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Application of Directional Bat Algorithm to Economic Load Dispatch problems with various practical constraints

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ABSTRACT—This publication discusses the Directional Bat Algorithm (DBA)and has suggested getting the better results for Economic and Emission Dispatch (EED issues. The preliminary aim of the EED is to diminish both emission and its allied installation expenses while satiating the system constraints. Standard Bat algorithm (SBA) based on echolocation behaviour of microbats, has been used in the past to investigate the local/global finest solution. But SBA has less exploration ability, so premature convergence can occur. To avoid this drawback, an investigative approach based on the capability of directional echolocation characteristics of micro-bats is introduced to the SBA for improve its exploration and exploitation capabilities. The DBA has been executed on different test cases. To show the effectiveness of DBA, it is in turn linked with various techniques that has been discussed in the literatures published earlier. The outcome also show that the DBA is more efficient

KEY WORDS: economic dispatch, emission dispatch, transmission losses, prohibited operating zones, mathematical modeling, bat algorithm and directional bat algorithm.

I. INTRODUCTION

Economic Dispatch (ED) problem can be an overcritical concern in electrical system operation and planning [1]. Demand is forecasted for some period of time, based on the demand an unit commitment program is intended which can give the information about the unit to be operated in that particular period of time. ED is a step in process of apportioning the generation levels to the respective generating units based on demand. From 2014 onwards a new rule has been passed by the government had put a restriction on the carbon emissions and therefore new strategies developed for power production has to reduce the emissions [2], thus consideration of the EED had become a must.

EED is an optimization technique which deals with the minimization of both emission and cost also considering system constraints. In this regard for solving EED problems, plenty of optimization methodologies have been implemented. The conventional strategies are listed, mainly lambda iteration methodology gradient methodology, Lagrange's methodology, linear programming technique and dynamic programming technique [3]. These strategies involve a long process get stuck when more number of constraints are involved and cannot perform efficiently in solving the EED problem. During the past decades, a lot of research works successfully implemented some intelligent techniques to solve EED problem such as dynamic programming [4], Differential Evolution [5], genetic algorithm [6], Artificial Immune System [7], Hopfield Neural Networks [8], Seeker Optimization Algorithm [9] and Group Search Optimizer [10], all these optimization methods attempt to acquire better solutions utilizing various techniques. The major drawbacks of these methodologies are their random characteristics, long computational time with ambiguity in arriving at the optimal stage.

Several of the authors have carried out the instantaneous optimization of multi-objective in ED problem utilizing evolutionary algorithms. Various evolutionary approaches have been utilized to solve EED problem for different test systems through ε - constraint method [3], Gravitational Search Algorithm (GSA) and Opposition-Based Gravitational Search Algorithm (OGSA) [11, 12], Hybrid Bacterial algorithm (BF-NM) [13], dissolute Successive Linear Programming algorithm (SLP) [14], Analytical Solution (AS) [15], and Nonlinear Fractional Programming [16].

To solve and enhance the performance of EED problems many algorithms are implemented likely Particle Swarm Optimization (PSO), Random Drift Particle Swarm Optimization [17, 18], Artificial Bee Colony (ABC), algorithms [19, 20], Firefly, modified firefly algorithms [21, 22], Cuckoo Search, improved cuckoo search algorithms [23, 24], Differential search algorithm [25], Bat, binary Bat algorithms [26, 27], social spider algorithm and modified social spider algorithms [28, 29] are a few noteworthy.

In this paper to enhance the performance of the SBA by enlarging its exploration and exploitation abilities along with SBA spirits, alike directional echolocation and extra three improvements have been embedded into the SBA. The suggested methodology is utilized for solving EED problems. The main intention of EED is minimizing both emission and cost of the unit simultaneously while meeting system constraints and demand.

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DBA is exploring to govern the optimal allocation of power generators in a plant. Numerouscomparative results illustrate the effectuality of the method discussed.The outcome also demonstrates that the suggested changes enhance the conjunction in comparison with recently published techniques.

II. PROBLEM FORMULATION

(a) Design of ED Problem:

The ED problem is a technique for finding the optimum combination of different levels and stages of power production, which diminishes the total fuel cost incured simultaneously satiating the system constraints and demand.

The cost functionl parameter for the fuel consumed of ED problem is described as follows.

Minimize

$$F_T = \sum_{i=1}^{ng} F_i(P_{gi}) = \sum_{i=1}^{ng} a_i P_{gi}^2 + b_i P_{gi} + c_i \quad (\$/h) \qquad (1)$$

F_T is total cost ($/h),

P_{gi} is the total power generation of i^{th} unit in (MW).

a_i, b_i and c_i are cost of i^{th} unit and ng is total number of power generating units.

Subjected to

Power Equilibrium:

The total power generated must be equal to total power demand along with transmission losses as described as follows.

$$\sum_{i=1}^{ng} P_{gi} - (P_D + P_L) = 0 \qquad \ldots (2)$$

where P_D is the total demand (MW) and P_L is transmission losses (MW).

The complete loss equation for estimating the losses in the transmission system is given by

$$P_L = \sum_{i=1}^{ng} \sum_{\substack{j=1 \\ j \neq i}}^{ng} P_{gi} B_{ij} P_j + \sum_{i=1}^{ng} B_{i0} P_{gi} + B_{00} \qquad \ldots (3)$$

where B_{ij} represents loss coefficients

Inequality Constraint:

Real power must lie in between its least and optimum specified real powers by the inequality equation:

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad \ldots (4)$$

where $P_i^{\min}$ and $P_i^{\max}$ are respectively .

Proscribed Operational Zones (POZ):

The input cum output curve of multiple valve points. These multiple valve points may create multiple POZ. In real time operation, the generation output of any unit must escape unit from POZ. The potential operational zones of a unit stated as follows.

$$\left.\begin{array}{ll} P_{gi}^{\min} \le P_{gi} \le P_{gi1}^{L} & (i = 1,2,\ldots,ng) \\ P_{gi\,j-1}^{U} \le P_{gi} \le P_{gi\,j}^{L} & (i = 1,2,\ldots,nz) \\ P_{gi\,nz}^{U} \le P_{gi} \le P_{gi1}^{\max} & (i = 1,2,\ldots,ng) \end{array}\right\} \qquad \ldots (5)$$

where nz is number of prohibited operating zones of i^{th} unit, $P_{gi\,j}^{L}$ is lower bound of j^{th} prohibited operating zones of i^{th} unit, $P_{gi\,j}^{U}$ is upper bound of j^{th} prohibited operating zones of i^{th} unit.

(b) Formulation of EmD Problem:

The pollutants spread across the atmospheric air such as NOx, emitted by fossil fuel fired generators can be demonstrated separately. The total emission, has been indicated as the summation of a quadratic and an exponential functional variable, described as follow.

$$E_T = \sum_{i=1}^{ng} E_i(P_{gi}) = \sum_{i=1}^{ng} \alpha_i P_{gi}^2 + \beta_i P_{gi} + \gamma_i \quad (kg/h) \qquad \ldots (6)$$

here α_i, β_i and γ_i denote emission coefficients i^{th} unit, and ng denote the generating units in total.

(c) Formulation of EED Problem:

Minimization of cost and expenses incured has been articulated with the aid of classical EED including emission constraints along the flow line. For which the problem is given as

$$\text{Minimize} \quad F = \sum_{i=1}^{ng} \{F_i(P_{gi}), E_i(P_{gi})\} \qquad \ldots (7)$$

The minimum value of the above objective function has to be found out subject to system constraints, given by equations (2), (4) and (5). The dual-objective problem is converted into single objective problem by utilizing a price penalty factor h as follows.

$$\text{Minimize} \quad F = F_T + h_i \times E_T \qquad \ldots (8)$$

where h is price penalty factor ($/kg), which is the ratio between the maximum fuel cost incured and maximum emission of corresponding generator in $/kg, blends the emission with fuel cost incured, then F is the total operating cost in $.

$$h_i = \frac{F_i(P_i^{\max})}{E_i(P_i^{\max})} \ (\$/h) \qquad i=1, 2 \ldots ng \qquad \ldots (9)$$

Thus, optimum scheduling of thermal plants can be determined by taking into account of both economic and emission dispatch.

III. DIRECTIONAL BAT ALGORITHM

The directional bat algorithm is more similar to the standard bat algorithm. Asma Chakri et. al., [30] introduced variations to improve its capabilities of bat algorithm so as to get better the BA performance.

(a) The First modification:

All bats utilized directional echo oriented location for navigation. During their movements, bats emit pulses, pulses move in several orders, and we ought to assume that each bat emits two different pulses into several applicable directions before deciding the directionof migration that it can be employed to stimulate the time period difference or periodical delay arising between any of the echoes received by two ears. If they confirm that their food exists around the close vicinity the two bats, the designated bat moves to a direction at the surrounding neighbourhood of the two bats where the food is supposed to exist in surplus amount. If not, it moves towards the best bat at the

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vicinity. The mathematical formulas for movements are as follow.

$$\left.\begin{array}{ll} x_i^{t+1} = x_i^t + (x^* - x_i^t)\times f_1 + (x_k^t - x_i^t)\times f_2 & \text{if } F(x_k^t) < F(x_i^t) \\ x_i^{t+1} = x_i^t + (x^* - x_i^t)\times f_1 & otherwise \end{array}\right\} \quad \ldots (10)$$

where x_i^t is the location of any one of the bat that is selected randomly ($k \neq i$) and x^* is the apt solution, f_1 and f_2 are the frequencies of the two pulses designated as :.

$$\left.\begin{array}{l} f_1 = f_{\min} + (f_{\max} - f_{\min})\times rand \\ f_2 = f_{\min} + (f_{\max} - f_{\min})\times rand \end{array}\right\} \quad (11)$$

where rand is a random value 0 and 1.

This mechanism allows the BA to exploit more around the best position; however, if the best bat position is not near the global optimality, the solutions generated by such moves could be trapped in local optima when the moves are not far enough to reach the global optima. In this situation, the suggested algorithm can escape local optima, the suggested movement in Eq. (10) has the capability to expand the moving directions which can increase the exploration capability, and can avoid premature convergence.

(b) The second modification

The second alteration with local search mechanisms of bat algorithm claims that bats are endorsed to move from their postions at initial stage to any new postion randomly asper their choice. Here, Asma Chakri et. al. modified this movement by the following equation.

$$x_{new} = x_{old} + \langle A^{t+1} \rangle \varepsilon \times w_i^t \quad (12)$$

where A^{t+1} denotes average loudness of all bats and $\varepsilon \in [-1,1]$ is a random vector. Here, w_i is a monotonically decreasing functional variable giving stability to the algorithm.

$$w_i^t = \frac{w_{i0} - w_{i\infty}}{1 - t_{\max}} \times (t - t_{\max}) + w_{i\infty} \quad (13)$$

here, w_{i0} and $w_{i\infty}$ are the initial value and final value, respectively. By utilizing w_i we can control the iteration procedure through

$$w_{i0} = (Ub_i - Lb_i)/4 \quad \ldots (14)$$

$$w_{i\infty} = w_{i0}/100 \quad \ldots (15)$$

t is the current iteration

t_{max} is the maximum number of iterations.

Ub_i and Lb_i are the upper and lower bounds, respectively. Initially, w_i starts with a huge value allowing the bats to migrate randomly which upsurges the exploration ability and explore the entire search space much efficiently. Finally w_i decreases, reducing the search region with exploitation capability being enhanced.

(c) The 3rd modification

Asma Chakri et. al., updated the loudness and pulse rate by monotonically increasing, and decreasing to achieve their optimal value throughout, and auto switch to local search from global search due to a huge pulse rate, and the leading to a new solution..

$$r^t = \left(\frac{r_0 - r_\infty}{1 - t_{\max}}\right) \times (t - t_{\max}) + r_\infty \quad (16)$$

$$A^t = \left(\frac{A_0 - A_\infty}{1 - t_{\max}}\right) \times (t - t_{\max}) + A_\infty \quad (17)$$

index 0 and ∞ stand for the initial value and final value, respectively.

The pulse rate controls the migration of the bats and DBA tends to encourage global search over local random walks so as to explore the search space more effectively. The loudness A controls the getting or rejection of a newly generated solution.

Table 1: The Directional Bat Algorithm.

Define objective functional parameter
Initialize the bat populace $Lb_i \le x_i \le Ub_i$ (i = 1, 2,.., n)
Evaluate fitness ststistics $F_i\ (x_i)$
Initialize pulse quantity r_i loudness A_i and w_i
while ($t \le t_{max}$)
Select a bat randomly (k= i)
Generate frequency by Eq. (11)
Update locations Eq. (10)
if ($rand > r_i$)
Generate a local solution by Eq. (12)
Update w_i Eq. (13)
end if
if ($rand < F(x_i^{t+1}) < F(x_i^t)$
Accept the new solutions
Increase r_i Eq. (16)
Reduce A_i Eq. (17)
end if
if $F(x_k^t) < F(x_i^t)$
Update the best solution x^*
end
end while
Output results for post-processing

The final modification was suggested to arrive at a new solution and also to fulfill the following regulations.

Initially, the solution should havelower value than the current one. Secondly, a randomly generated number lower than the current corresponding loudness. Therefore, Asma Chakri et. al. allowed the algorithm to update the global best location whenever the bat's random walk produces a solution with an improved fitness value even if it was not accepted to update the bat's position. To summarize the above modifications, the pseudo-code of the DBA is illustrated in table 1.

IV. SIMULATION RESULTS

To estimate the performance of the suggested DBA for the solution of EED problem, it has been implemented for real-time applications in two cases. Case one having six generating units along with NOx emission and losses for two different power demands. Case two having six

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pwer generating units along with losses and prohibited thefunctional operation zonal sectors. All programs are implemented with MATLAB 7.10 and run on 2.00 GHz

Intel (R) Core (TM) i3-5005U PC device with 4 GB RAM. The description of all test cases and simulation are illustrated below.

Case 1: The suggested DBA is tested with six generating units along with NOx emissions with details such as the cost incured, emission statistics and loss coefficients and their corresponding operating limits were taken from [12]. The results obtained from the suggested DBA are compared with other algorithms in MW and tabulated from table 2 to table 3. Proves that DBA outstrips all the methodology in all aspects.

Table 2: Best compromised solutions of fuel cost incured and NO_x emission for case 1 (700 MW).

Unit	Method			
	NSGA-II	BBO	SOS	DBA
P1 in MW	86.2860	93.069693	93.0456	94.47634
P2 in MW	60.2880	66.729002	66.7444	65.33117
P3 in MW	73.0640	83.3378	83.2719	82.64248
P4 in MW	109.0360	110.70267	110.7896	109.6154
P5 in MW	223.4480	205.79919	205.8610	202.9805
P6 in MW	184.1110	178.79133	178.7032	179.2712
Total Power Output (in MW)	736.2340	738.42968	738.4157	734.3171
Power Loss (in MW)	36.2340	38.429683	38.4157	34.3171
Fuel cost incured ($/h)	38,671.8130	39000.1500	38999.319	38823.7799
NO_x Emission (kg/h)	484.9310	472.66855	472.6861	468.2273
Total Cost ($/h)	60,390.8982	60170.0251	60170.0120	59794.7422
Simulation time (Sec.)	NA	NA	NA	1.0288

The results obtained for the best compromise solution where NOx a power demand of 700 MW using suggested DBA provided in table 2 shows that in comparison with SOS, DBA gives a reduction in total cost by 375.2698 ($/h) than SOS. The in Fig. 1 shows the convergence curves of DBA can estimate the best fueling cost incurred and best NOx emission outrages in the previous emission iterations.

The results obtained for best-compromised solution of the expense incured, NOx emission for a power demand of 900 MW using suggested DBA provided in table 3 shows that in comparison with SOS, DBA gives a reduction in total cost by 848.3479 ($/h) . The convergent paths in Fig. 2 show that DBA can estimate the best fuel cost incured and best NOx emission values in prompt iterations obtained at the earlier stage.

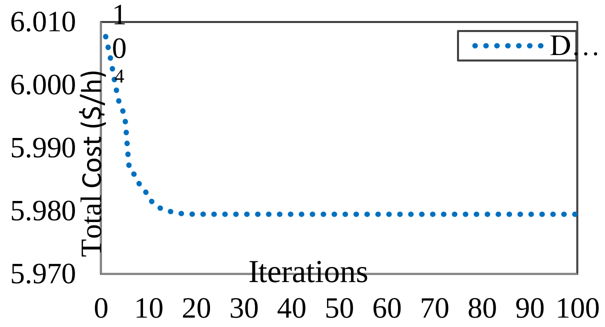

Fig. 1 Convergence curve of total cost obtained from DBA for case 1 at 700 MW.

Table 3: Best compromised solutions of fuel cost incured and NO_x emission for case 1 (900 MW).

Unit	Method			
	NSGA-II	BBO	SOS	DBA
P1 (MW)	120.0587	124.9838	125.0000	125.0000
P2 (MW)	85.20200	95.46890	96.0322	94.35173
P3 (MW)	89.56500	99.83320	100.4100	99.72585
P4 (MW)	140.2780	141.3275	141.5092	139.9082
P5 (MW)	288.6140	271.4903	270.6763	266.6030
P6 (MW)	233.6870	227.9015	227.6978	229.0964
Total Power Output (MW)	957.4050	961.0052	961.3255	954.6851
Power Loss (MW)	57.40500	61.00520	61.3255	54.68510
Fuel cost incured ($/h)	50126.0590	50596.1857	50621.8177	50272.4303
NO_x Emission (kg/h)	784.696000	766.814800	766.257600	755.824000
Total Cost ($/h)	87651.9794	87266.9869	87265.9729	86417.6250
Simulation time (Sec.)	NA	NA	NA	1.1370

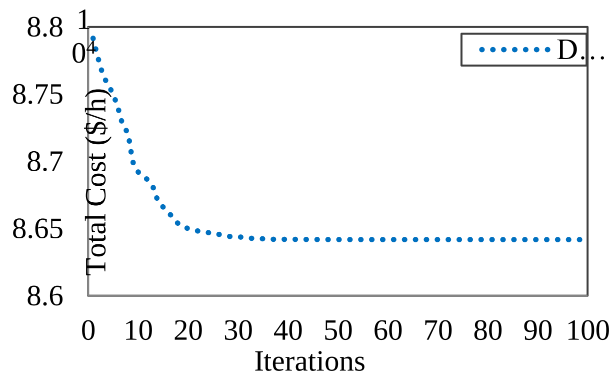

Fig. 2 Convergence path of total cost incurd obtained from DBA as per case 1 at 900 MW.

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Case 2: The cost and loss coefficients and prohibited operating zones data are duplicated from [28]. The simulation results obtained from the suggested DBA are compared with other algorithms such as GA, PSO and MSSA and tabulated from table 4. It is observed that DBA outperforms all these methods in all aspects.

The results obtained for best compromised solution of the fuel cost incured for a power demand of 1263 MW using suggested DBA provided in table 4 shows that in comparison with MSSA, the DBA gives a reduction in fuel cost incured and time consumption for simulation by 0.6326 ($/h) and 0.4416 (Sec.) respectively than MSSA. Fig. 3 shows the convergence curves of DBA very close to the best fuel cost incured in early iterations.

Table 4: Best solutions of six units with POZ for 1263 MW demand.

Unit	Method			
	GA	PSO	MSSA	DBA
P1 (MW)	474.8066	447.4970	447.5029	436.65070
P2 (MW)	178.6363	173.3221	173.3186	163.03130
P3 (MW)	262.2089	263.4745	263.4630	276.85270
P4 (MW)	134.2826	139.0594	139.0656	98.436610
P5 (MW)	151.9039	165.4761	165.4730	212.66080
P6 (MW)	74.18120	87.12800	87.13490	86.190370
Total Power Output (MW)	1276.030	1276.010	1275.958	1273.8225
Power Loss (MW)	13.02170	12.95840	12.95800	10.822500
Fuel cost incured ($/h)	15459.00	15450.00	15449.8995	15449.2669
Simulation time (Sec.)	NA	NA	1.16	0.7184

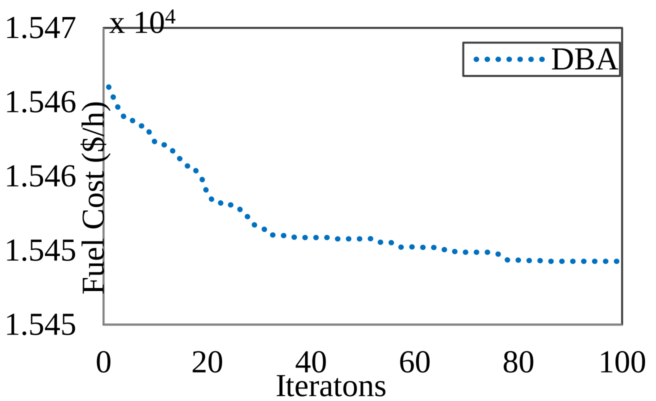

Fig. 3 Convergence path of fuel cost incured obtained from DBA case 2 at 1263 MW.

V. CONCLUSION

This article illustrates the outcome of the DBA implemented for resolving the EED problem by testing for two different cases on two different systems. An obtained result has been compared with all other meta-heuristic optimization algorithms which clearly portrays that the DBA decreases the fuel cost incured incured, surges down emission rates, diminishes total cost and simulation time.

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