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Emission Constrained Economic Dispatch Using Moth Flame Optimization and Bat Hybrid Algorithm

Wilbert Ruta

Department of Electrical, Pan African University Institute for Basic Sciences, Technology and Innovation, P.O. BOX 62,000-00200, Nairobi, Kenya.

[*]Corresponding Author

Michael Saulo

Department of Electrical and Electronic Engineering, Technical University of Mombasa, P.O. BOX 90420 - 80100, Mombasa, Kenya.

Nicodemus Abungu Odero

Department of Electrical and Electronic Engineering, Machakos University, P.O. BOX 136 - 90100, Machakos, Kenya.

Abstract

This paper presents the application of a novel Moth flame optimization and Bat hybrid algorithm in the area of emission constrained economic dispatch with the main goal of minimizing the total cost of electric generation while using thermal power plants with the considering of emissions reduction. This area is crucial due to rise of air pollution caused by greenhouse gases from thermal power plants and manufacturing industries, also the cost of generating electric power using thermal power plants is at elevated level which turns the electric energy to be expensive. The multi-objective economic dispatch with the consideration of emission was converted into single objective problem by using the price penalty factor method while the IEEE-30 bus test system was used for implementing the study. The results of Moth flame optimization and Bat hybrid algorithm were compared with other methods reported in the literature and found to be promising in terms of reduction of total cost of electric generation and greenhouse gases emissions from thermal power plants.

Keywords: Economic dispatch; Emission dispatch; exploitation; exploration; multi-objective optimization; price penalty factor

1. INTRODUCTION

Having different sources of energy and levels of efficiency, the cost of generating electric energy tend to differ from one plant to another. It was the culture to determine the economic dispatch which involves determination of power output of each unit in the given power system in order to minimizing overall cost of fuel used for generation of electric power [1]. With the increase of production activities globally as well as demand of electric energy, numerous investments have been done on thermal generation. Based on current statistics 42% of total global electric generation is from coal, which is the main source of pollutants gases which are NOx, COx and SOx [2]. As a result of increase of pollutants gases from electric power generation activities, the concept of environmental economic dispatch is the major concern whereby the generation of electric energy is no longer focused on reduction of cost of fuel alone but also the issue of reducing pollutant emissions has become the major concern. The emission constrained economic dispatch has been adopted which is the multi-objective problem focused on reduction of both cost of fuel and emissions from the power system which comprises thermal power plants [3]. In order to in-cooperate the emission constrain in the problem of economic dispatch, recently the max-max price penalty factor method has proven to be most effective method for finding the best compromise solution of the emission constrained economic dispatch multi-objective problem[4] .The emission constrained economic dispatch have been solved by using both conventional and artificial intelligent based methods. Among the conventional methods which have been used in this area are Newton Raphson (NR) method [5], Liner Programming [6], Interval Gradient (IG) method [7], etc. These method they are convenient when dealing with convex objective function with their capability of finding the optimal solution very quickly. But when dealing with the non-convex optimization proper, the methods are weak since they are more vulnerable to local solution stagnation. Also artificial intelligence methods have been applied in this area, some of these methods are Genetic Algorithm [8],Particle Swarm Optimization [9], Water Wave Optimization (WWO) [10], etc. These methods have been effective in finding the global optimal solution in both convex and non-convex cost function since in these methods stochastic approach is applied for facilitating random searching of the optimal solution hence avoidance of local stagnation. However these methods suffers from the problem of finding the precisely global optimal solution.

For improving the quality of solutions, this paper present the Moth Flame Optimization and Bat hybrid algorithm (MFO_BAT) for solving emissions constrained economic dispatch (ECED). The hybrid algorithm is developed from two recent artificial intelligent algorithms which are Moth Flame Optimization and Bat algorithm being having two different strengths in terms of exploration and exploitation. The results of hybrid MFO_BAT algorithm are compared with other methods reported in the literature which are Biogeography-Based Optimization (BBO), Fuzzy logic Controlled Genetic Algorithms (FCGA), Augmented Lagrange Hopfield Network (ALHN), Water Wave Optimization Algorithm (WWOA), Genetic Algorithm (GA), Non Sorting Genetic Algorithm (NSGA), Differential Evolution (DE) and Differential Evolution and Biogeography-Based Optimization hybrid algorithm (DE_BBO). The MFO_BAT results are more promising compared to other methods reported in the literature.

2. PROBLEM FORMULATION

The formulation of emission constrained economic dispatch is achieved from parent objective functions which are economic dispatch and emission dispatch objective function.

2.1 ECONOMIC DISPATCH OBJECTIVE FUNCTION

$$Min(\text{fuel cost}) = \sum_{i=1}^{NG} a_i P_i^2 + b_i P_i + c_i \quad (\$/hr) \tag{1}$$

Where a_i, b_i, c_i are fuel cost coefficient of i^{th} unit, P_i is generated power by of i^{th} unit and NG is the total number of generating units.

2.2 EMISSION DISPATCH OBJECTIVE FUNCTION.

$$Min(emissions) = \sum_{i=1}^{NG} \alpha_i P_i^2 + \beta_i P_i + \gamma_i \quad (Kg/hr) \tag{2}$$

Where α_i, βi, γ_i are coefficient of emission of the i^{th} generating unit, P_i is generated power by of i^{th} unit and NG is the total number of generating units.

2.3 CONSTRAINED EMISSION ECONOMIC DISPATCH

As it given in (3), the multi-objective Optimization problem is converted into single objective problem by using the price penalty factor (h).

$$Min(\text{cost}) = \sum_{i=1}^{N} ((a_i P_i^2 + b_i P_i + c_i) + h(\alpha_i P_i^2 + \beta_i P_i + \gamma_i)) \quad (\$/hr) \tag{3}$$

In [11] price penalty factor "*h"* is given by equation (4).

$$h_i = \frac{a_i P_{i(\max)}^2 + b_i P_{i(\max)} + c_i}{\alpha_i P_{i(\max)}^2 + \beta_i P_{i(\max)} + \gamma_i} \quad (\$/Kg) \tag{4}$$

2.4 CONSTRAINTS

The optimization problem presented in this paper are subjected to two constraints which are equality constraint and inequality constraint. The equality constraint is based on the power balance of the system in such the way that the total generated power must be equal to power demand (P_D) with addition of system losses as it given in (5).

$$P_G = \sum_{i=1}^{NG} P_D + P_L \tag{5}$$

The total losses of the system (P_L) are given by Kron's formula [11] as in (6).

$$P_L = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{io} P_i + B_{oo} \qquad (MW) \tag{6}$$

Where NG is the total number of generators, B, Bio and Boo are loss coefficients matrices and P_i is the generated power by unit i$^{th.}$
The inequality constraint is based on the generators' maximum and minimum generating power limits and is given by;

$$P_{i(\min)} \le P_i \le P_{i(\max)}$$

Where P_i is power generated by unit ith

3. ALGORITHMS

The implementation of three algorithms employed in this study which are Moth flame optimization, Bat algorithm and the developed Moth flame optimization and Bat hybrid algorithm is presented under this section.

3.1 MOTH FLAME OPTIMIZATION

Moth Flame Optimization is the recently population based algorithm which was developed in 2015 by Seyedali Mirjalili [12], in this algorithm, the moth navigation is based on transverse (spiral movement) around the best solution which is the flame position.

In Moth Flame Optimization, each moth navigate around its flame for searching the best solution. It is by this property of MFO which makes it to be very difficult to suffer from local stagnation and to be useful for search purpose. The position updating of Moths is achieved by using the logarithmic spiral mechanism [13]given in (7) below:

$$S\left(M_i, F_j\right) = D_i e^{bt} \cos\left(2\pi t\right) + F_j \tag{7}$$

The distance between the moth and the flame (*D*) is calculated as it shown in (8);

$$D_i = \left| F_j - M_i \right| \tag{8}$$

Where

b is a constant of defining the shape of logarithmic spiral

t is random number in [-1, 1]

l is current number of iterations

N is a maximum number of flames

T is a maximum number of iterations

F_j is a position of jth flame

M_i is a position of ith moth

In each iteration, number of flames are normally updated for removing the flame with the poor solution, this is achieved by employing (9).

$$Flame(number) = round\left(N - l \times \frac{N - l}{T} \right) \tag{9}$$

Through fine tuning of parameters connected to (7) which are *t* and *b* the algorithm can be switched successfully between the exploration and exploitation mode [14].

3.1.1 DETAILED PSEUDOCODE OF THE MFO ALGORITHM FOR CONSTRAINED EMISSION ECONOMIC DISPATCH

Step 1: Define the load demand,maximum and minimum power limits of generators

Step 2: Define the constrained emission economic dispatch objective function and equality constraints using power balance violation

Step 3: Map the moths position to the generators power

Step 4: Define the dimension of moth position depending on the amount of generating units

Step 5: Initialize the positions of moths based on the maximum and minimum limits of generators

Step 6: Set iteration to 1

Step 7: Update flame number using (9)

Step 8: Bring back the moths which are outside the search space with the reference to generator power limits

Step 9: Evaluate the objective function fitness using Moths positions with the consideration of equality constraints

Step 10: If iteration count is 1 sort moth's fitness and position ,select the best moth based on the fitness sorted and assigned it to the flame

Step 11: If iteration count is greater than 1 sort moth's fitness and position based on the previous iteration and current iteration, select the best moth's fitness and position based on the fitness sorted and assigned it to the flame

Step 10: Compute "a" using (10)

$$a = (-1 + current\ iteration) \times \left(\frac{-1}{Maximumi\ iteration} \right) \tag{10}$$

Step 11: Compute "t" using (11)

$$t = (a - 1) \times rand + 1 \tag{11}$$

Step 12: Calculate the distance of month with respect to the corresponding flame using (8)

Step 13: Update moths position using (7)

Step 14: Increase the iteration

Step 15: Repeat step 7-14 untill the the maximum number of iteration is reached

Step 16: Display the best flame fitness which gives the value of objective function which is the total cost of generation and and corresponding moth position which gives the amount of power generated in each unit

3.2 BAT ALGORITHM

The bat algorithm is the bio-inspired algorithm which is inspired from the behavior of micro bats. The micro bat uses the echolocation mechanisms for detecting their prey when hunting for food. This echolocation behavior of micro bat navigation is the one which Xin sheng Yang in 2010 used for developing the bat algorithm. The micro bat normally emit the voice and wait for sonar in order to detect the location of the prey or if there is any obstacles like walls in their navigation path [15].

In bat algorithm, the amplitude (loudness) of bat tend to decrease when the target is near to the bat while the pulse rate tend to increase as the bat approaches the prey. Through fine tuning of loudness and pulse rate parameters, the algorithm can be successfully switched between the exploration and exploitation mode [15].

In bat algorithm, the position of bat is the one which represents the solution where by the fitness of the optimized function is computed from the bat position. Decision variables determines the dimension of bats and this depends on the nature of problem being optimized. Equation (12-14) shows how the solutions of bat algorithm (position of bats) can be updated from one iteration to another by using frequency and velocity [16].

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \tag{12}$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_*) f_i \tag{13}$$

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

Where *f, v and x* represents frequency, velocity and position respectively

The Loudness (*A*) and pulse rate (*r*) of bat algorithm are normally updated iteratively using (15) and (16) respectively.

$$A_i^{t+1} = \alpha A_i^t \tag{15}$$

$$r_i^{t+1} = r_i^0 [1 - \exp(-\gamma t)] \tag{16}$$

With the condition that $0 < \alpha < 1$ and $\gamma > 0$

3.2.1 DETAILED PSEUDOCODE OF THE BAT ALGORITHM FOR ECONOMIC DISPATCH CONSIDERING EMISSIONS

Step 1: Define the load demand,maximum and minimum power limits of generators

Step 2: Define the constrained emission economic dispatch objective function and equality constraints using power balance violation

Step 3: Define the maximum and minimum frequency, initialize the value of pulse rate and loudness.

Step 4: Map the bats position to the generators power

Step 5: Define the dimensions of bats positions depending on the amount of generating units

Step 6: Initialize the velocity and frequency of bats

Step 7: Initialize the positions of bats based on the maximum and minimum limits of generators

Step 8: Evaluate the fitness of the constrained emission economic dispatch objective function using bat position

Step 9: Select the minimum fitness among all with its corresponding position as the global best values

Step 10: Set iteration to 1

Step 11: Compute the new position of bat using equation (14) after updating frequency and velocity using equation (12) and (13) respectively

Step 12: If random number is greater than the pulse rate, generate the best position of bat

Step13: Bring back the bats which are outside the search space with the reference to generator power limits

Step 14: Evaluate the new fitness of the constrained emission economic dispatch objective function while satisfying the equality constraints using power balance by using bat position computed in step 10

Step 15: If the new fitness is less than the previous fitness and random number less than loudness, update the fitness and its corresponding position as the local best values

Step 16: Update loudness and pulse rate using equation (15) and (16) respectively

Step 17: If the among the new fitnesses is less the the previous best fitness, update it as the global best including its position as the global best position

Step 18: Repeat step 11-17 until the maximum iteration is reached

Step 19: Display the global best fitness which gives the value of objective function which is the total cost of generation and corresponding global best position which gives the amount of power generated in each unit

3.3 HYBRIDIZATION OF MOTH FLAME OPTIMIZATION AND BAT ALGORITHMS

The bat algorithm is the very effective algorithm in exploiting the possible best solution but limited when it comes the case of searching the solutions across the search space. For the case of MFO, each individual moth normally navigate in the spiral path subjected to the corresponding solution (flame) which makes this algorithm to be more effective for searching the search space and capable of avoiding local stagnation. In order to come up with the strong algorithm the strong property of MFO (exploration) is combined with the strong property of Bat (exploitation) hence in hybrid MFO_BAT algorithm, Moth Flame Optimization is used for exploration while Bat algorithm is used for exploitation. Equation (17-20) are updating equation of MFO_BAT whereby the MFO is dedicated to position updating in order to ensure the successfully exploration of the search space while Bat algorithm remaining with the task of finding the best optimal solution in order to improve the solution quality.

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \tag{17}$$

$$v_i^t = v_i^{t\text{-}1} + (Moth\_position_i^t \text{ - } x_*) f_i \tag{18}$$

$$x_i^t = Moth\_position_i^{t-1} + v_i^t \tag{19}$$

$$x_* = x_{old} + \partial A^t \tag{20}$$

In MFO_BAT hybrid algorithm, the Bat algorithm is switched into exploitation mode through adjusting the values of loudness and pulse rate while the MFO algorithm switched into full exploration mode through adjusting the value of "*b*" in (7).

4. TEST SYSTEM

This study is implemented in MATLAB 2016 using IEEE-30 bus test system which is the system of six generators, the load demands of 500MW, 700MW and 900MW are used for testing the algorithms at different demand levels. The population used for both MFO, Bat and MFO_BAT algorithms is 40 while tuning parameters for the case of normal MFO b=1 and for the case of normal Bat the initial values of A and r are 0.8 and 0.2 respectively. For the case of MFO_BAT hybrid algorithm the tuning parameters are set at b=5 for MFO part while A= 0.9 and r=0.001 in the part of Bat. In both cases the maximum and minimum frequency of Bat algorithm are 0.333 and -0.333 respectively. The number of iteration in both cases are 400 iterations.

The economic dispatch coefficients (a_i , b_i , c_i), emissions dispatch coefficients (α_i, βi, γ_i), maximum power limits (*Pmax*), minimum power limits (*Pmin*) and transmission losses coefficients matrices data was taken from [10].

5. RESULTS AND DISCUSSION

The results of the MFO_BAT hybrid algorithm are compared with results of MFO and BAT at different loading condition. Then for further validation of the results, the results from developed MFO_BAT hybrid algorithm are also compared with other results reported in the literature.

Assessing the performance of the hybrid MFO_BAT in the area of constrained emission economic dispatch with the comparison to parents algorithms which are MFO and BAT, the system was tested under three loading condition which are 500MW, 700MW and 900MW as it show in Table 1 and Table 2. At 500MW the total cost optimized by MFO_BAT is lower by 371.8121 $/hr and 509.7468 $/hr from the total cost of MFO and BAT respectively. The cost of fuel from MFO_BAT is 120 $/hr higher than MFO and 214 $/hr lower than BAT. In terms of emission the hybrid MFO_BAT emissions is 11.4022 Kg/hr and 6.8456 Kg/hr lower than MFO and BAT respectively while the system losses by MFO_BAT are 4.933 MW and 0.1031MW higher than MFO and BAT respectively. The convergence curve of constrained emission economic dispatch at a system load of 500MW is shown in Fig.1.

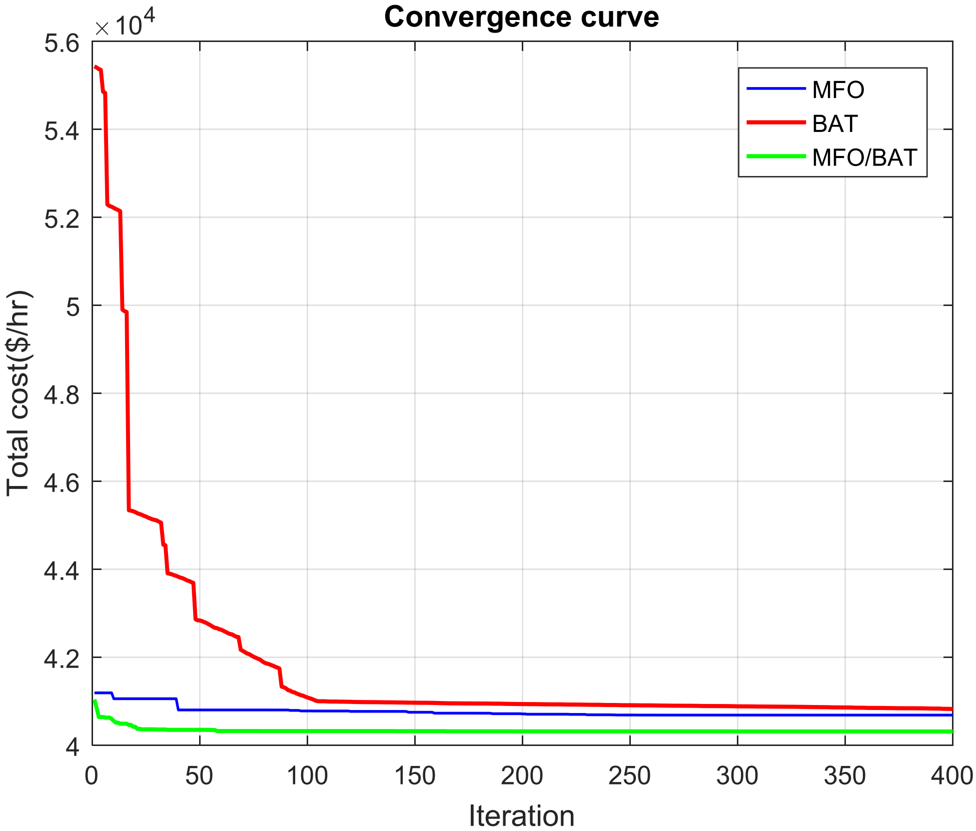

Fig.1. Convergence curve of ECED at a load of 500MW

At a load of 700MW the multi-objective total cost by MFO_BAT is lower by 17.3358$/hr and 937.7351$/hr from the total cost of MFO and BAT respectively while fuel cost of MFO_BAT is 68$/hr higher than MFO and 93$/hr lower than BAT.

The hybrid MFO_BAT performed well in emission with 1.9068Kg/hr and 18.8667Kg/hr lower than MFO and BAT respectively. Losses due to MFO_BAT are recorded to be 0.7214MW and 7.3185MW lower than MFO and BAT respectively

Table 1: Performance Comparison of MFO, BAT and MFO_BAT at 500MW and 700MW

LOAD	500MW			700MW		
Generator	MFO	BAT	MFO_BAT	MFO	BAT	MFO_BAT
P1(MW)	59.0900	52.2615	57.0900	90.7887	72.1289	94.0534
P2(MW)	42.7629	58.0558	37.4090	63.8034	76.3761	65.6911
P3(MW)	40.0000	53.2604	64.6480	83.6857	87.5312	82.2747
P4(MW)	91.5993	75.4425	82.6557	108.2828	87.6265	109.4433
P5(MW)	157.2761	131.5383	146.4039	207.0946	206.3405	203.0048
P6(MW)	125.0000	149.9996	132.4544	181.3405	211.5895	179.8069
Emissions(Kg/hr)	287.9305	283.3739	276.5283	470.2457	487.2056	468.3389
Fuel cost ($/hr)	28261	28595	28381	38748	38909	38816
Losses (MW)	15.7282	20.5581	20.6612	34.9956	41.5927	34.2742
Generation(MW)	515.7282	520.5581	520.6612	734.9956	741.5927	734.2742
Total cost ($/hr)	40685.7053	40823.364	40313.8932	59808.9441	60729.3434	59791.6083

Table 2. Performance Comparison of MFO, BAT and MFO_BAT at 900MW

Generator	MFO	BAT	MFO_BAT
P1(MW)	125.0000	114.2561	125.0000
P2(MW)	93.8346	97.5516	94.2835
P3(MW)	101.8987	115 .4511	99.1034
P4(MW)	141.3462	117.0681	141.0399
P5(MW)	264.9542	289.0905	266.0903
P6(MW)	228.6492	225.4764	229.1069
Emissions (Kg/hr)	755.1190	772.4356	755.8161
Fuel cost ($/hr)	50307	50238	50269
Losses MW)	55.6829	58.8937	54.6241
Total generation (MW)	955.6829	958.8937	954.6241
Total cost ($/hr)	86418.9461	87177.2885	86413.7755

As shown in Table 2 at a load of 900MW the total cost from MFO_BAT is 5.1706$/hr and 763.513$/hr lower that MFO and BAT respectively. The fuel cost of MFO_BAT is 38$/hr lower than MFO and 31$/hr higher than BAT. The emission produced by hybrid MFO_BAT is 0.6971Kg/hr higher than MFO and 16.6195Kg/hr lower BAT. Losses due to MFO_BAT are 1.0588MW and 4.2696 MW lower than MFO and BAT respectively. The convergence curve of constrained emission economic dispatch at a system load of 900MW is shown in Fig. 2.

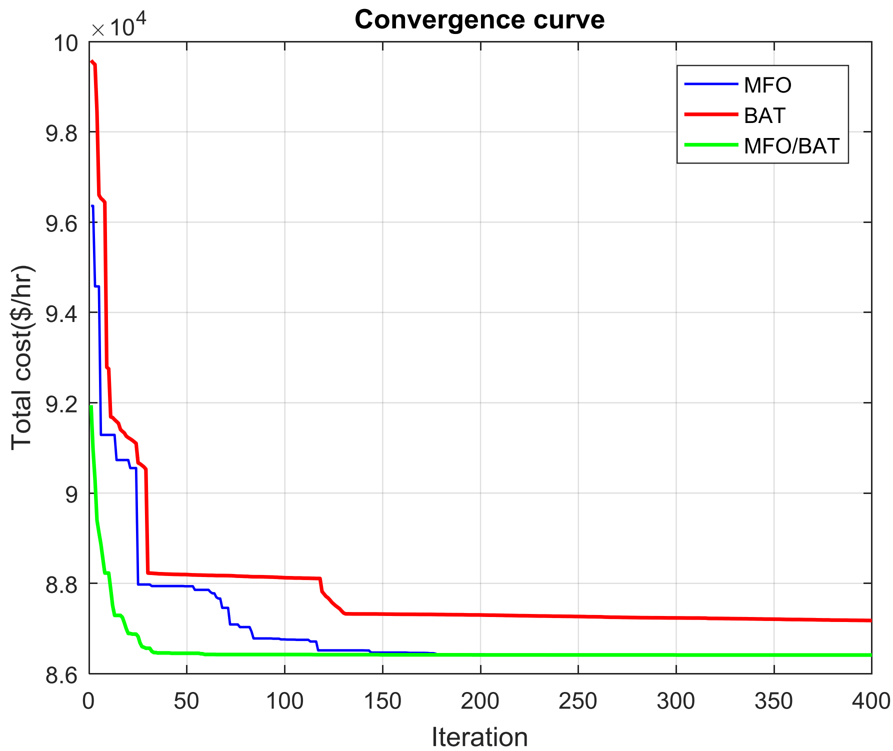

Fig. 2. Convergence curve of ECED at a load of 900MW

The results of hybrid MFO_BAT are also compared with other results from the literature which are results from BBO, NSGA-II, GA, ALH, WWO and DE_BBO algorithms in a study of constrained emission economic dispatch. Three load condition are considered which are 500MW, 700MW and 900MW.

Table 3 shows the validation of the study at a load of 500MW, the hybrid MFO_BAT total cost is 334.20764$/hr, 460.26931$/hr and 892.9516$/hr lower than BBO, NSGA-II and ALH total cost respectively. The fuel cost of MFO_BAT is 75.29451$/hr, 94$/hr and 42.7037$/hr lower that BBO, GA and ALH respectively but it is 89.881$/hr higher than NSGA-II. The emission dispatch is more promising than other compared algorithm in the way that the MFO_BAT emission is 1.200191Kg/hr,7.8337Kg/hr, 0.8895Kg/hr and 3.78Kg/hr lower than BBO, NSGA-II, GA and ALH respectively.Losses of MFO-BAT are 1.9083MW, 1.9879MW lower than BBO and GA respectively and 0.1532MW higher than NSGA-II.

Table 3. Validation of best compromising solution at a load of 500MW

Generating unit	BB0 [17]	NSGA-II [18]	GA [8]	ALH [19]	MFO_BAT
P1(MW)	55.9211	54.048	55.3071	-	57.0900
P2(MW)	38.1085	34.25	40.1529	-	37.4090
P3(MW)	65.3674	54.497	66.5698	-	64.6480
P4(MW)	82.1178	80.413	80.2377	-	82.6557
P5(MW)	147.8045	161.874	147.4310	-	146.4039
P6(MW)	133.2502	135.426	132.9505	-	132.4544
Generation(MW)	522.5695	520.508	522.6490	-	520.6612
Ploss(MW)	22.5695	20.508	22.6491	-	20.6612
Fuel cost ($/hr)	28,456.294513	28,291.119	28475	28423.7037	28381
Emission (kg/hr)	277.728491	284.362	277.4178	280.3083	276.5283
Total cost ($/hr)	40,648.100843	40,774.162518	NA	41,206.8448	40313.8932

Table 4 presents the validation of MFO_BAT hybrid algorithm performance at a load of 700MW. The MFO_BAT hybrid total cost is 378.41687$/hr, 599.28996$/hr and 1105.9685$/hr lower than BBO, NSGA-II and ALH respectively. In terms of fuel cost, the cost of MFO_BAT is 184.15002$/hr, 192$/hr, 0.1969$/hr, 96$/hr lower than BBO, GA, ALH and WWO respectively and 144.187$/hr higher than NSGA-II. The hybrid MFO_BAT performed well in terms of emission having emission of 4.329651Kg/hr, 16.5921Kg/hr, 4.2013Kg/hr, 11.5486Kg/hr and 7.2864Kg/hr lower than BBO, NSGA-II, GA, ALH and WWO respectively. The losses of MFO_BAT are 4.155483MW, 1.9598MW, 4.0471MW and 3.8883MW lower than BBO, NSGA-II, GA and WWO respectively.

Table 4. Validation of best compromising solution at a load of 700MW

Generating unit	BB0 [17]	NSGA-II [18]	GA [8]	ALH [19]	WWOA [10]	MFO_BAT
P1(MW)	93.069693	86.286	93.4380	-	91.2235	94.0534
P2(MW)	66.729002	60.288	66.9674	-	64.7522	65.6911
P3(MW)	83.337800	73.064	82.2116	-	84.5232	82.2747
P4(MW)	110.702668	109.036	111.7986	-	103.2023	109.4433
P5(MW)	205.799186	223.448	204.2191	-	211.4939	203.0048
P6(MW)	178.791334	184.111	179.6866	-	182.9675	179.8069
Generation(MW)	738.429683	736.234	738.3213	-	738.1625	734.2742
Ploss (MW)	38.429683	36.234	38.3213	-	38.1625	34.2742
Fuel cost ($/hr)	39,000.150029	38,671.813	39008	38816.1969	38912	38816
Emission (kg/hr)	472.668551	484.931	472.5402	479.8875	475.6253	468.3389
Total cost ($/hr)	60,170.025173	60,390.898263	NA	60,897.5768	NA	59791.6083

Table 5 shows the validation of the results at a load of 900MW. In this case the total cost produced by MFO_BAT hybrid algorithm is 852.187557$/hr, 853.21143$/hr, 1,238.20313$/hr and 1,047.8545$/hr lower than DE_BBO, BBO, NSGA-II and ALH respectively.

The fuel cost of MFO_BAT is 353.18194$/hr,327.18572$/hr,870$/hr,71.082$/hr lower than DE_BBO, BBO, GA and ALH respectively and 142.941$/hr higher than NSGA-II. For the case of emission, Moth Flame Optimization and Bat hybrid algorithm is 10.433685Kg/hr, 10.998696Kg/hr, 28.8799Kg/hr, 8.419Kg/hr and 20.4249Kg/hr lower than DE_BBO, BBO, NSGA-II, GA and ALH respectively and at the same time producing the losses of 6.709446MW, 6.3811MW, 2.7809MW and 9.677MW lower than DE_BBO, BBO, NSGA-II and GA respectively.

Table 5. Validation of best compromising solution at a load of 900MW

Generating unit	DE_BBO [20]	BB0 [17]	NSGA-II [18]	GA [8]	ALH [19]	MFO_BAT
P1(MW)	125.00000	124.9838	120.0587	123.288	-	125.0000
P2(MW)	96.032034	95.4689	85.202	116.287	-	94.2835
P3(MW)	100.422108	99.8332	89.565	98.4371	-	99.1034
P4(MW)	141.523563	141.3275	140.278	134.939	-	141.0399
P5(MW)	270.654667	271.4903	288.614	263.038	-	266.0903
P6(MW)	227.701173	227.9015	233.687	228.315	-	229.1069
Generation(MW)	961.333546	961.0052	957.405	964.301	-	954.6241
Ploss (MW)	61.333546	61.0052	57.405	64.3011	-	54.6241
Fuel cost ($/hr)	50,622.181947	50,596.18572	50,126.059	51139	50340.082	50269
Emission (kg/hr)	766.249785	766.814796	784.696	764.235	776.2410	755.8161
Total cost ($/hr)	87,265.963070	87,266.98693	87,651.97943	NA	87,461.63	86,413.775

6. CONCLUSION

This paper has presented the innovation of hybridizing Moth Flame Optimization with Bat algorithm. The developed hybrid Moth Flame Optimization and Bat algorithm was implemented in IEEE 30 bus test system for performing the constrained emission economic dispatch. The results obtained were compared with other results from the literature and found to be better in terms of reduction of cost of electric power generation and emissions from thermal power plants.

As part of future work, the MFO_BAT hybrid algorithm can be applied in complex larger system than the test system employed. The application of MFO_BAT hybrid algorithm for solving optimization problem of multi-objective function having more than two objective function is also the potential future work.

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