	1	2	3	4	5	6
Pmin (MW)	10	10	35	35	130	125
Pmax (MW)	125	150	225	210	325	315

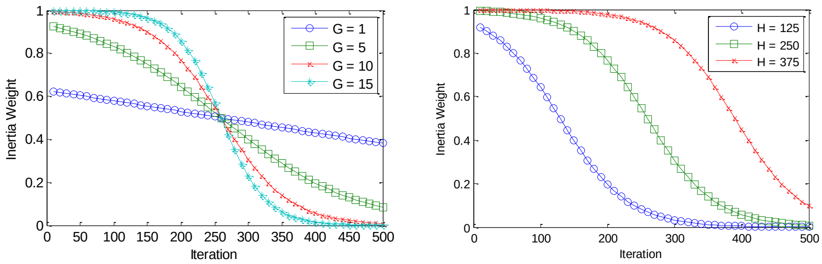
Table 2. Fuel cost coefficients.

No.	*a*	*b*	*c*
1	0.15240	38.53973	756.79886
2	0.10587	46.15916	451.32513
3	0.02803	40.39655	1049.9977
4	0.03546	38.30553	1243.5311
5	0.02111	36.32782	1658.5596
6	0.01799	38.27041	1356.6592

Table 3. Optimization parameters.

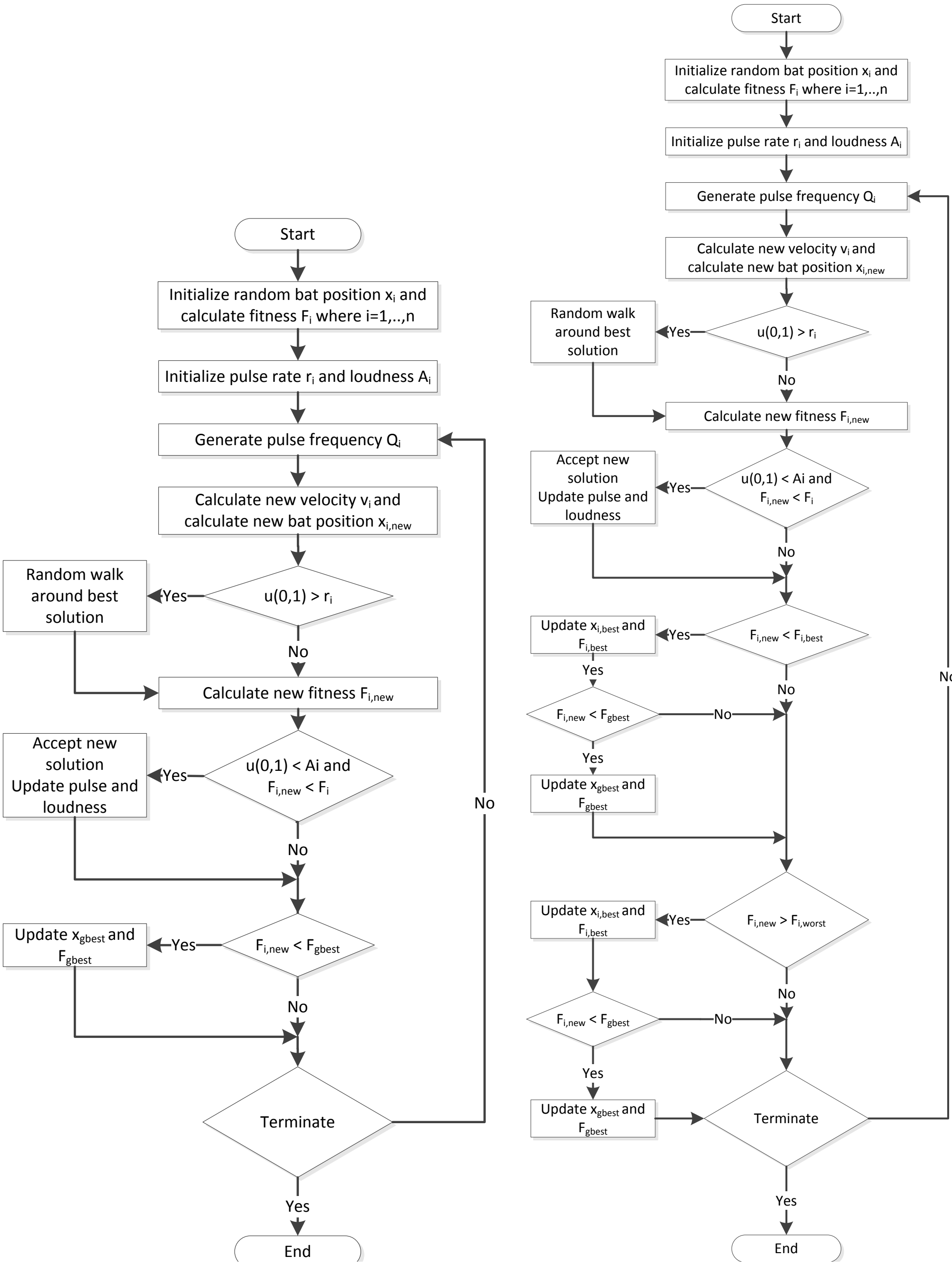
Parameter	Value
$A_i^{(0)}$	0.9
$r_i^{(0)}$	0.1
$[\zeta \quad \varsigma]$	[0.97 0.95]
$[W_{min} \quad W_{max}]$	[0.4 0.9]
$[C_1 \quad C_2 \quad C_3 \quad C_4]$	[u(0,3) u(0,2) u(0,1) u(0,1)]
p	2000
$[G \quad H]$	[10 200]

Figure 1. (**a**) Effect of tuning parameter G; (**b**) Effect of tuning parameter H.



(**a**) (**b**)

Figure 2. (**a**) Bat Algorithm (**b**); Modified Bat Algorithm.



(**a**) (**b**)

For the purpose of comparison real coded GA was used with roulette wheel selection, arithmetic crossover and uniform mutation. The crossover and mutation probabilities were 0.9 and 0.02 respectively. Also for the purpose of comparison, PSO was implemented with inertia weight decreasing linearly form 0.9 to 0.4. Velocity constant was set to 2 for all the experiments. Values used for the tuning parameters while simulating test case 1 are in Table 3. The results are presented in Table 4.

In the first experiment MBA attained better results than the original BA. The mean and standard deviation reduced by $0.41 and 16% respectively. However, PSO performed better that the both of them by achieving the lowest mean. The worst value achieved by PSO was $36927.72 which was far greater than $36916.93 (BA) and $36916.12 (MBA). This resulted in a higher standard deviation for PSO.

Table 4. Economic dispatch comparison.

		P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	Loss (MW)	Cost ($/h)
λ Iteration		28.304	10	118.897	118.733	230.733	212.831	19.433	**36912.14**
	Best	26.79976	15.89313	107.3073	123.932	228.3426	217.1609	19.44	**36924.15**
GA	**Avg.**	45.57365	48.619	105.8057	106.478	211.4508	200.6767	18.61	**37505.72**
	Std	19.7706	28.6733	43.3288	36.2062	45.62	45.0436	1.325	**382.88**
	Best	28.30223	9.999884	118.9522	118.6706	230.7563	212.7375	19.431	**36911.54**
PSO	**Avg.**	28.39792	10.02338	119.0863	118.5947	230.588	212.7238	19.4262	**36911.75**
	Std	0.85864	0.13943	0.83555	0.62292	1.1889	0.4948	0.027862	**1.4869**
	Best	28.07394	10.05693	119.9855	117.7729	231.1333	212.3918	19.4238	**36911.79**
BA	**Avg.**	28.39414	10.26771	119.159	119.0363	230.2951	212.2449	19.4092	**36912.54**
	Std	0.69285	0.26761	2.2262	1.7091	2.9539	3.8	0.059993	**1.0006**
	Best	28.14831	10.03893	119.7243	118.052	231.0219	212.4194	19.4239	**36911.27**
MBA	**Avg.**	28.28837	10.21736	119.3942	118.6366	230.4744	212.3904	19.4146	**36912.13**
	Std	0.73114	0.19558	2.485	1.8194	3.38	3.6097	0.065668	**0.84625**

Total System Demand = 700 MW, Population Size = 40, Maximum Iterations = 500, Sample Size = 200.

In the next experiment the total system demand was increased from 700 MW to 800 MW. The system parameters remained the same. The results of the experiment are detailed in Table 5.

Table 5. Economic dispatch comparison.

		P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	Loss (MW)	Cost ($/h)
λ Iteration		32.599	14.483	141.544	136.041	257.6588	243.003	25.330	**41896.63**
	Best	39.63015	13.23341	170.317	155.1286	232.4949	213.4204	24.2359	**41976.08**
GA	**Avg.**	55.35765	54.95395	130.4268	134.2949	230.3903	218.5409	23.9787	**42614.68**
	Std	25.9155	30.1187	45.3717	39.9879	49.7911	45.6905	1.3105	**436.61**
	Best	32.59937	14.48227	141.5412	136.0392	257.6555	242.9997	25.3299	**41895.98**
PSO	**Avg.**	32.5959	14.51256	141.4859	135.9388	257.6442	243.1419	25.3322	**41896.02**
	Std	0.19817	0.2575	0.31681	0.66662	0.33471	0.86126	0.020216	**0.23259**
	Best	32.46774	14.34427	141.9097	135.7294	257.7276	243.1421	25.3359	**41895.88**
BA	**Avg.**	32.58662	14.49149	141.7122	136.2057	257.3597	242.9548	25.3232	**41896.17**
	Std	0.38275	0.49502	0.97076	0.88628	1.2144	1.3829	0.037035	**0.25826**
	Best	32.49975	14.43056	141.6805	135.9817	257.502	243.2203	25.3329	**41895.71**
MBA	**Avg.**	32.6766	14.35507	142.1353	135.802	257.5361	242.803	25.3222	**41896.09**
	Std	0.12392	0.37326	0.61012	0.59674	0.31035	1.0403	0.03666	**0.21975**

Total System Demand = 800 MW, Population Size = 40, Maximum Iterations = 500, Sample Size = 200.

In the second experiment the MBA again out performed BA. The mean and standard deviation reduced by \$0.08 and 15% respectively. In this experiment also PSO achieved the lowest mean. It is important to note that in both the experiments MBA attained the lowest standard deviation.

5.2. Test Case 2–Five-Generator Test System with System Losses

The second test case was a five-generator system. Simulation was carried out for a total demand of 730 MW. This test case included the added effect of steam valve operation and thereby resulting in non-convex optimization problem. Transmission line losses were neglected for this experiment. The data for the test system is given in Tables 6 and 7, the results are presented in Table 8.

Table 6. Generator active power limits.

Generator	1	2	3	4	5
Pmin (MW)	50	20	30	10	40
Pmax (MW)	300	125	175	75	250

Table 7. Fuel cost coefficients.

No.	*a*	*b*	*c*	*d*	*e*
1	0.0015	1.8	40	200	0.035
2	0.0030	1.8	60	140	0.040
3	0.0012	2.1	100	160	0.038
4	0.0080	2.0	25	100	0.042
5	0.0010	2.0	120	180	0.037

Table 8. Economic dispatch comparison.

		P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	Cost ($/h)
	Best	234.82	100.92	112.80	71.46	209.99	**2068.06**
GA	**Avg.**	253.89	91.39	127.71	49.37	207.62	**2357.02**
	Std	29.12	19.19	27.23	15.85	23.30	**111.80**
	Best	229.51	102.98	112.67	75.00	209.81	**2029.63**
PSO	**Avg.**	248.71	94.28	126.39	55.04	205.56	**2165.08**
	Std	30.85	19.33	27.77	23.06	26.58	**104.24**
	Best	229.14	101.30	114.05	74.26	211.23	**2042.88**
BA	**Avg.**	250.69	90.03	133.26	53.18	202.84	**2176.06**
	Std	38.69	26.89	32.47	27.81	28.00	**106.92**
	Best	231.06	99.59	113.48	74.42	211.44	**2032.23**
MBA	**Avg.**	256.94	96.53	131.55	47.81	197.14	**2141.50**
	Std	35.60	17.06	29.09	29.65	30.24	**95.39**

Total System Demand = 730 MW, Population Size = 40, Maximum Iterations = 500, Sample Size = 100

For this experiment C_1 and C_2 were reduced to $\mathfrak{u}(0,1)$. G was set at 6 and H was set at 350. In this test case MBA produced the best results in comparison to GA, PSO and BA. The mean attained by MBA is \$23.58 and \$34.56 lower than PSO and BA respectively. It also achieved the lowest standard deviation which is 8.5% and 10.8% lower that PSO and BA.

6. Conclusions

This paper proposes two modifications to the original bat algorithm. The modified algorithm is then tested for solving the economic load dispatch problem and was compared with various metaheuristic optimization techniques. The proposed modifications improved the results. One important observation from the results of all three experiments is that MBA achieved the lowest standard deviation. It can hence be deduced that MBA is the most robust algorithm for the experiments performed. This work can be extended to test the algorithm's robustness for high dimensional problems or for multi objective optimization problems.

Author Contributions

All the authors contributed equally to the content of this paper. Aadil Latif conducted the simulations, collected the results and prepared the initial draft. Peter was responsible for the major reviews. Both authors discussed the results before the publishing them.

Conflicts of Interest

The authors declare no conflict of interest.

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