

Lévy Opposition-Based Learning Bat Algorithm for Combined Economic and Emission Dispatch

Mallikarjuna Bestha¹, Y. V. Siva Reddy², R. Kiranmayi³

¹Research Scholar, JNTUA, Department of EEE, Ananthapuramu, Andhra Pradesh, India.

²Professor, Department of EEE, G. Pulla Reddy Engineering College, Kurnool, Andhra Pradesh, India.

³Professor, Department of EEE, JNTUA, Ananthapuramu, Andhra Pradesh, India.

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Abstract: Electricity demand is increasing daily due to the growth of industries. To meet this demand, it is essential to increase power generation, improve economic efficiency, and control pollutant emissions. A power system focuses on grid stability, which neglects economic efficiency and pollutant emissions. To overcome this problem, a Combined Economic and Emission Dispatch (CEED) problem is proposed. By solving the CEED problem, both the total cost and emissions, including NO_x, SO₂, and CO₂, are minimized. The Lévy Opposition-Based Learning Bat Algorithm (LOBL-BA) is proposed to solve the CEED problem. The Bat Algorithm (BA) suffers from slow convergence and can get stuck in local optima due to its limited exploration. To address these limitations, three strategies are proposed: Firstly, the Random Inertia Weight improves search capability. Lévy Opposition-Based Learning is proposed to enhance the exploration-exploitation trade-off, thereby increasing robustness in tackling complex optimization problems. Finally, a Sine Function-driven Local Search is proposed to refine solutions and improve the ability to escape local optima. Finally, the improved LOBL-BA is tested on a 6-unit system with four different loads (150 MW, 175 MW, 200 MW, and 225 MW). The performance of the enhanced algorithm is assessed and compared with that of the following algorithms: BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME. The outcomes of the enhanced algorithm consistently achieve total costs and reduced emissions across all test cases.

Keywords: Bat Algorithm, Random Inertia Weight, Lévy Opposition-Based Learning, Sine Function-Driven Local Search, Combined Economic and Emission Dispatch Problem.

I. INTRODUCTION

As global electricity demand continues to rise, driven by rapid advances in digital technologies, industrial growth, and urbanization, optimizing power system operations has become a critical focus. Power systems, traditionally designed to prioritize grid stability, often neglect economic efficiency and pollutant emissions associated with energy production. In this context, balancing a stable, cost-effective electricity supply with minimizing harmful emissions has emerged as one of the most significant challenges in modern power system operations. The traditional approach to power generation has primarily relied on fossil fuels, which, although cost-effective, have substantial environmental drawbacks. The combustion of fossil fuels releases harmful emissions, including nitrogen oxides (NO_x), sulfur oxides (SO₂), and carbon oxides (CO₂), all of which contribute to global warming, air pollution, and a range of adverse public health outcomes. As concerns about environmental sustainability intensify, there is growing pressure to reconcile the need for reliable, affordable electricity with the imperative to reduce pollutant emissions. The Price Penalty Factor (PPF) is used to integrate these various objectives into a single objective function; this problem may be viewed as a CEED problem. The proposed strategies can help optimize power generation systems to reduce their carbon footprint without compromising reliability or economic viability, paving the way for a more sustainable energy future.

Optimization is essential for navigating the complex trade-offs between costs and emissions in power system operations. By utilizing advanced computational techniques, optimization enhances energy generation efficiency, ensuring that electricity is produced in the most economical and environmentally friendly way. Modern optimization methods, including linear programming and mixed-integer programming algorithms, aid in identifying the most effective dispatch strategies. These techniques improve the efficiency of traditional power generation and reduce its pollutant emissions. Ultimately, adopting optimization strategies enables power systems to transition toward a more sustainable future, ensuring that energy demands are met while minimizing pollutant emissions and maximizing economic benefits. In recent decades, many researchers have utilized optimization strategies, such as Sakthivel et al., who present MOSSA for the CEEPD problem, optimizing fuel cost and emissions using Pareto dominance and fuzzy decision-making, and outperforming existing methods in terms of solution quality and efficiency [1]. El-Shorbagy & Mousa propose EOA for the CEEPD problem, minimizing generation costs and emissions, using dominance criteria, a repair algorithm, and clustering to optimize solutions and outperform traditional methods [2]. Dey et al. compare the PPF and FP methods for the CEED problem, using the hybrid CSA-JAYA algorithm, which outperforms others in

minimizing costs, emissions, convergence, and computational time [3]. Hassan et al. developed the CAEO algorithm for the CEED problem, which minimizes fuel costs and emissions. It outperforms AEO, PSO, and GA, while also improving convergence and multi-objective optimization using MOCAEO4 [4]. Fayyaz et al. introduce the IPBO algorithm, which incorporates a chaotic population variant, for the CEED problem. This approach improves cost reduction, emission control, and convergence, outperforming PBO and other techniques in simulations [5]. Ajay & Reolyn Heymann apply the Moth Swarm Algorithm (MSA) to the CEED problem, integrating renewable energy and spinning reserve, outperforming other algorithms in minimizing costs, emissions, and solar generation [6]. Hassan et al. present the MMPA for single- and multi-objective CEED problems, demonstrating its superiority over MPA in terms of fuel cost, emission reduction, convergence, and solution reliability across various test systems [7]. Hao et al. present an enhanced AOA for the CEED problem that uses probability distributions and a variable penalty strategy, which outperforms other algorithms in terms of fuel cost and emission reduction across various load demands [8]. Mohapatra applies Competitive Swarm Optimization (CSO) to the CEED problem in hybrid power systems, demonstrates superior fuel-cost minimization, improved emission control, and faster convergence, particularly in the thermal-wind-solar configuration [9]. Zaoui & Belmadani present the OWP-based OMF algorithm for the CEED problem, which outperforms GA and DE in minimizing fuel costs, reducing emissions, and minimizing operating costs across multiple test systems [10]. Verma & Parouha present the ihPSODE algorithm, which combines nDE and nPSO to solve the CEED problem, outperforming GA, PSO, and DE in terms of cost minimization, emission reduction, and convergence across multiple test systems [11]. Basak et al. introduce the hybrid CSA-JAYA algorithm for the CEED problem, which balances fuel cost reduction and emission control, outperforming other methods in terms of cost and emission reductions across 30- and 40-unit test systems [12]. Srivastava et al. present the Q-CTO algorithm, which enhances CTO with quantum mechanics to solve the CEED problem. It outperforms PSO and CTO in fuel cost and emission optimization, with faster convergence [13]. Luo et al. propose the RLDE algorithm, integrating reinforcement learning to optimize mutation and crossover, and demonstrate faster convergence and optimal solutions compared to other metaheuristics for the CEED problem [14]. Sutar & Jadhav propose a hybrid ABC-NSGA-II algorithm for the MOEED problem that minimizes fuel costs and emissions, yielding superior results across 6, 10, and 40-unit systems with no constraint violations [15]. Lin et al. propose a fast, data-driven optimization method for large-scale, high-dimensional MACEED problems. This method integrates SVR surrogate models, knowledge distillation, and an improved NSGA-III algorithm, reducing computation time while maintaining accuracy [16]. Y. P. Li et al. introduce the AOA algorithm, which incorporates Cauchy mutation and trigonometric search, for the CEED problem, outperforming traditional methods in minimizing fuel costs and emissions across various load demands [17]. Manikandan & Thangavelu introduce SATA for the CEED problem, optimizing fuel costs and emissions, outperforming ABC-PSO, SA, and DE in multi-objective optimization [18]. Hao et al. introduce a multi-objective AOA with random search strategies for the CEED problem, outperforming traditional methods in reducing fuel costs and minimizing emissions, with TMOAOA being the most effective strategy [19]. Khlaif & Atyia review optimization approaches for the CEED problem, comparing conventional, non-conventional, and hybrid methods, highlighting the challenges of balancing economic costs, emissions, and renewable energy integration [20]. Gajić et al. introduce the PSO-CGSA algorithm, a hybrid of PSO and CGSA, for the CEED problem. This algorithm outperforms others in minimizing fuel costs, emissions, and convergence speed, particularly in the presence of valve-point effects [21]. Lin et al. propose a data-driven, surrogate-assisted method for MACEED problems that combines DBNs, BP regression, and transfer learning, thereby reducing computation time and improving accuracy in large-scale power systems [22]. Asif et al. explore QPSO and its variants (EQPSO, ALA-QPSO) for the CEED problem, showing QPSO's superior fuel cost and emission balance, faster convergence, and robustness compared to conventional algorithms [23]. Muraleedharan et al. introduce the QPSO-Chi2 algorithm, which uses the Chi-square distribution to enhance swarm diversity and mitigate local optima, outperforming PSO and QPSO variants in terms of fuel cost reduction, emission control, and convergence [24]. F. Wang et al. propose MOHBA for the CEEPD problem, integrating Pareto dominance, congestion distance, and fuzzy decision-making. This approach outperforms NSGA-II, MOPSO, and MODA in terms of convergence speed, solution diversity, and optimality [25]. Y. X. Li et al. present an enhanced AOA using chaotic mappings in spherical coordinates for the CEED problem, demonstrating improved convergence, reduced cost, and emission minimization, and outperforming traditional AOA and other algorithms [26]. Y. Wang et al. introduce IRLDE, a reinforcement learning-based differential evolution algorithm for the CEED problem. It enhances adaptability, convergence, stability, and cost efficiency, outperforming other algorithms in power system optimization [27]. Yu et al. introduce D3QN-CDCA, a deep reinforcement learning-assisted dual-population coevolutionary algorithm for multi-objective CEED problems, which outperforms traditional methods in terms of solution quality, convergence, and handling complex constraints [28]. Arkwaee & Ali Abttan introduce the IMZOA, which outperforms traditional Zebra Optimization in CEED by improving cost, emissions control, and stability across systems such as the six-unit IEEE and the 110-unit, proving its real-world effectiveness [29]. X. Y. Zhang et al. propose a nonlinear convergence factor-based MRFO algorithm for the CEED problem, which enhances search capabilities and outperforms PSO in terms of fuel cost reduction and emission control, with S6MRFO yielding the best results [30]. Chan et al. introduce the Epsilon-MOGA algorithm for the CEED problem, which combines Epsilon constraints with genetic algorithms and outperforms MOGA and RNSGA-II in terms of solution diversity, convergence speed, and efficiency [31].

The Bat Algorithm (BA) [32] is modelled with the echolocation behaviour of bats. BA suffers from slow convergence and can get stuck in local optima due to its limited exploration. Recently, considerable efforts have been made to improve BA efficiency. This paper introduces three methods, each with a distinct strategy: Random Inertia Weight, Lévy Opposition-Based Learning, and Sine Function-Driven Local Search. These strategies enhance both the global and local search efficiency of BA, thereby improving its optimization performance.

The main contributions are as follows:

- ❖ The Random Inertia Weight is introduced to enhance the algorithm's balance between exploration and exploitation.

- ❖ Lévy Opposition-Based Learning was proposed to improve the exploration-exploitation trade-off, leading to faster convergence, higher solution accuracy, and greater robustness in tackling complex optimization problems.
- ❖ Sine Function-Driven Local Search is proposed to refine solutions and quickly converge to high-quality solutions.
- ❖ The LOBL-BA algorithm is applied to the Classical benchmark function and the CEED problem, and its performance is compared with other algorithms to validate its effectiveness in solving CEED problems.

The article's structure is as follows: Section 2 discusses the CEED Problem. Section 3 presents the Bat Algorithm. Section 4 presents the Lévy Opposition-Based Learning Bat Algorithm. Section 5 covers the simulation experiments and analysis of results. Section 6 provides the conclusions and outlines future work.

II. PROBLEM FORMULATION

Combined Economic Emission Dispatch Problem

Objective Function (OF)

“CEED problems are generally defined as minimizing fuel costs and pollutant emissions while meeting total load requirements and all other equality and inequality constraints” [26]. In this paper, NO_x , SO_2 , and CO_2 Emissions are considered the objective functions for pollutant emissions. The multi-objective CEED problem is defined as the combination of the cubic criterion function of four objectives. “The maximum/maximum Price Penalty Factor (PPF) is used to transform a multi-objective optimization problem into a single-objective problem” [8]. Thus, the objective function of total fuel cost (\$/h) can be expressed as:

$$F(P) = \sum_{i=1}^{ng} a_i P_i^3 + b_i P_i^2 + c_i P_i + d_i \quad (1)$$

where ng is the total number of generators; P_i is the generating capacity of the i^{th} generator; a_i , b_i , c_i and d_i are the fuel cost coefficient of the i^{th} generator. The pollutant emission objective function is split into three individual objectives, each expressed by the following mathematical equation.

$$E_{\text{NO}_x}(P) = \sum_{i=1}^{ng} e_{\text{NO}_x i} P_i^3 + f_{\text{NO}_x i} P_i^2 + g_{\text{NO}_x i} P_i + h_{\text{NO}_x i} \quad (2)$$

$$E_{\text{SO}_2}(P) = \sum_{i=1}^{ng} e_{\text{SO}_2 i} P_i^3 + f_{\text{SO}_2 i} P_i^2 + g_{\text{SO}_2 i} P_i + h_{\text{SO}_2 i} \quad (3)$$

$$E_{\text{CO}_2}(P) = \sum_{i=1}^{ng} e_{\text{CO}_2 i} P_i^3 + f_{\text{CO}_2 i} P_i^2 + g_{\text{CO}_2 i} P_i + h_{\text{CO}_2 i} \quad (4)$$

where $E_{\text{NO}_x}(P)$, $E_{\text{SO}_2}(P)$, and $E_{\text{CO}_2}(P)$ are the total emissions of NO_x , SO_2 , and CO_2 , respectively. The $e_{\text{NO}_x i}$, $f_{\text{NO}_x i}$, $g_{\text{NO}_x i}$, $h_{\text{NO}_x i}$, $e_{\text{SO}_2 i}$, $f_{\text{SO}_2 i}$, $g_{\text{SO}_2 i}$, $h_{\text{SO}_2 i}$, $e_{\text{CO}_2 i}$, $f_{\text{CO}_2 i}$, $g_{\text{CO}_2 i}$, and $h_{\text{CO}_2 i}$ are the emission coefficients of the i^{th} generator NO_x , SO_2 , and CO_2 , respectively.

In this paper, a unit-wise maximum/maximum Price Penalty Factor (PPF) [48] is considered to convert the fuel cost minimization objective function and the emission minimization objective function of NO_x , SO_2 , and CO_2 emissions into a single objective optimization problem. The final objective function is to minimize the total cost (\$/h). The mathematical model is described as follows.

$$\text{OF} = \min(F_T) \quad (5)$$

$$F_T = F(P_i) + h_{\text{Ni}} E_{\text{NO}_x}(P_i) + h_{\text{Si}} E_{\text{SO}_x}(P_i) + h_{\text{Ci}} E_{\text{CO}_x}(P_i) \quad (6)$$

$$h_{\text{Ni}} = \sum_{i=1}^{ng} \frac{F(P_{i, \max})}{E_{\text{NO}_x}(P_{i, \max})} \quad (7)$$

$$h_{\text{Si}} = \sum_{i=1}^{ng} \frac{F(P_{i, \max})}{E_{\text{SO}_x}(P_{i, \max})} \quad (8)$$

$$h_{\text{Ci}} = \sum_{i=1}^{ng} \frac{F(P_{i, \max})}{E_{\text{CO}_x}(P_{i, \max})} \quad (9)$$

where, F_T (\$/h) is the total cost of the power generation system; $F(P_{i, \max})$ is the fuel cost at the maximum output power of the i^{th} generator; $E_{\text{NO}_x}(P_{i, \max})$, $E_{\text{SO}_2}(P_{i, \max})$, and $E_{\text{CO}_2}(P_{i, \max})$ are the total emissions of NO_x , SO_2 , and CO_2 , at the maximum output power of the i^{th} generator, respectively; h_{Ni} , h_{Si} and h_{Ci} are the penalty factors of NO_x , SO_2 , and CO_2 emitted by the i^{th} generator, respectively.

Constraints

“Many equality and inequality constraints must be satisfied in the optimization process of CEED problems” [15]. The following section explains the concepts of power balance and generator power constraints.

Power Balance Equation

The power balance constraint states that the sum of generating capacities of all units, adjusted for transmission losses, must equal the total load. This can be mathematically expressed as:

$$\sum_{i=1}^{ng} P_{gi} + P_D + P_L = 0 \quad (10)$$

where n is the number of generators, P_D does the load require the total power, and P_L is the total transmission loss.

$$P_L = \sum_{i=1}^n \sum_{j=1}^n P_i B_{ij} P_j + \sum_{i=1}^n B_{0i} P_i + B_{00} \quad (11)$$

where B_{ij} represents loss coefficients.

Generator Power Constraints

“The output power of each thermal generator set has upper and lower limits, and its output power must be within this range, between the maximum and minimum power” [19]. Thus, the mathematical equation is as follows:

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad (12)$$

where, P_i is the output power of the i^{th} generator, $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum allowable output power of the i^{th} generator, respectively.

III. PROPOSED METHOD

Bat Algorithm

“The Bat Algorithm (BA) is a Metaheuristic Algorithm (MA) inspired by the echolocation behavior of microbats, developed by Xin-She Yang” [32].

Microbats use echolocation to detect prey, bypass obstacles, and find nests in the dark. While hunting, they emit a sound pulse and listen for the echo to gauge the size and distance of their prey and navigate obstructions. If they detect prey, they lower the pulse's loudness and increase its frequency. This behavior can be modelled to optimize objective functions, leading to new optimization algorithms. The BA optimization model is based on frequency (f), loudness (A), and pulse rate (r), with iterations that include global and local search phases.

The bat algorithm operates through a continuous, iterative process in which the bat velocity and position are updated at each step. The position vector of each bat represents a potential solution within the search space. As the global optimal position is not known in advance, the bats are initialized randomly. The initial equation is defined as follows:

$$x_{i,j} = x_{lb} + (x_{ub} - x_{lb}) * \text{rand} \quad (13)$$

where $i=1, 2, \dots, n$; n denotes population size, $j = 1, 2, \dots, d$; d denotes the dimension size; x_{lb} is the lower limit and x_{ub} is the upper limit; rand lies between $[0, 1]$. Individual bats update their frequency, velocities, and locations based on the following equations [32]:

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \quad (14)$$

$$V_i^{it} = V_i^{it-1} + (X_i^{it} - X^*) * Q_i \quad (15)$$

$$X_i^{it} = X_i^{it-1} + V_i^{it} \quad (16)$$

where β lies between $[0, 1]$, X^* is the present best solution, where the change in frequency f determines the velocity and position. The following equation describes the bat's location update during a local search [32]:

$$X_{\text{new}} = X_{\text{old}} + \epsilon A^{it} \quad (17)$$

where ϵ lies between $[-1, 1]$, A^{it} is the loudness in the current iteration; as the bat nears the prey, the loudness reduces, while the pulse emission rate rises. A^{it} helps to update the bat location. The update of A^{it} and r_o^{it} as follows:

$$A^{it} = \langle A^{it} \rangle \quad (18)$$

$$A^{it+1} = \alpha A_o^{it} \quad (19)$$

$$r_o^{it+1} = r_o^{it} (1 - \exp(-\gamma \times it)) \quad (20)$$

$$A^{it+1} = \alpha A_o^{it} \quad (21)$$

where r_o^{it} is pulse emission, which helps to control the diversification of the bat algorithm. For a selected time-bound A^{it} reached zero and r_o^{it} reaches to r_o^0 .

Lévy Opposition-Based Learning Bat Algorithm

Random Inertia Weight

The stochastic inertia weight [33] regulates the balance between exploration and exploitation by modulating the magnitude of the velocity ω . The revised equation is presented below:

$$\omega = \omega_{\max} - \omega_{\min} * \frac{(it_{\max} - it)}{A * it_{\max}} + \omega_{\min} * \mathcal{R} \quad (22)$$

where ω is a decreasing weight coefficient, $\omega_{\min}$ is 0.2, $\omega_{\max}$ is 1.0, it is the present iteration, $it_{\max}$ is the maximum iteration number, and $\mathcal{R}$ is the random distribution between (0, 1), then the updated new velocities and locations follow:

$$V_i^{it} = \omega * V_i^{it-1} + (X_i^{it} - X^*) * Q_i \quad (23)$$

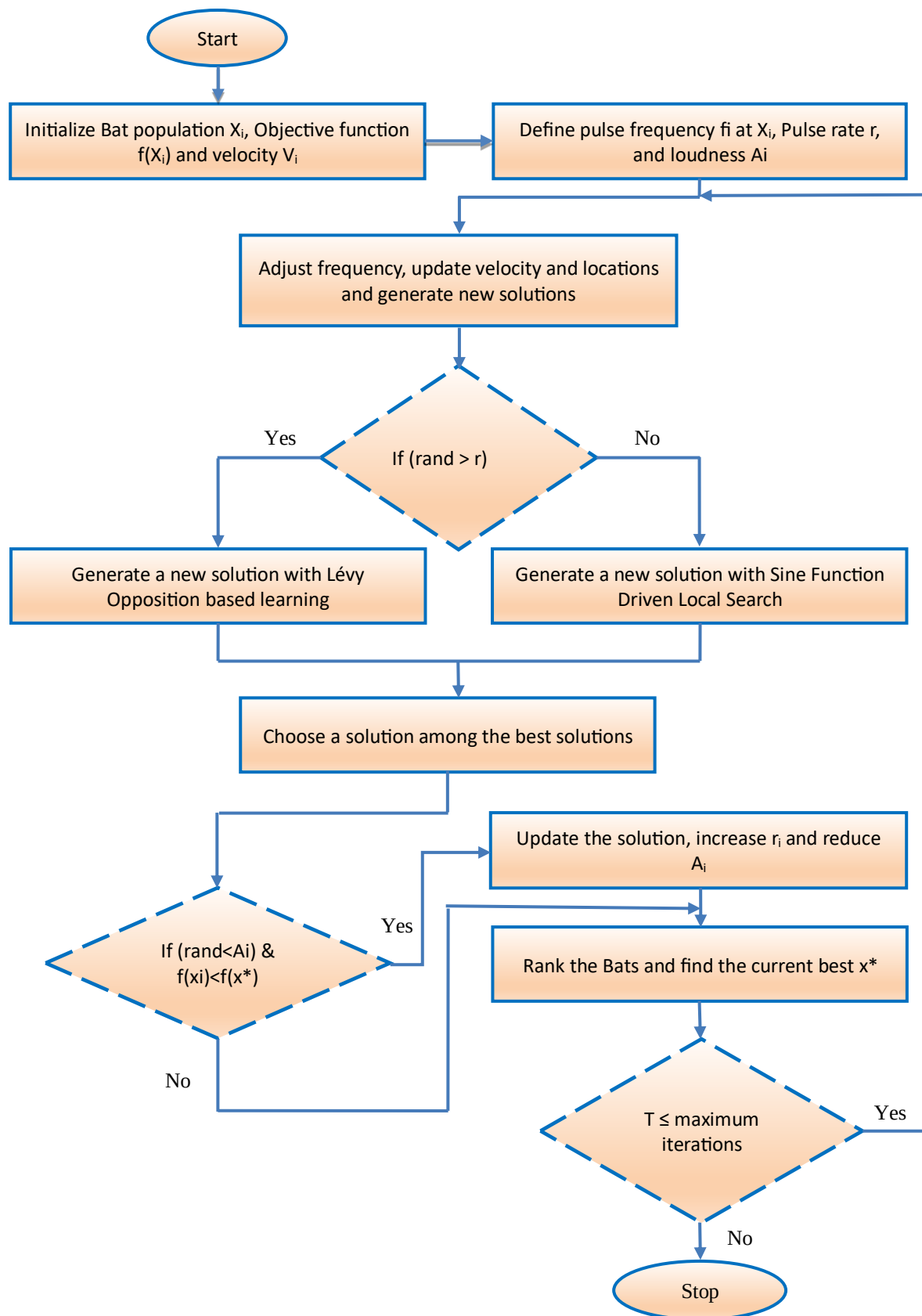
$$X_i^{it} = X_i^{it-1} + V_i^{it} \quad (24)$$

Lévy Opposition-Based Learning

Many initial solutions used by MAs are completely at random. The method converges quickly if these starting solutions are close to the global solution; otherwise, convergence is slow, highlighting the difficulty and the need to drastically reduce convergence time. Tizhoosh [34] introduced OBL to the MAs. This OBL, an efficient optimization strategy, enhances the performance of MAs in problem-solving. The mathematical representation of OBL is as follows:

$$X_{\text{op}} = lb + ub - X \quad (25)$$

where X_{op} is the opposite solution; X is the current solution; lb and ub are the lower and upper bounds, respectively.



Flowchart 1. Flow Chart of LOBL-BA.

As the optimization process progresses, the opposite solution may converge to a local optimum. As a result, other individuals converge toward this area, leading to premature convergence and reduced solution accuracy. To tackle this complexity and premature convergence, W. Long [35] modified the OBL by adding a random value to Equation (25) as follows:

$$X_{\text{rop}} = lb + ub - \text{rand} * X \quad (26)$$

where X_{top} is the new random opposite solution; rand lies in $[0, 1]$; and X is the current location, respectively. A ROBL exhibits improved population diversity and effectively avoids local optima, though its convergence time remains inadequate. This paper introduces a Lévy flight distribution into the ROBL to tackle this complexity and reduce the convergence time. The OBL is modified by replacing rand with Lévy flight in Equation (26) as follows:

$$X_{\text{top}} = lb + ub - \text{Lévy}(d) \cdot X \quad (27)$$

where $\text{Lévy}(d)$ is the arbitrary random vector, and d is the dimension size.

Sine Function-Driven Local Search

In the local search phase, upon selecting a solution from the current location, a new location for every bat is produced locally through a random walk, using a sine function as follows:

$$X = X + \text{rand}_1 \cdot \sin(\text{rand}_2 - 0.5) \cdot A \quad (28)$$

where rand_1 is the random number distribution between $[0, 1]$; the $\sin(\text{rand}_2 - 0.5)$ is utilized to escape from local optima effectively, and A is equivalent to BA . The Flowchart and Pseudo-code of the LOBL-BA are shown in Flowchart 1 and Algorithm 1, respectively.

Algorithm No. 1. LOBL-BA Pseudo-Code.

Objective function $f(x)$, $x = (x_1, \dots, x_d)^T$
Initialize the bat population x_i ($i = 1, 2, \dots, n$) and v_i
Define pulse frequency f_i at x_i
Initialize pulse rates r_i and the loudness A_i
while ($t < \text{maximum number of iterations}$)
 Update the frequency using equation (14),
 Update the Random Inertia Weight using equation
(22),
 Update the new velocities using equation (23),
 Update the new locations/solutions using equation
(24),
 if ($\text{rand} > r$)
 Update the locations/solutions using equation (27),
 else
 Update the locations/solutions using equation (28),
 end if
 Accept the new solutions
 if ($\text{rand} < A \ \& \ f(x_i) < f(x^*)$)
 Accept the new solutions
 Update the r_i and A_i using equations (20 & 21),
 end if
 Rank the bats and locate the current best x^*
end while
Postprocess Results and Visualization

IV.RESULT AND DISCUSSIONS

The proposed Lévy Opposition-Based Learning Bat Algorithm (LOBL-BA) was applied CEED problem, to demonstrate the algorithm's superior performance across all aspects. All these algorithms for CEED problem have been executed for a maximum of 500 iterations, with a population size of 50, across 30 independent runs for a fair comparison in MATLAB R2024a on a PC with 8 GB RAM and an 11th Gen Intel Core i5-11300H @ 3.10GHz processor.

Combined Economic and Emission Dispatch Problem

To estimate the performance of the suggested LOBL-BA for solving the CEED problem, real-time applications have been tested on the test case. The test case involves generating units with NO_x , SO_2 , and CO_2 emissions. The cost coefficients, emission coefficients, generator limits, and a power demand of 150 MW, 175 MW, 200 MW, and 225 MW were taken from [26, 44]. The CEED problem was addressed using the LOBL-BA in conjunction with the BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME algorithms.

Table No. 1 presents the solution to the CEED Problem for a 150 MW load demand using different algorithms, along with a comparison of total cost, fuel cost, and emissions, including NO_x , SO_2 , and CO_2 . The LOBL-BA algorithm performs best, with the lowest total cost of \$10,145 per hour, the lowest fuel cost of \$2,903.20 per hour, and the lowest NO_x , SO_2 , and CO_2 emissions of 2,315.5986 kg/h, 2,930.9098 kg/h, and 2,495.5739 kg/h, respectively. In contrast, the FPA performs the worst, with the highest total cost of \$10,294 per hour. The BA demonstrates the poorest performance, exhibiting the highest fuel cost of \$2,950.1 per hour and the highest NO_x emissions at 2,334.2455 kg/h. Similarly, FPA also demonstrates the poorest performance, with the highest SO_2 emissions of 2,983.0154 kg/h and the highest CO_2 emissions of 2,572.6430 kg/h. Overall, LOBL-BA is the most efficient at minimizing both costs and emissions, whereas FPA incurs higher costs and emissions. The convergence curve in Figure 1 illustrates the reduction in total cost over time for different optimization algorithms.

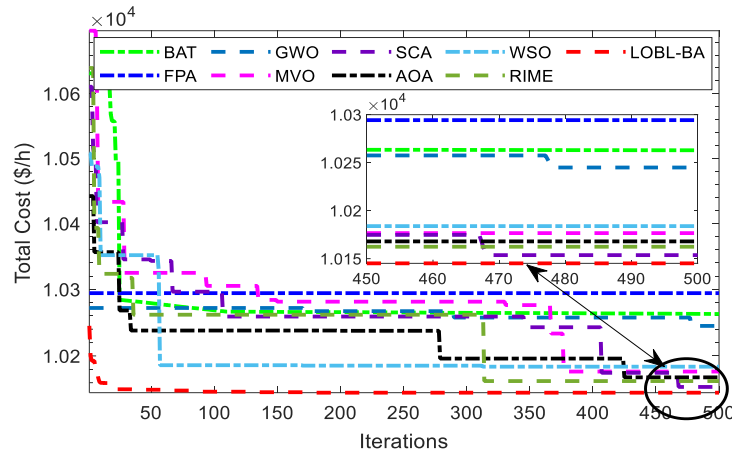


Figure 1: Convergence of various algorithms for a load demand of 150 MW.

Units	BA	FPA	GWO	MVO	SCA	AOA	WSO	RIME	LOBL-BA
PG1	50.0004	51.4949	50.3083	50.0270	50.0065	50.1470	50.6405	50.2361	50
PG2	45.8079	41.7552	45.2658	26.8216	36.5420	37.6548	35.7021	35.8088	33.1686
PG3	15.5841	15	15	23.4872	18.6103	17.9639	18.4073	18.8554	20.1561
PG4	10.7349	10	10	17.5025	14.6999	14.9418	15.3716	15.1390	15.7231
PG5	15.2243	19.7499	17.4260	20.1617	18.1413	17.2925	17.8784	17.9608	18.8695
PG6	12.6485	12	12	12	12	12	12	12	12.0827
NO _x Emission (kg/h)	2334.2455	2321.5583	2322.1757	2323.6196	2316.1057	2325.2576	2330.4868	2322.4511	2315.5986
SO ₂ Emission (kg/h)	2950.3366	2983.0154	2963.5003	2936.4265	2932.8803	2937.9034	2946.1086	2935.3138	2930.9098
CO ₂ Emission (kg/h)	2537.4926	2572.6430	2552.7224	2501.0737	2499.0192	2497.8719	2504.2165	2498.6045	2495.5739
Fuel Cost (\$/h)	2.9501E+03	2.9312E+03	2.9446E+03	2.9170E+03	2.9065E+03	2.9077E+03	2.9051E+03	2.9070E+03	2.9032E+03
Total Cost (\$/h)	1.0263E+04	1.0294E+04	1.0272E+04	1.0177E+04	1.0154E+04	1.0168E+04	1.0184E+04	1.0162E+04	1.0145E+04

Table No. 1: Results attained by various algorithms for the CEED Problem for a 150 MW load demand.

Table No. 2 presents the solution to the CEED Problem for a 175 MW load demand using different algorithms, along with a comparison of total cost, fuel cost, and emissions, including NO_x, SO₂, and CO₂. The LOBL-BA algorithm performs best, with the lowest total cost of \$12,127 per hour, the lowest fuel cost of \$3,436.70 per hour, and the lowest NO_x emissions of 2,738.6591 kg/h, SO₂ emissions of 3,536.3978 kg/h, and CO₂ emissions of 3,017.2466 kg/h. In contrast, the GWO performs worst, with the highest total cost of \$12,299 per hour. The FPA demonstrates the poorest performance, exhibiting the highest fuel cost of \$3,513.7 per hour, the BA demonstrates the poorest performance, exhibiting the highest NO_x emissions at 2,813.0011 kg/h, the MVO demonstrates the poorest performance, exhibiting the highest SO₂ emissions at 3,626.0542 kg/h and the WSO demonstrates the poorest performance, exhibiting the highest CO₂ emissions at 3,059.2296 kg/h. Overall, LOBL-BA is the most efficient in minimizing both costs and emissions. The convergence curve in Figure 2 illustrates the reduction in total cost over time for different optimization algorithms.

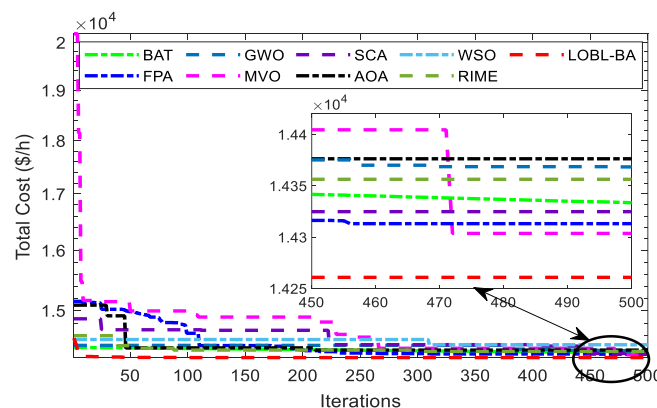


Figure 2: Convergence of various algorithms for a load demand of 175 MW.

Units	BA	FPA	GWO	MVO	SCA	AOA	WSO	RIME	LOBL-BA
PG1	50	50.3869	50.4962	51.4217	50.4262	50.4838	51.9098	50.0164	50
PG2	50.7856	51.8885	52.4806	36.5335	41.3271	37.2945	43.5796	33.9653	38.7486
PG3	21.2679	20.2126	18.1094	21.2304	22.6235	23.9917	22.6268	25.6200	23.5065
PG4	18.0954	19.5760	19.3647	24.3308	20.5095	22.2383	17.8466	21.5645	21.4680
PG5	12.9720	20.9359	20.3316	29.4836	23.2157	23.9412	20.2563	23.6977	23.3104
PG6	21.8790	12	14.2176	12	16.8980	17.0505	18.7809	20.1362	17.9666
NO _x Emission (kg/h)	2813.0011	2768.3181	2775.0947	2739.2308	2741.1047	2746.2435	2775.4714	2742.6137	2738.6591
SO ₂ Emission (kg/h)	3545.6521	3564.8962	3593.8679	3626.0542	3539.9673	3544.0983	3539.8148	3537.0266	3536.3978
CO ₂ Emission (kg/h)	3052.6995	3036.2773	3055.6072	3046.6196	3025.0979	3018.3796	3059.2296	3032.5975	3017.2466
Fuel Cost (\$/h)	3.4975E+03	3.5137E+03	3.4832E+03	3.4392E+03	3.4490E+03	3.4447E+03	3.4811E+03	3.4396E+03	3.4367E+03
Total Cost (\$/h)	1.2296E+04	1.2278E+04	1.2299E+04	1.2249E+04	1.2152E+04	1.2152E+04	1.2243E+04	1.2147E+04	1.2127E+04

Table No. 2: Results attained by various algorithms for the CEED Problem for a 175 MW load demand.

Table No. 3 presents the solution to the CEED Problem for a 200 MW load demand using different algorithms, along with a comparison of total cost, fuel cost, and emissions, including NO_x, SO₂, and CO₂. The LOBL-BA algorithm performs best, with the lowest total cost of \$14,261 per hour, the lowest fuel cost of \$4,012.50 per hour, and the lowest NO_x emissions of 3,188.5401 kg/h, SO₂ emissions of 4,191.2625 kg/h, and CO₂ emissions of 3,578.7971 kg/h. In contrast, the WSO performs the worst, with the highest total cost of \$14,459 per hour. The GWO demonstrates the poorest performance, exhibiting the highest fuel cost of \$4,093.2 per hour, the SCA demonstrates the poorest performance, exhibiting the highest NO_x emissions at 3,212.8417 kg/h, the AOA demonstrates the poorest performance, exhibiting the highest SO₂ emissions at 4,245.0252 kg/h and the WSO demonstrates the poorest performance, exhibiting the highest CO₂ emissions at 3,689.4399 kg/h. Overall, LOBL-BA is the most efficient in minimizing both costs and emissions. The convergence curve in Figure 3 illustrates the reduction in total cost over time for different optimization algorithms.

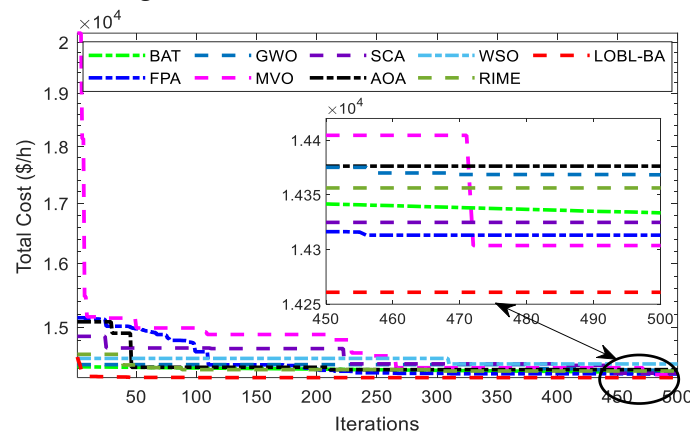


Figure 3: Convergence of various algorithms for a load demand of 200 MW.

Units	BA	FPA	GWO	MVO	SCA	AOA	WSO	RIME	LOBL-BA
PG1	51.2411	51.0701	52.0342	50.7757	51.4693	52.5625	53.7296	51.6436	50
PG2	46.6001	41.0679	54.9840	42.3169	42.3254	44.7261	47.0407	38.9746	44.4472
PG3	25.0548	27.6517	24.8341	27.7124	27.6879	24.7319	26.4697	29.0892	26.9104
PG4	28.6736	26.0723	20.2149	25.5350	28.1422	26.1173	19.9850	25.0650	27.1292
PG5	29.6571	29.3054	27.2012	26.7546	28.4090	30.1274	30.8418	30.3429	27.8914
PG6	18.7732	24.8326	20.7317	26.9054	21.9663	21.7347	21.9332	24.8847	23.6218
NO _x Emission (kg/h)	3203.0390	3191.4663	3202.2710	3203.8646	3212.8417	3204.5344	3193.3221	3191.7469	3188.5401
SO ₂ Emission (kg/h)	4231.7275	4205.6259	4215.5706	4193.1004	4202.7931	4245.0252	4217.6208	4202.4462	4191.2625
CO ₂ Emission (kg/h)	3581.1921	3613.1739	3667.1577	3609.4879	3583.6140	3628.9491	3689.4399	3634.0715	3578.7871
Fuel Cost (\$/h)	4.0267E+03	4.0199E+03	4.0932E+03	4.0149E+03	4.0376E+03	4.0166E+03	4.0912E+03	4.0498E+03	4.0125E+03
Total Cost (\$/h)	1.4334E+04	1.4313E+04	1.4449E+04	1.4304E+04	1.4325E+04	1.4376E+04	1.4459E+04	1.4356E+04	1.4261E+04

Table No. 3: Results attained by various algorithms for the CEED Problem for a 200 MW load demand.

Table No. 4 presents the solution to the CEED Problem for a 225 MW load demand using different algorithms, along with a comparison of total cost, fuel cost, and emissions, including NO_x, SO₂, and CO₂. The LOBL-BA algorithm performs best, with the lowest total cost of \$16,632 per hour, the lowest fuel cost of \$4,635.8 per hour, and the lowest NO_x, SO₂, and CO₂ emissions of 3,669.0519 kg/h, 4,900.8459 kg/h, and 4,186.2958 kg/h, respectively. In contrast, the BA performs the worst, with the highest total cost of \$16,994 per hour. The WSO exhibits the worst performance, with the highest fuel cost of \$4,713.90 per hour and the highest CO₂ emissions at 4,237.7953 kg/h. The BA demonstrates the poorest performance, with the highest NO_x emissions of 3,793.6923 kg/h and the highest SO₂ emissions of 5,030.3430 kg/h. Overall, LOBL-BA is the most efficient in minimizing both costs and emissions. The convergence curve in Figure 4 illustrates the reduction in total cost over time for different optimization algorithms.

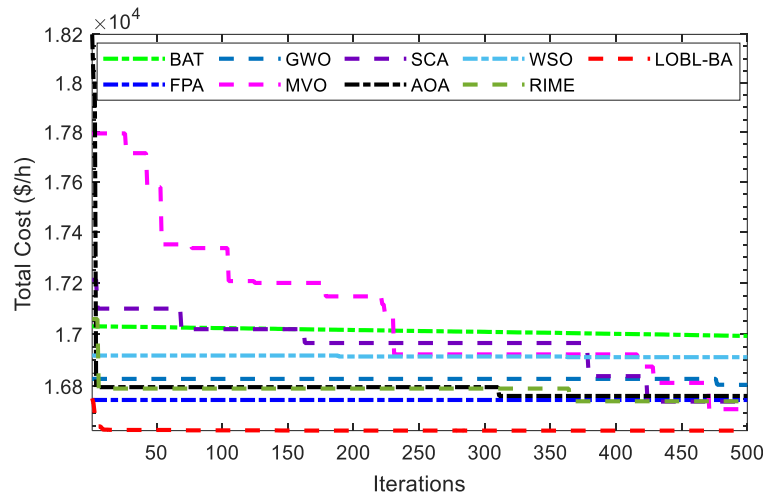


Figure 12: Convergence of various algorithms for a load demand of 225 MW.

Units	BA	FPA	GWO	MVO	SCA	AOA	WSO	RIME	LOBL-BA
PG1	53.4301	50.6498	50.7004	50.2095	50.4451	51.8435	54.7696	50.9259	50
PG2	36.9837	57.1253	38.0966	44.9018	43.0173	46.4021	51.6539	45.1263	50.2424
PG3	32.6330	29.5117	33.2164	32.4297	32.5357	32.1635	29.0175	32.1484	30.4406
PG4	41.9995	31.8494	37.2690	33.9994	33.7658	34.1609	32.8745	33.7426	32.6783
PG5	35.1644	30.6812	36.1425	34.0304	32.7277	34.1609	36.0126	30.4882	32.5394
PG6	24.7893	25.1827	29.5751	29.4292	32.5085	26.2692	20.6718	32.5686	29.0994
NO _x Emission (kg/h)	3793.6923	3689.7456	3705.0255	3675.4553	3693.7133	3694.3041	3714.4572	3713.9187	3669.0519
SO ₂ Emission (kg/h)	5030.3430	4904.0600	4966.8349	4902.8429	4916.7613	4906.1076	4965.3859	4908.2614	4900.8459
Co ₂ Emission (kg/h)	4190.7967	4190.4603	4207.2419	4187.0911	4204.8922	4187.0966	4237.7953	4194.6773	4186.2958
Fuel Cost (\$/h)	4.6876E+03	4.6769E+03	4.6618E+03	4.6592E+03	4.6419E+03	4.6883E+03	4.7139E+03	4.6414E+03	4.6358E+03
Total Cost (\$/h)	1.6994E+04	1.6748E+04	1.6828E+04	1.6713E+04	1.6742E+04	1.6763E+04	1.6912E+04	1.6743E+04	1.6632E+04

Table No. 4: Results attained by various algorithms for the CEED Problem for a 225 MW load demand.

	Total Cost (\$/h)			
	150 MW	175 MW	200 MW	225 MW
QPSO [45]	10255.25	12241.71	14413.77	16783.83
SA [46]	10261.49	12280.04	14421.30	16790.69
QBA [47]	10255.28	12241.74	14413.88	16783.91
AOA [8]	10320.44	12271.78	14424.40	16753.15
eAOA [8]	10245.30	12225.58	14361.74	16711.15
rAOA [8]	10261.66	12223.02	14375.62	16724.24
nAOA [8]	10222.74	12214.79	14347.27	16678.66
bAOA [8]	10233.73	12250.31	14365.97	16678.71
gAOA [8]	10254.80	12234.53	14352.98	16682.63
SCA [48]	10255.00	12242.00	14414.00	16784.00
AOA [26]	10331.00	12331.00	14413.00	16766.00
IAOA-r [26]	10201.00	12194.00	14321.00	16664.00
RSA [26]	10501.00	12835.00	15288.00	17717.00
PDO [26]	10294.00	12323.00	14521.00	16904.00
BAT [26]	10590.00	12971.00	15120.00	17583.00

WOA [26]	10255.00	12528.00	14808.00	17333.00
HHO [26]	10292.00	12362.00	14493.00	16844.00
RSO [26]	11386.00	13284.00	15764.00	18183.00
BA	10262.93	12295.73	14333.57	16993.72
FPA	10294.33	12277.50	14313.18	16747.96
GWO	10271.96	12299.25	14449.44	16828.43
MVO	10176.60	12248.67	14303.69	16712.87
SCA	10153.68	12152.01	14324.88	16741.80
AOA	10167.96	12151.59	14376.35	16763.22
WSO	10183.90	12242.98	14458.69	16911.77
RIME	10162.42	12146.74	14356.39	16743.01
LOBA	10145.10	12127.40	14260.92	16631.61

Table No.5: Results attained by various algorithms for the CEED Problem

Table No. 5 presents the results of solving the CEED problem using various algorithms, showing the total cost at four different cost levels: 150 MW, 175 MW, 200 MW, and 225 MW. The methods listed include a range of optimization techniques such as SA, QBA, QPSO, and the AOA, along with several variants of AOA such as eAOA, rAOA, nAOA, bAOA, gAOA, SCA, and other algorithms like the RSA, PSO with Differential Operator (PDO), BA, WOA, HHO, and RSO. All methods are evaluated across four total costs, with costs varying across algorithms, allowing a comparison of their performance in terms of total cost. The best performance in terms of cost is observed with the LOBL-BA, which consistently shows the lowest total costs across all levels, ranging from \$10,145.10 at 150 MW to \$16,631.61 at 225 MW on the other hand, the worst performance is observed with the RSO method, which incurs the highest costs, starting at \$11,386.00 at 150 MW and rising to \$18,183.00 at 225 MW. This data enables the evaluation of the trade-offs between total cost and pollutant emissions for each method at different levels, helping identify the most and least efficient algorithms. The proposed LOBL-BA shows significant improvement in solving the CEED problem and reduces both the total cost and pollutant emissions.

V.CONCLUSIONS

This paper highlights the effectiveness of the proposed LOBL-BA in addressing the CEED problem, a critical challenge in power generation systems that involves balancing total costs and pollutant emissions. The proposed CEED problem optimizes both the total cost of electricity generation and pollutant emissions, including NO_x, SO₂, and CO₂. The LOBL-BA improves the Bat Algorithm by overcoming its limitations of slow convergence and susceptibility to local optima. This is achieved through three strategies: Random Inertia Weight to enhance search capability, Lévy Opposition-Based Learning to improve the exploration-exploitation trade-off, and a Sine Function-Driven Local Search to refine solutions and avoid local optima. Simulations with a six-unit power generation system at varying loads of 150 MW, 175 MW, 200 MW, and 225 MW demonstrate that LOBL-BA consistently outperforms other algorithms, including BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME, achieving optimal cost reduction and emission minimization. The algorithm not only minimizes both operational costs and pollution but also demonstrates remarkable consistency, with minimal standard deviations and excellent performance rankings in all test cases. In contrast, other algorithms, such as FPA and BA, exhibit higher variability and perform sub-optimally. Future research could explore the application of LOBL-BA, incorporate additional factors such as renewable energy sources and dynamic power demands, and apply it to real-world and other engineering problems, including multi-objective optimization scenarios.

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