Hybridized Modified Bat Algorithm with Cardinal Priority Ranking for Solving Multi Area Environmental Economic Dispatch Problem

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Abstract—**The Bat Algorithm (BA) is a metaheuristic algorithm which is inspired by echolocation behavior of micro bats. It has successfully been used in solving many tough optimization problems in various fields. BA however has a weak diversification capability which leads to premature convergence and getting stuck in local optima when used in higher-dimensional optimization problems. This paper presents modifications to the velocity and frequency equations of BA to improve its exploitation and exploration capability. The Modified Bat Algorithm (MBA) is further hybridized using the Differential Evolution (DE) to increase its accuracy. The Hybridized Modified Bat Algorithm (HMBA) is then used to solve the Multi Area Environmental Economic Dispatch (MAEED) problem which is a multi-objective, nonlinear power system optimization problem. A weighted sum method is used to convert the multi objective function into a single objective one and optimal solutions are selected using cardinal priority ranking. HMBA is tested on a four-area system and results in lower fuel costs and lower emissions as compared to BA, MBA and Particle Swarm Optimization.**

Keywords-Bat Algorithm (BA); Differential Evolution (DE); Hybridized Modified Bat Algorithm (HMBA); Modified Bat Algorithm (MBA); Multi Area Environmental Economic Dispatch (MAEED)

I. INTRODUCTION

Optimization algorithms can be classified as deterministic or heuristic. Deterministic algorithms are the traditional mathematical programming techniques with specific rules for moving within the search space such as Linear Programming Method and Direct Newton–Raphson Method among others. Heuristic algorithms employ probabilistic translation rules and random walk [1], which include among others, Bat Algorithm (BA), Particle Swarm Optimization (PSO), Backtracking Search Algorithm (BSA), Flower Pollination Algorithm and Differential Evolution (DE) .

The Multi Area Environmental Economic Dispatch (MAEED) problem is one of the most important aspects of power systems planning and operation which aims at optimally scheduling generating levels of all thermal generating units to adequately supply the demand, such that the total fuel cost and emissions in all areas are simultaneously curtailed while satisfying all physical and operational constraints[2].

This paper proposes a Hybridized Modified Bat Algorithm (HMBA) used to solve the MAEED problem.

Paper Organization: The rest of this paper is organized as follows: Section II reviews previous works by various researchers on the Bat Algorithm. A detailed MAEED problem formulation is given in Section III, Section IV presents the proposed methodology, results analysis and discussions are done in Section V and then conclusions drawn in Section VI.

II. REVIEW OF PREVIOUS WORKS ON BAT ALGORITHM

This section reviews the works that have been done by researchers in solving various problems using BA. Economic Dispatch (ED) problems solved using BA have been extensively discussed.

A. Applications of BA

The Bat Algorithm has been applied in various fields which include among others; mathematical problems e.g. numerical problems with variables of continuous nature [3]; data mining applications [4]; biomedical systems like in [5] where it was used for diagnosis of Diabetes Mellitus; network and routing problems [6]; image processing [7]; scheduling [8]; and in power systems where it has been used in optimal capacitor placement [9] and economic dispatch.

B. Economic Dispatch Using BA

Bat and it's variants have been used to solve various aspects of ED such as: (i) the Multi Area Economic Dispatch (MAED) problem which was solved in [10], [11] and [12] using the Improved Bat Algorithm (IBA) where BA was improved by using a dynamic frequency varying concept; (ii) classic ED problem which was solved in [13] using a Novel Bat Algorithm (NBA) which incorporated the Doppler Effect and the movement of bats between different habitats, in [14] using the Modified Bat Algorithm, where BA was modified by adding bad experience component to steer the solution away from bad positions and non-linear inertia weight component used to provide a balance between local and global exploitation for better convergence, and in [15] using the traditional BA; and (iii) the Environmental Economic Dispatch (EED) problem which was solved in [16] using the traditional BA and in [17] using Hybridized Bat Algorithm (HBA) where DE was used to improve the local search part of BA operations and also using Mutated Bat Algorithm, where a mutation operator was embedded in BA to provide a more powerful exploration of the solution space.

The BA has been proven to provide superior results compared to other algorithms when used in solving ED, EED and MAED problems. Moreover, HBA has been shown in [17] to provide even better results for EED compared to traditional BA and hybrids of other algorithms.

The BA has an excellent intensification capability and a weak diversification capability which leads to premature convergence and getting stuck in local optima when used in higher-dimensional optimization problems like MAEED, therefore hybridization and modifications are proposed in this paper.

Contribution: A more robust algorithm is developed by modifying the Bat Algorithm and hybridizing it using the Differential Evolution method. Cardinal Priority ranking is used to select optimal solutions. The Hybridized Modified Bat Algorithm (HMBA) with Cardinal Priority ranking is presented for the first time and used to solve MAEED problem resulting in lower fuel costs and lower emissions.

III. MAEED FORMULATION

The MAEED problem is formulated as a multi objective optimization problem which simultaneously seeks to minimize fuel cost and emissions of thermal plants subject to, generator constraints and area power balance constraints.

A. Objective Functions

1) Objective 1: Minimization of Fuel Costs

a) Generator Fuel Cost Function

The generator fuel cost curves are modeled as a simple quadratic function expressed as

$$F_C(P_{Gkj}) = \sum_{k=1}^{N}\sum_{j=1}^{N_{Gk}} a_{kj} + b_{kj}P_{Gkj} + c_{kj}P_{Gkj}^2 \tag{1}$$

where N is the number of areas, N_{Gk} is the number of generators committed to the operating system in area k, a_{kj}, b_{kj}, c_{kj} are the fuel cost coefficients of the j^{th} generator in area k, and P_{Gkj} is the real power output of the j^{th} thermal generator in area k.

2) Objective 2: Minimization of Emissions

The main gaseous pollutant emission of fossil fuelled thermal plants which is Nitrogen Oxides (NO_x) is modelled as in [18] as a quadratic function expressed as

$$F_E(P_{Gkj}) = \sum_{k=1}^{N}\sum_{j=1}^{N_{Gk}} \alpha_{kj} + \beta_{kj}P_{Gkj} + \gamma_{kj}P_{Gkj}^2 \tag{2}$$

where α_{kj}, β_{kj} and γ_{kj} are the emission coefficients of the j^{th} thermal generator in area k

The two conflicting objectives are combined into one objective in (3) using weighted function method as in [19],

$$Min\,F = [\mu F_C(P_{Gkj}) + (1-\mu)F_E(P_{Gkj})] \tag{3}$$

where μ is the weighting factor which is decreased in steps from 1 through to 0 and cardinal priority ranking used to determine the best combined objective. .

B. Constraints

The objective function in (3) is solved subject to the following constraints:-

1) Generator capacity constraint

The power output of each generator is restricted within its minimum and maximum limits for stable operation. These limits are expressed as in [20] as

$$P_{Gkj}^{min} \le P_{Gkj} \le P_{Gkj}^{max} \tag{4}$$

where P_{Gkj}^{min} and P_{Gkj}^{max} are the minimum and maximum power produced by the j^{th} thermal generator in area *k.*

2) Active Area power balance Constraint

The total power generation in area k must satisfy the total demand in area k (P_{Dk}) while considering exports, imports and transmission losses in area k as in [21]. This is expressed as

$$\sum_{j=1}^{N_{Gk}} P_{Gkj} = P_{Dk} + P_{Lk} + \sum_{l,l\neq k}^{k} P_{Tkl} \tag{5}$$

where P_{Gkj} is the power generated by j^{th} thermal plant in area k, P_{Dk} is the total demand in area k, P_{Tkl} is the power transferred from area k, and P_{Lk} is the total transmission loss in area k which is defined by Kron's Formula in [22] and expressed as

$$\sum_{k}^{N} P_{Lk} = \sum_{k}^{N}\left(\sum_{i=1}^{N_{Gk}}\sum_{j=1}^{N_{Gk}} P_{Gkj}B_{kij}P_{Gki} + \sum_{j=1}^{N_{Gk}} B_{0kj}P_{Gkj} + B_{00k}\right) \tag{6}$$

where i and j are generators in area k, and B_{kij}, B_{0kj} and B_{00k} are the line loss coefficients.

This formulation leads to a bi-objective, nonlinear and nonconvex type of problem with multiple local optima positions which this paper proposes to solve using a Hybridized Modified Bat Algorithm.

IV. METHODOLOGY

A. Previous Methods

From a review of publications in IEEE xplore digital library [23], researchers have used deterministic and heuristic methods to solve the MAED problem as summarized in Figure I. It's evident that there has been an increase in the use of heuristic/metaheuristic methods in the recent past, and this can be attributed to the increased development of new metaheuristic algorithms, the ability of metaheuristic algorithms to handle large and complex optimization problems efficiently as well as their flexibility to hybridize with other algorithms.

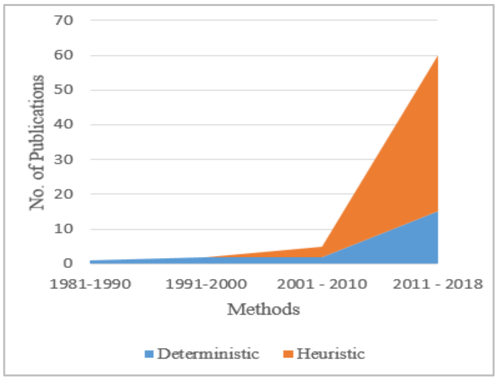

Figure 1. Comparison of methods used in solving MAED

Moreover, the MAED problem has been solved by various researchers using hybrid methods such as: *Musau et al* [24], [25] introduced a hybrid of three-methods consisting of a Modified Firefly Algorithm with Levy Flights and Derived Mutation; *Nguyen et al* [26] proposed a hybrid of the Cuckoo Search Algorithm with Teaching-Learning Based Optimization (TLBO); *Rasoul et al* [27] presented a hybrid of the Gradient Search Method (GSM) and Improved Jaya Algorithm (IJA); *Prasanna et al* [28] presented two sets of Hybrids, one consisting of a fuzzy logic strategy incorporated in Evolutionary Programming called Fuzzy Mutated Evolutionary Programming (FMEP) and another one incorporating a fuzzy logic strategy and Tabu Search Algorithm termed Fuzzy Guided Tabu Search (FGTS).

Generally, the hybrids have shown great improvement in addressing MAED problem by improving the quality of solutions, in terms of reduced fuel costs, reduced emissions, better convergence and faster computation times.

B. *Proposed Methodology*

In this paper, a new metaheuristic algorithm known as Bat Algorithm (BA) which is inspired by the echolocation behaviour of micro bats is modified and then hybridized using Differential Evolution (DE). A weighted sum method is used to convert the multi objective function into a single objective one and Cardinal Priority ranking used to select optimal solutions. BA is proven in [29] to have all the major advantages of PSO, GA and Harmony Search and can achieve faster convergence by fine tuning of its parameters. The efficiency and accuracy of BA has also been proven to be superior to other algorithms.

1) *Bat algorithm*

Bats are flying mammals that have advanced echolocation capability. Micro bats use echolocation to detect prey, locate their roosting crevices and avoid obstacles in the dark.

The Bat Algorithm (BA) is a metaheuristic algorithm developed by Xin She Yang in 2010 [29] which is inspired by the echolocation behaviour of micro bats.

The BA can be formulated when some echolocation characteristics are idealized.

For simplicity, the following rules are considered:

i) All bats have a way to differentiate food, prey and other background barriers when they sense the distance to these objects by using echolocation.

ii) To search for food, bats fly randomly with velocity V_i at position x_i with a fixed frequency f_{min} , varying wavelength λ and loudness A_o. Depending on how close their targets are, bats either increase or decrease the wavelength (or frequency) of their emitted pulses and the rate of pulse emission r automatically.

iii) The loudness is assumed to vary from a large value A_o to a minimum constant value A_{min}.

In BA, the frequency $\boldsymbol{f_i}$ and velocities $\boldsymbol{v_i}$ are updated using (7) and (8) respectively and thereafter positions $\boldsymbol{x_i}$ are updated using (9) to obtain new solutions at time step t in the search space.

$$f_i = f_{min} + (f_{max} - f_{min})\beta \tag{7}$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_{best}) f_i \tag{8}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{9}$$

where: β is a random number between [0, 1] and x_{best} is the current global best location (or solution).

Local search is done by random walk where upon selection of the current best solutions, new solutions are generated locally by:

$$x_{new} = x_{old} + \varepsilon A^t \tag{10}$$

where: ε is a random number between [0, 1], and A^t is the average loudness of all the bats in this time step.

Bats increase pulse emission rates while decreasing the loudness as they approach the target. This is implemented by

$$A_i^{t+1} = \alpha A_i^t \tag{11}$$

$$r_i^{t+1} = r_i^0[1 - exp(-\gamma t)] \tag{12}$$

2) *Modifications of BA*

To overcome the challenges of premature convergence and getting stuck in local minima, two modifications are proposed in this paper.

a) *Incorporation of a bad experience component*

In order to enhance the exploration capability of BA, the velocity update equation (8) is modified as:

$$v_i^{(t)} = v_i^{(t-1)} + \{f_i^{(t)}[C_1\left(x_i^{(t)} - x_{best}\right) + C_2\left(x_{worst} - x_i^{(t)}\right)]\} \tag{13}$$

Where x_{best} and x_{worst} are the global best and worst positions respectively. C_1 is a random number between [0,2] that accelerates the bat towards global best position and C_2 is a random number between [0,1] that steers the bat away from the global worst position [14].

This modification steers bats away from bad positions thereby allowing them to accelerate towards better positions.

b) Dynamic frequency varying concept

To enhance the exploitation capability of the BA, a dynamic frequency varying concept is used instead of a random generation of frequency. This ensures that bats near the global best position do not steer further to irrelevant positions. This is implemented as:

$$D_i = \sqrt{(x_i - x_{best})^2} \tag{14}$$

$$d = \max(D_i) - \min(D_i) \tag{15}$$

$$f_i = f_{\min} + \left(\frac{\sqrt{(\min(D_i) - D_i)^2}}{d}\right) * (f_{\max} - f_{\min}) \tag{16}$$

The Modified Bat Algorithm (MBA) is then hybridized using DE where DE is used in local search rather than a random walk to increase the accuracy of the results.

3) Differential evolution

Differential Evolution (DE) [30] was introduced by Price and Storn in 1996. DE is implemented by combining the existing candidate vectors (solutions) to obtain new solutions and a vector with the best fitness/score depending on the objective function value is maintained.

The steps involved in the DE algorithm are mutation, crossover and selection.

Mutation

Two solutions are randomly selected, and a weighted difference between them is added to a third solution. This process is called mutation and is expressed as:

$$u_i^t = x_{r1}^t + MF\left(x_{r2}^t - x_{r3}^t\right) \tag{17}$$

where: i = 1,2, . . .,.NP and NP is the population size, $MF \in [0,1]$ is a scaling factor that controls the rate of amplification and $x_{r1}^t, x_{r2}^t, x_{r3}^t$, are randomly selected with $r_1,\ r_2,\ r_3 \in \{1,2,\dots,NP\}$ and $r_1 \neq r_2 \neq r_3 \neq i$

Crossover

To make the population more diverse, a differential crossover operator is applied where parameters of the target vector are mixed with the parameters of the mutated vector and a trial vector q_i is created as

$$q_{ij}^t = \begin{cases} u_{ij}^t, if\ rand(j) \le CR\ or\ j = j_{rand} \\ x_{ij}^t, if\ rand(j) > CR\ and\ j \neq j_{rand} \end{cases} \tag{18}$$

where: $rand(j) \in [0,1]$ is a uniformly distributed random number newly generated for the j[th] parameter of the i[th] vector, CR is the crossover constant within [0,1], j_{rand} is a random integer from [1,2,…,D] and D is the number of real parameters in the objective function. This ensures that at least one parameter from the mutated vector is selected for the trial vector.

Selection

Differential selection is then carried out using (19)

$$x_i^{t+1} = \begin{cases} q_i^t, f\left(q_i^t\right) > f\left(x_i^t\right) \\ x_i^t, f\left(q_i^t\right) \le f\left(x_i^t\right) \end{cases} \tag{19}$$

This DE scheme is denoted as *DE/rand/1/bin*.

4) Cardinal priority ranking

Equation (3) generates non inferior solutions with explicit trade-offs between the conflicting objectives. By exploiting the fuzzy decision making theory, membership functions are defined which relate to the objectives and are used to find the optimal trade-off level among the non inferior solutions. The membership function $\mu(F_i)$ is given by:

$$\mu(F_i) = \begin{cases} 1; F_i \le F_{imin} \\ \dfrac{F_{imax} - F_i}{F_{imax} - F_{imin}} \quad ; F_{imin} \le F_i \le F_{imax} \\ 0; F_{imax} \le F_i \end{cases} \tag{20}$$

where F_{imax} and F_{imin} are the minimum and maximum values of i^{th} objective function where the solution is expected.

The value of the membership function indicate how much a non-dominated solution has satisfied the i^{th} objective.

The 'accomplishment' of each solution in satisfying the objectives is then normalized over the sum of the 'accomplishments' of all the non-dominated solutions as:

$$\mu_D^k = \frac{\sum_{i=1}^{L} \mu_k(F_i)}{\sum_{k=1}^{N} \sum_{i=1}^{L} \mu_k(F_i)} \tag{21}$$

The accomplishments μ_D^k result in a set of non dominated solutions, from which the maximum value is selected as the optimal result.

The parameters of HMBA are as shown in Table I.

TABLE I. PARAMETERS OF HMBA

Parameter	Value
Population	30
Fitness	Weighted Fuel cost at maximum accomplishment
Velocity v_i	From 0
Position X_i	$P_{Gkj}^{min} \le P_{Gkj} \le P_{Gkj}^{max}$
Frequency f_i	Rand [0,1.5]
Pulse rate A_i	Rand [1,2]
Loudness r_i	Rand [0,1]
Alpha (α)	0.99
DE Crossover Constant (CR)	0.5
DE Scaling Factor	0.8
Maximum number of iterations	20

5) *Hybridized modified bat algorithm pseudo code*

Objective function f(x), $x = (x_1, ..., x_d)^T$
Randomly initialize the bat population i.e. Position x_i *and velocities* V_i for i = 1, 2, ..., n
Define pulse frequency f_i *at* x_i
Initialize pulse rates r_i *and the loudness* A_i
while *(t <Max number of iterations)*
Generate new solutions x_f *by adjusting frequency using equation (16),*
and updating velocities and locations/solutions using equations (13) and (9)
if *(rand >* r_i*)*
Modify the solution using ***DE/rand/1/bin*** to get a local solution x_l
end if
Select the best solution x_{best} *among* x_l *and* x_f
if *(rand <* A_i & $f(x_i) < f(x_{best})$*)*
Accept the new solutions
Increase r_i *and reduce* A_i *(11 & 12)*
end if
Rank the bats and find the current best x_{best}
end while
Post-process results and visualization

V. RESULTS DISCUSSIONS AND ANALYSIS

A. MBA and HMBA Results

This section discusses the results of the simulations used to evaluate the performance of MBA and HMBA. The algorithm was implemented in Matlab R2015a on an Intel Core i7, 2.5GHz PC with 8GB memory. The MAEED problem is solved for a four- area, twelve generating units test system whose data is taken from [31].

Results of the MAEED problem solved using a traditional BA for the same system are taken from [32] where BA resulted in a total fuel cost of 2226.17$/hr and emissions of 2034.74Kg/hr as shown in Table II.

The results of MBA are shown in Table III and indicate a total fuel cost of 2120.87$/hr which is a reduction of 4.7% when compared to BA and total emissions of 1890.22kg/hr, which is an emission reduction of 7.1% when compared to BA.

HMBA resulted in total fuel cost is 2079.67$/hr which is a reduction of 1.9% and 6.6% when compared to MBA and BA respectively; and emissions of 1765.21kg/hr, which is an emission reduction of 6.6% and 13.2% when compared to MBA and BA respectively.

HMBA results are given in Table IV whereas a summary of comparisons between the results of BA, MBA and HMBA is presented in Table V.

B. Comparison of HMBA and PSO

The results of HMBA were compared to those of PSO taken from [31] for the same MAEED system and tabulated in Table VI. HMBA resulted in a reduction of total fuel cost of 47.6% and an increase in emissions of 13% when compared to PSO. The increase in emissions is attributed to the use of Cardinal Priority ranking in selecting the optimal trade-off level among the results.

TABLE II. MAEED USING BA [32]

	Area 1	**Area 2**	**Area 3**	**Area 4**
P1(MW)	38.44	141.51	162.38	174.28
P2(MW)	275.59	96.17	91.94	113.45
P3(MW)	199.73	177.51	335.00	327.70
P_{loss} (MW)	13.08	5.66	12.36	18.86
P_{total}	513.77	415.20	588.53	615.44
Emissions (Kg/hr)	406.04	294.15	890.93	443.62
Total Emissions (Kg/hr)	2034.74			
Fuel Cost($/hr)	396.71	394.61	761.59	673.28
Total Fuel Cost ($/hr)	2226.19			

TABLE III. MAEED USING MBA

	Area 1	**Area 2**	**Area 3**	**Area 4**
P1(MW)	49.02	115.20	174.17	174.95
P2(MW)	170.49	108.89	132.81	138.07
P3(MW)	293.36	191.08	284.14	303.22
P_{loss} (MW)	13.48	5.57	12.55	18.5
P_{total}	512.86	415.17	519.12	616.26
Emissions (Kg/hr)	409.14	307.29	759.39	414.40
Total Emissions (Kg/hr)	1890.22			
Fuel Cost($/hr)	396.36	290.83	682.66	651.01
Total Fuel Cost ($/hr)	2120.87			

TABLE IV. MAEED USING HMBA

	Area 1	**Area 2**	**Area 3**	**Area 4**
P1(MW)	67.33	137.16	123.23	144.27
P2(MW)	169.79	106.35	179.92	171.65
P3(MW)	275.59	171.71	288.16	301.50
P_{loss} (MW)	13.00	5.70	11.68	18.69
P_{total}	512.71	415.22	591.31	617.42
Emissions Kg/hr)	375.47	289.97	706.17	393.61
Total Emissions (Kg/hr)	1765.21			
Fuel Cost($/hr)	389.67	388.76	662.02	639.22
Total Fuel Cost ($/hr)	2079.67			

TABLE V. COMPARISON OF BA, MBA AND HMBA

	BA [32]	**MBA**	**HMBA**
Total Fuel Cost ($/hr)	2226.19	2120.87	2079.67
Total Emissions (Kg/hr)	2034.74	1890.22	1765.21

TABLE VI. COMPARISON OF HMBA AND PSO

	PSO [31]	**HMBA**	**% Reduction**
Fuel Cost($/hr)	4046.21	2120.87	47.6%
Emissions Kg/hr)	1645.20	1890.22	-13%

VI. CONCLUSION

This paper proposed a hybrid of Modified Bat Algorithm and Differential Evolution (MBA-DE) where two modifications were effected on the original Bat Algorithm and then hybridized with Differential Evolution. The Hybridized Modified Bat Algorithm was then tested by solving the MAEED problem for a four-area system and the results obtained were compared to those of the original BA, MBA and PSO. It was evident from the results that HMBA was superior and robust in solving complex multi-objective optimization problems like MAEED problem.

In future work, HMBA can be tested for even larger and more complex multi-objective optimization problems like the MAEED problem for a practical larger power pool.

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