

Lévy Opposition-Based Bat Algorithm For Economic And Emission Dispatch With Wind And Solar Power

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Abstract - The Economic Emission Dispatch (EED) problem of a power system is a classical optimization problem that tries to reduce the economic cost and emissions. The Economic Dispatch (ED) problem traditionally has prioritized thermal generators with little consideration of important security limitations. Regarding environmental sustainability, it is necessary to minimize emissions, and an effort is underway to incorporate the use of wind and solar power into the grid. These renewable sources, however, cause some infirmities and intermittency, which significantly compound the dispatch problem. As a result, the goal has shifted to optimize the ED not only regarding emissions but also based on the security limits, being specific to consider the stochastic variability of the renewable energy sources. The LOBL-BA algorithm has been designed to solve these problems. Convergence speed and vulnerability to local optima are common problems that afflict the typical Bat Algorithm (BA). The presented strategy alleviates these problems in three different ways: a Random Inertia Weight is used to make the global search more efficient; a Lévy Opposition-Based Learning is to balance between the exploration and exploitation stages; a Sine function -driven Local search refreshes the candidate solutions and precludes the use of local optima. Applying the LOBL-BA algorithm to the IEEE 30-bus system outperforms in terms of overall costs and overall emissions to the environment in the two test cases, which substantiates the effectiveness of its application in meeting the two-fold goals of economic and environmental efficacy.

Keywords - Economic Emission Dispatch, Renewable Energy Sources, Bat Algorithm, Lévy Opposition-Based Learning, Emissions Reduction, Security Constraints.

1. Introduction

The modern world's urgency is associated with the shift towards energy systems producing fewer pollutants and being more sustainable. Economic dispatch (ED) in connection with this aspect, the debilitation of the economic efficiency and environmental prudence of power systems is a crucial factor in harmonizing these two roles. In the past, optimization methods in this area have focused mostly on the reduction of the financial expense of producing electricity, leaving environmental implications as a secondary issue. Conventional ED has been focused to a great extent on thermal generators, albeit cost-effective, the segment that makes up the greatest proportion of the generation mix in terms of pollution. Nevertheless, in the changing environment of the current atmosphere of modern power networks, this method cannot be considered sufficient; it does not take into account the key aspects, including the control of emissions, security limitations, and the growth of interdependence that occurs with renewable energy sources.

More modern sources of renewable energy, such as wind and solar, are used to fight these greenhouse gas emissions and reduce pollution of the atmosphere. Moreover, the use of renewable resources is expected to reduce the economic cost of traditional energy production. The use of renewables, however, does not pass without its own challenges; the main challenges are due to the fact of its inherent intermittency and variability. The generation of wind and solar power is highly dependent on the weather and the location of the site, which is strongly contrary to the regular thermal power plants that provide a constant and predictable output factor, which in turn creates a sense of intermittency and creates a significant amount of uncertainty. This volatility makes it harder to control the grid, and even balancing the energy demand and supply is getting difficult in the quest to achieve economic efficiency as well as environmental sustainability. In turn, this

variability contributes to the complications of optimal dispatch of electricity, especially in the process of trying to achieve economic and environmental goals at the same time.

The EED, which targets reducing the costs of power generation and system emissions, poses serious optimization challenges. The system stability and the security constraint in the dispatch decision, along with the impact of renewable energy sources on overall stability, are also to be considered. The cost approaches that utilize traditional and renewable energy have proposed an OPF solution by most researchers, like Biswas et al., and optimize costs using an algorithm approach to the SHADE algorithm, which incorporates constraint-handling and converges quickly which making the system both fast and efficient [1]. Guvenc et al. improve the Adaptive Genetic-Directed Embedding (AGDE) algorithm with the Frequency-Driven Balancing (FDB) scheme in order to solve the Security-Constrained Optimal Power Flow (SCOPF) problem in the presence of renewable generation and thus obtain a better convergence rate, robustness, and solution quality in all the complex operation conditions [2]. Shaheen et al. presents the Heap Optimization Algorithm (HOA) to solve Optimal Power Flow (OPF) problems that accelerate the convergence and lower fuel consumption as well as increase computational efficiency compared to traditional methodologies when used on grids with renewable resources [3]. Farhat et al. present the Jellyfish Search Optimization (JS) heuristic of OPF, skilfully handling uncertainties in the supply of renewable energy and the complicated cost construction, and displaying better convergence and cost savings when compared to the SHADE-SF algorithm [4]. Ahmad et al. introduce Bird Swarm Algorithm (BSA) as a solution technique of OPF in hybrid power systems that use renewable energy sources and successfully optimizes the economic cost parameter as well as emission parameter, and is well capable of addressing the uncertainties in load demand and generation output [5]. Nguyen et al. create an Enhanced Equilibrium Optimizer (IEEO) of OPF with renewable generation, which outperforms existing algorithms in terms of cost, emission reduction, and efficiency [6]. Hassan et al. provide a variant of Chaotic Bonobo Optimizer (CB05) adapted to OPF with renewable integration to improve the global search capacities and improve the global search abilities of the established optimization methods [7]. Farhat et al. propose the Enhanced Slime Mould Algorithm (ESMA) of OPF, which incorporates renewable energy sources with ease, at the same time reducing power expenses, emissions, and transmission losses in the face of uncertainty [8]. Ali et al. define the White Shark Optimizer (WSO) as a powerful technique for solving OPF issues in power networks, which delivers high performance in terms of efficient assimilation of renewable energy sources in comparison with other algorithms [9]. Flow Direction Algorithm (FDA) is a proposal by Maheshwari et al. to solve OPF when stochastic renewable resources are available, which proves to be more cost-effective, stable, and functional compared to SSA, ALO, and WOA without violating realistic system constraints [10]. Hassan, Kamel, & Hussien introduce enhanced Wild Horse Optimizer (EESWHO), an enhanced Wild Horse Optimizer, outperforming WHO in minimizing fuel costs and improving efficiency for OPF with RES uncertainties [11].

Recently, Emam et al. presented the Modified Artificial Hummingbird Algorithm (mAHA) that proves to be a better performer compared to the traditional AHA, Harris Hawks Optimization (HHO), and the Whale Optimization Algorithm (WOA). Their experimental assessment of results shows a significant decrease in fuel-cost minimization, power-loss reduction, and voltage stability in optimal power flow (OPF) models of renewable energy-integrated systems [12]. Gao et al. introduce a Probabilistic Optimal Power Flow (POPF) scheme containing the use of Bayesian Deep Neural Networks (BDNNs). Their model outperforms the current methods in accuracy and calculation efficiency in large-scale electricity systems, thus making it easy to incorporate source generators of renewable sources into the grid in a more effective and efficient way [13]. In another paper, Gurumoorthi and others refer to the application of a Hybrid Deep Reinforcement Learning and Quantum-Inspired Genetic Algorithm (HDRL-QIGA) as a method of solving optimal power flow problems in hybrid renewable energy systems (HRES). According to their findings, they show significant decreases in fuel price, greater optimization efficiency and greater ability to withstand the uncertainties that are inherent in the openness of renewable energy sources, doing better than traditional algorithms [14]. Shaheen et al. solve the POPF problem applying the Catch Fish Optimization Algorithm (CFOA), which has better convergence behaviour and strength than Particle Swarm Optimization (PSO) and the Heap algorithm. The CFOA has been able to provide considerable savings on fuel costs in cases of integration of renewable energy [15]. Lastly, Jowkar et al. present the Enhanced Coulomb Laws Algorithm for the solution of OPF tasks: ECFA. Such an

approach shows superiority to the Slime Mold Algorithm (SSA), the Bees Algorithm (BA), and the traditional CFA by the merit of minimizing the cost, reducing emissions, and the speed of convergence, which makes it very applicable in renewable-energy-based power systems [16]. Jamal et al. propose improved pelican optimization algorithm (IPOA) for the S-OPF problem, improving the pelican optimization algorithm to minimize generation costs and emissions, outperforming SCSO, GWO, and POA [17] and many more algorithms.

The edges of a power system become one of the central elements in the economic energy dispatch (EED) issue. Even though a surge of studies has been done covering different aspects of EED, a comparatively small number of studies have factored in network security limitations. However, the extent of practical use is that the limits of transmission lines and the voltage constraints of load buses are seen as important parameters. We discuss in the given work a customized version of the Bat Algorithm that makes an explicit consideration of these network security constraints, as well as constraints on the capabilities of generators. The Bat Algorithm (BA) [18] was initially developed to replicate the bat species echolocation behaviour. A large literature has tried to enhance the algorithmic performance of BA over several years, and a variety of suggested improvements have been proposed. This legacy is continued in the current work, which presents a Levy-inspired Opposition-Based Learning scheme that is aimed at improving the performance of BA. In particular, the proposed methodology combines three methods: a Random Inertia Weight (RIW) scheme, a Levy Opposition-Based Learning (LOBL), and a Sine-function-based Local Search (SF-BLS). All these strategies will increase the global and local exploration capabilities of BA, hence significantly enhancing its optimization results.

The key contributions that the study made are listed below:

- ❖ The addition of random inertia weight enhances the ability of the algorithm to balance between exploration and exploitation, hence providing a better search efficiency.
- ❖ The introduction of Lévy Opposition-Based Learning better solves the exploration-exploitation trade-off; the convergence is faster, the solution is more accurate, and the robustness of the approach to complex optimization problems is greater.
- ❖ Local Search enables candidate solutions to be narrowed down to the use of a Sine-based Local Search, which assists in achieving high-quality optima fast.
- ❖ The EED problem formulation includes thermal, wind, and solar energy sources and directly addresses the network security issues due to the constraints on the optimization problem.

The paper structure is as follows: Section 2 is problem formulation; Section 3 presents Bat Algorithm; Section 4 presents Levy Opposition-Based Learning Bat Algorithm; Section 5 is the simulating experiments and analysis of the results; the conclusion of the work is done in the Section 6.

2. Problem Formulation

2.1. Cost Calculation of Thermal Power

The modified IEEE_30 bus system includes thermal, wind and solar generators, the essential parameters are outlined in Table 1. The variable wind and power outputs balanced by all generators [1].

The objective is to identify the most efficient power schedule that fulfils demand while minimizing costs; fuel cost (\$/h) is approximately expressed by a quadratic equation:

$$C_T(P_{TG}) = \sum_{i=1}^{N_{TG}} a_i + b_i P_{TGi} + c_i P_{TGi}^2 \quad (\$/h) \quad (1)$$

where a_i , b_i , c_i are the cost coefficients of the i^{th} unit, P_{TG} is the power output of thermal unit, N_{TG} is total number of thermal units.

Table 1: Essential parameters of test system.

Items	Quantity	Details
Buses	30	[1]
Branches	41	[1]

Thermal Generators (TG1, TG2, TG3)	3	Buses: 1 (swing), 2 and 8
Wind generators (WG1, WG2)	2	Buses: 5 and 11
Solar PV unit (SPV)	1	Bus: 13
Control variables	11	Scheduled real power for 5 Nos. Generators: TG2, TG3, WG1, WG2 and SPV; bus voltages of all generator buses (6 Nos.)
Connected load	-	283.4 MW, 126.2 MVar
Load bus voltage range allowed	24	[0.95-1.05] p.u.

In practical applications, the VPLEs must be taken into account; therefore, the fuel cost function is determined as follows [19]:

$$C_T(P_{TG}) = \sum_{i=1}^{N_{TG}} a_i + b_i P_{TGi} + c_i P_{TGi}^2 + \left| d_i \times \sin \left(e_i \times (P_{TGi}^{\min} - P_{TGi}) \right) \right| \quad (\$/h) \quad (2)$$

where d_i , and e_i are the coefficients of valve-point effect. $P_{TGi}^{\min}$ is minimum power generation of i^{th} unit.

Power production from traditional sources increases emissions. Thermal generator emissions (ton/h) are calculated as follows:

$$E_T = \sum_{i=1}^{N_{TG}} \left[(\alpha_i + \beta_i P_{TGi} + \gamma_i P_{TGi}^2) \times 0.01 + \omega_i e^{(\mu_i P_{TGi})} \right] \quad (\text{t/h}) \quad (3)$$

where, α_i , β_i , γ_i , ω_i , and μ_i are all emission coefficients. The values for the generator linked to bus 1 have been slightly modified; otherwise, the coefficients are outlined in Table 2 and same as in [21].

2.2. Cost Calculation of Renewable Power

Wind and solar units generate power without fuel, and the Independent System Operator (ISO) incurs no costs for owning solar or wind installations, as there are no initial investment or maintenance expenses. For privately owned facilities, the ISO pays electricity rates based on contractual agreements.

The direct cost of wind power from the j^{th} plant is modelled as a function of the scheduled power, as shown below:

$$C_{W,j}(SP_{W,j}) = g_j SP_{W,j} \quad (4)$$

where g_j is the direct cost coefficient, $SP_{W,j}$ is wind scheduled power of j^{th} unit respectively.

The direct cost of solar power from the j^{th} plant is modelled as a function of the scheduled power, as shown below:

$$C_{S,j}(SP_{S,j}) = h_j SP_{S,j} \quad (5)$$

where, h_j is the direct cost coefficient, $SP_{S,j}$ is solar scheduled power of k^{th} unit respectively.

Table 2: displays the cost and emission coefficients.

Generator	Buses	a	b	c	d	e	α	β	γ	ω	μ
TG1	1	0	2	0.00375	18	0.037	4.091	-5.554	6.49	0.0002	6.667
TG2	2	0	1.75	0.0175	16	0.038	2.543	-6.047	5.638	0.0005	3.333
TG3	8	0	3.25	0.00834	12	0.045	5.326	-3.55	3.38	0.002	2

2.3. Wind and Solar Power Uncertainty Cost Calculation

2.3.1. Overestimation Cost Calculation

A situation may arise in which the actual output of a wind farm and solar unit is below the estimated value, a phenomenon known as overestimation. In such cases, the system operator is required to maintain spinning reserves, which incurs the reserve cost.

Wind farm reserve cost as follows:

$$C_{W_{rc},j}(SP_{W,j}-AP_{W,j})=K_{W_{rc},j}(SP_{W,j}-AP_{W,j}) \quad (6)$$

$$SP_{W,j}-AP_{W,j}=K_{W_{rc},j} \int_0^{SP_{W,j}} (SP_{W,j}-P_{W,j}) f_W(P_{W,j}) dp_{W,j} \quad (7)$$

where $C_{W_{rc},j}$ is wind reserve cost, $AP_{W,j}$ is wind actual available power, $K_{W_{rc},j}$ is wind reserve cost coefficient, $f_W(P_{W,j}) dp_{W,j}$ is wind PDF.

Solar unit reserve cost as follows:

$$C_{S_{rc},k}(SP_{S,k}-AP_{S,k})=K_{S_{rc},k}(SP_{S,k}-AP_{S,k}) \quad (8)$$

$$K_{S_{rc},k}(SP_{S,k}-AP_{S,k})=K_{S_{rc},k} \times f_s(AP_{S,k} < SP_{S,k}) \times [SP_{S,k} - E(AP_{S,k} < SP_{S,k})] \quad (9)$$

where $C_{S_{rc},k}$ is solar reserve cost, $AP_{S,k}$ is solar actual available power, $K_{S_{rc},k}$ is solar reserve cost coefficient, $E(AP_{S,k} < SP_{S,k})$ is solar power expectation below $SP_{S,k}$.

2.3.2. Underestimation Cost Calculation

A situation may arise in which the actual output of a wind farm and solar unit exceeds the estimated value, a phenomenon known as underestimation. If surplus power cannot be used by reducing conventional generation, it will be wasted, and the ISO will incur a penalty for the excess.

Wind farm penalty cost as follows:

$$C_{W_{pc},l}(AP_{W,l}-SP_{W,l})=K_{W_{pc},l}(AP_{W,l}-SP_{W,l}) \quad (10)$$

$$K_{W_{pc},l}(AP_{W,l}-SP_{W,l})=K_{W_{pc},l} \int_0^{SP_{W,l}} (P_{W,l}-SP_{W,l}) f_W(P_{W,l}) dp_{W,l} \quad (11)$$

where $C_{W_{pc},l}$ is wind penalty cost, $K_{W_{pc},l}$ is wind penalty cost coefficient.

Solar unit reserve cost as follows:

$$C_{S_{pc},m}(AP_{S,m}-SP_{S,m})=K_{S_{pc},m}(AP_{S,m}-SP_{S,m}) \quad (12)$$

$$K_{S_{pc},m}(AP_{S,m}-SP_{S,m})=K_{S_{pc},m} \times f_s(AP_{S,m} > SP_{S,m}) \times [\epsilon(AP_{S,m} > SP_{S,m}) - SP_{S,m}] \quad (13)$$

where $C_{S_{pc},m}$ is solar penalty cost, $K_{S_{pc},m}$ is solar penalty cost coefficient, $\epsilon(AP_{S,m} > SP_{S,m}) - SP_{S,m}$ is solar power expectation above $SP_{S,m}$.

2.4. Objective Function

The objective function is formulated with all cost functions. The first objective excludes emission costs, while the second goal is to examine how a carbon tax might affect the schedule for power production.

Total cost of wind power generation as follows:

$$TC_W(P_W)=\sum_{l=1}^{N_{WG}} [C_{W,l}(SP_{W,l})+K_{W_{rc},l}(SP_{W,l}-AP_{W,l})+K_{W_{pc},l}(AP_{W,l}-SP_{W,l})] \quad (14)$$

Total cost of solar power generation as follows:

$$TC_S(P_S)=\sum_{l=1}^{N_{SG}} [C_{S,m}(SP_{S,m})+C_{S_{rc},m}(SP_{S,m}-AP_{S,m})+K_{S_{pc},m}(AP_{S,m}-SP_{S,m})] \quad (15)$$

where N_{WG} and N_{SG} are the total wind and solar units respectively.

First objective: Minimize fuel cost of the generation [1].

$$F_1 = C_T(P_{TG}) + TC_W(P_W) + TC_S(P_S) \quad (16)$$

Second objective: Minimize total cost, including emissions [1].

$$F_2 = F_1 + C_{tax} E_T \quad (17)$$

2.5. Equality Constraints

Equality constraints are power balance equations are as follows.

$$P_{Gp} - P_{Dp} - V_p \sum_{q=1}^{N_B} V_q [G_{pq} \cos(\delta_{pq}) + B_{pq} \sin(\delta_{pq})] = 0 \forall p \in NB \quad (18)$$

$$Q_{Gp} - Q_{Dp} - V_p \sum_{q=1}^{NB} V_q [G_{pq} \sin(\delta_{pq}) - B_{pq} \cos(\delta_{pq})] = 0 \forall p \in NB \quad (19)$$

where δ_p and δ_q for the voltage angles, NB for total buses, P_{Dp} and Q_{Dp} for real and reactive power demands. P_{Gp} and Q_{Gp} are real and reactive power production from conventional or wind and solar sources. The transfer conductance and susceptance between bus p and bus q are G_{pq} and B_{pq} .

2.6. Inequality Constraints

Inequality constraints including security constraints on lines, load buses, and other components.

2.6.1 Generator Constraints

$$P_{TGp}^{\min} \leq P_{TGp} \leq P_{TGp}^{\max} \quad p=1, \dots, N_{TG} \quad (20)$$

$$P_{ws,q}^{\min} \leq P_{ws,q} \leq P_{ws,q}^{\max} \quad q=1, \dots, N_{WG} \quad (21)$$

$$P_{SS,k}^{\min} \leq P_{SS,k} \leq P_{SS,k}^{\max} \quad k=1, \dots, N_{SG} \quad (22)$$

$$Q_{TGp}^{\min} \leq Q_{TGp} \leq Q_{TGp}^{\max} \quad p=1, \dots, N_{TG} \quad (23)$$

$$Q_{ws,q}^{\min} \leq Q_{ws,q} \leq Q_{ws,q}^{\max} \quad q=1, \dots, N_{WG} \quad (24)$$

$$Q_{SS,k}^{\min} \leq Q_{SS,k} \leq Q_{SS,k}^{\max} \quad k=1, \dots, N_{SG} \quad (25)$$

$$V_{Gp}^{\min} \leq V_{Gp} \leq V_{Gi}^{\max} \quad p=1, \dots, NG \quad (26)$$

2.6.2 Security Constraints

$$V_{Lp}^{\min} \leq V_{Lp} \leq V_{Lp}^{\max} \quad p=1, \dots, NL \quad (27)$$

$$S_{lq} \leq S_{lq}^{\max} \quad q=1, \dots, NL \quad (28)$$

Equations (15)-(17) provide thermal, solar, and wind power production limitations. In equations (18)-(20), the reactive power is defined. The generated bus voltage is limited by equation (21) and the load bus voltage by equation (22). Equation (23) constrains the network's NL line capacity.

This research emphasizes generator reactive power. The study offers narrower thermal generator ranges than [23]. We estimate the solar unit's reactive power capacity to be -0.4 to 0.5 p.u. for our investigation. Tables 6 and 7 in the simulation results list generator list the active (P) and reactive (Q) power limitations.

Key system parameters include real power losses and voltage deviations. Transmission losses result from line resistance, and the network loss and voltage deviations are calculated as follows:

$$P_{loss} = \sum_{p=1}^{NL} \sum_{q \neq p}^{NL} G_{pq} V_p^2 + V_q^2 - 2V_p V_q \cos(\delta_{pq}) \quad (29)$$

$$VD = \sum_{p=1}^{NL} |V_{Lp} - 1| \quad (30)$$

3. Bat Algorithm

The Bat Algorithm (BA) is inspired by the echo nature of microbats, developed by Xin-She Yang [18]. Bats use echo to detect prey, bypass barriers, 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 behaviour 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 BA operates through a continuous, iterative process in which the bat velocity and position are updated at each step. The location vector of each bat signifies a prospective solution inside the search area. The global ideal location is unknown beforehand; hence the bats are initiated randomly. The initial equation is defined as follows [18]:

$$x_{i,j} = x_{lb} + (x_{ub} - x_{lb}) * rand \quad (31)$$

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 [22]:

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \quad (32)$$

$$V_i^{it} = V_i^{it-1} + (X_i^{it} - X^*) * Q_i \quad (33)$$

$$X_i^{it} = X_i^{it-1} + V_i^{it} \quad (34)$$

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 [18]:

$$X_{\text{new}} = X_{\text{old}} + \varepsilon A^{it} \quad (35)$$

where ε lies between $[-1, 1]$, A^{it} is the loudness; as the bat nears the prey, as A value reduces, while the r_o^{it} rises. A^{it} helps to update the bat location.

The update of A^{it} and r_o^{it} as follows:

$$A^{it} = \langle A^{it} \rangle \quad (36)$$

$$A^{it+1} = \alpha A_o^{it} \quad (37)$$

$$r_o^{it+1} = r_i^o (1 - \exp(-\gamma \times it)) \quad (38)$$

$$A^{it+1} = \alpha A_o^{it} \quad (39)$$

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_i^o .

4. Lévy Opposition-Based Learning Bat Algorithm

4.1. Random Inertia Weight

"The stochastic inertia weight regulates the balance between exploration and exploitation by modulating the magnitude of the velocity ω . The revised equation is presented below" [29]:

$$\omega = \omega_{\max} - \omega_{\min} * \frac{(it_{\max} - it)}{A^{it_{\max}}} + \omega_{\min} * \mathcal{R} \quad (40)$$

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:

$$V_i^{it} = \omega * V_i^{it-1} + (X_i^{it} - X^*) * Q_i \quad (41)$$

$$X_i^{it} = X_i^{it-1} + V_i^{it} \quad (42)$$

4.2. Lévy Opposition-Based Learning

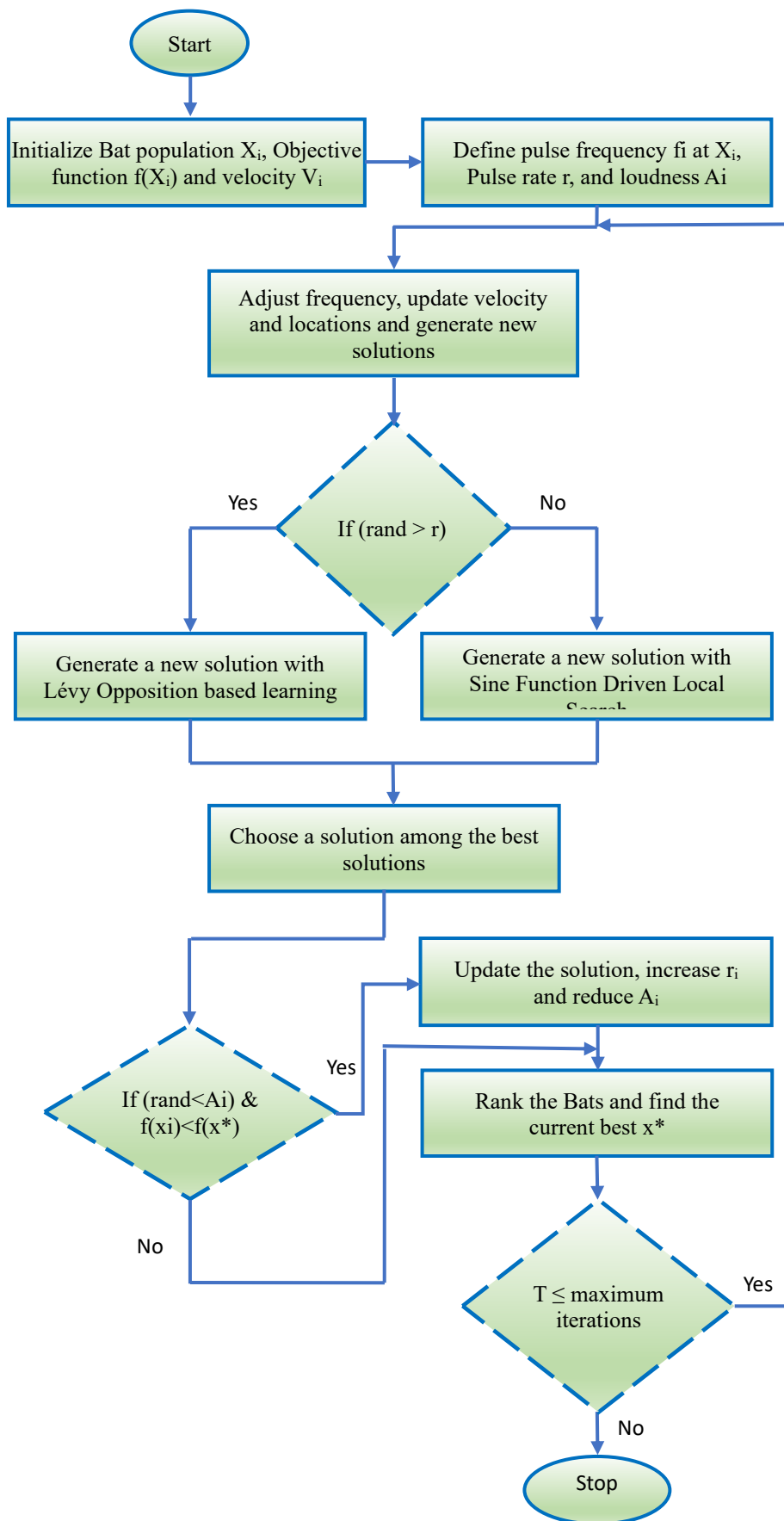
A large fraction of the initial solutions produced under most meta-heuristic algorithms are purely stochastic. As a result, the algorithm will quickly approach the global optimality in cases when the starting points are close to it; on the other hand, in cases when the starting points are far, the convergence rate will be significantly lower, which proves the inherent nature of difficulties and the importance of reducing the time of convergence significantly. Tizhoosh [30] was the first to apply Opposition-Based Learning to meta-heuristic methods; OBL, as an effective optimization method, significantly increases the performance of these approaches in dealing with problem-rich problem spaces.

The mathematical representation of OBL is as follows:

$$X_{op} = lb + ub - X \quad (43)$$

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

Fig. 1. Flow Chart of LOBL-BA.



The fact that a local optimum can be represented by two solutions, one of which is the opposite of the other, may happen during the optimization process; this also leads to other people being drawn to this area, thus causing premature convergence and loss of accuracy of solutions. To tackle this complexity and premature convergence, W. Long [31] modified the OBL by adding a random value to Equation (43) as follows:

$$X_{rop} = lb + ub - rand * X \quad (44)$$

where X_{rop} is the new random opposite solution; rand lies in [0, 1]; and X is the current location, respectively.

The augmented ROBL algorithm has a significant population diversity increase, thus avoiding local optima; however, the convergence latency is unsatisfactory. The paper is consequently a proposal of integrating a Levy flight distribution into the ROBL paradigm to deal with the complexity inherent in it and to reduce the convergence time.

The OBL is modified by replacing rand with Lévy flight in Equation (44) as follows:

$$X_{lop} = lb + ub - Lévy(d) * X \quad (45)$$

where Lévy(d) is the arbitrary random vector, and d is the dimension size.

4.3. 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:

$$X = X + rand_1 * \sin(rand_2 - 0.5) * A \quad (46)$$

where $rand_1$ is the random number distribution between [0, 1]; the $\sin(rand_2 - 0.5)$ is utilized to avoid from local optima effectively, and A is equivalent to BA. The Flowchart of the LOBL-BA are shown in Figure 1, respectively.

5. Results and Discussion

The proposed Lévy Opposition-Based Learning Bat Algorithm (LOBL-BA), along with BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME, was applied to solve ED and EED problems to demonstrate its superior performance across all aspects. The deployed algorithms that were used to solve the EED problem were run up to a maximum of 500 iterations with a population size of 50 in 30 independent runs, hence a proper comparison. The mathematical simulations were performed with MATLAB R2024a on a personal workstation with 8GB of memory and an Intel Core i5-11300H (11th-generation) processor with 3.10 GHz.

5.1. Case 1: Economic Dispatch

The proposed LOBL-BA is used to address the EED problem. The ED problem was addressed using LOBL-BA along with BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME algorithms.

Table 3 presents the simulation results for the ED problem obtained by different algorithms. The LOBL-BA method outperforms others in fuel cost, achieving the lowest at 781.607 (\$/h) with emissions of 1.762 (ton/h), identical to those of BA and FPA. In contrast, the AOA method performs the worst, with the highest fuel cost of 802.573 (\$/h) and emissions of 1.886 (t/h). Figure 2 shows the curve of convergence of fuel cost with time elapsed in various algorithms.

Table 3. Simulation results of several algorithms are used for Case 1

Control Variables	Min	Max	BA	FPA	GWO	MVO	SCA	AOA	WSO	RIME	LOBL-BA
PTG1 (MW)	50	140	134.909	134.908	134.918	134.914	134.346	135.989	132.867	134.886	134.912

PTG2 (MW)	20	80	28.314	26.958	28.782	27.750	29.253	38.023	32.475	26.899	27.777
PTG3 (MW)	10	35	42.745	36.909	42.597	44.004	43.370	73.745	44.009	43.116	10.000
Pws1 (MW)	0	75	10.000	13.343	10.000	10.000	10.481	14.921	10.471	10.000	44.063
Pws2 (MW)	0	60	35.849	40.779	36.903	37.145	31.288	19.921	31.045	37.980	35.745
Pss (MW)	0	50	37.411	36.613	36.145	35.456	40.702	22.751	37.137	36.394	36.687
V1 (p.u)	0.95	1.1	1.072	1.084	1.071	1.074	1.073	1.086	1.074	1.070	1.070
V2 (p.u)	0.95	1.1	1.057	1.066	0.967	0.979	1.060	1.029	1.054	0.950	1.056
V5 (p.u)	0.95	1.1	1.034	1.095	1.096	1.094	1.018	0.997	1.023	1.045	1.039
V8 (p.u)	0.95	1.1	1.100	1.055	1.071	1.038	1.098	1.054	1.050	1.073	1.088
V11 (p.u)	0.95	1.1	1.100	1.045	1.088	1.096	1.050	1.066	1.066	1.100	1.099
V13 (p.u)	0.95	1.1	1.047	0.983	1.099	1.069	1.091	1.084	1.092	1.074	1.050
QTG1 (MVar)	-20	150	0.867	10.249	12.062	17.387	-2.348	-20.000	8.824	8.928	-6.293
QTG2 (MVar)	-20	60	8.810	21.659	-20.000	-20.000	32.615	25.071	-20.000	-20.000	11.428
QTG3 (MVar)	-15	40	22.867	35.000	35.000	35.000	7.353	35.000	35.000	35.000	26.366

Qws1 (MVar)	-30	35	40.000	40.000	40.000	33.065	40.000	40.000	40.000	40.000	40.000
Qws2 (MVar)	-25	30	30.000	16.777	25.293	28.964	14.091	30.000	30.000	29.235	29.946
Qss (MVar)	-20	25	14.580	-4.283	25.000	22.943	25.000	19.846	25.000	24.383	15.412
Fuel Valve Cost (\$/h)			439.954	448.793	441.543	438.103	443.670	417.380	455.941	435.230	438.185
Wind Gen Cost (\$/h)			239.073	237.317	242.129	247.814	226.669	298.330	224.189	247.622	243.281
Solar Gen Cost (\$/h)			103.285	100.585	98.811	96.425	115.112	150.852	114.976	99.139	100.141
Total Cost (\$/h)			782.309	782.641	782.483	782.342	785.451	802.573	795.106	781.992	781.607
Emission (t/h)			1.762	1.762	1.763	1.763	1.702	1.886	1.555	1.763	1.762
Carbon Tax (\$/h)			-	-	-	-	-	-	-	-	-
Ploss (MW)			5.827	6.110	5.944	5.868	6.042	7.404	5.882	5.874	5.784
VD (p.u.)			0.450	0.691	0.512	0.502	0.448	2.478	0.425	0.545	0.463

Table 4. Simulation results from the literature show that several algorithms are used for Case 1.

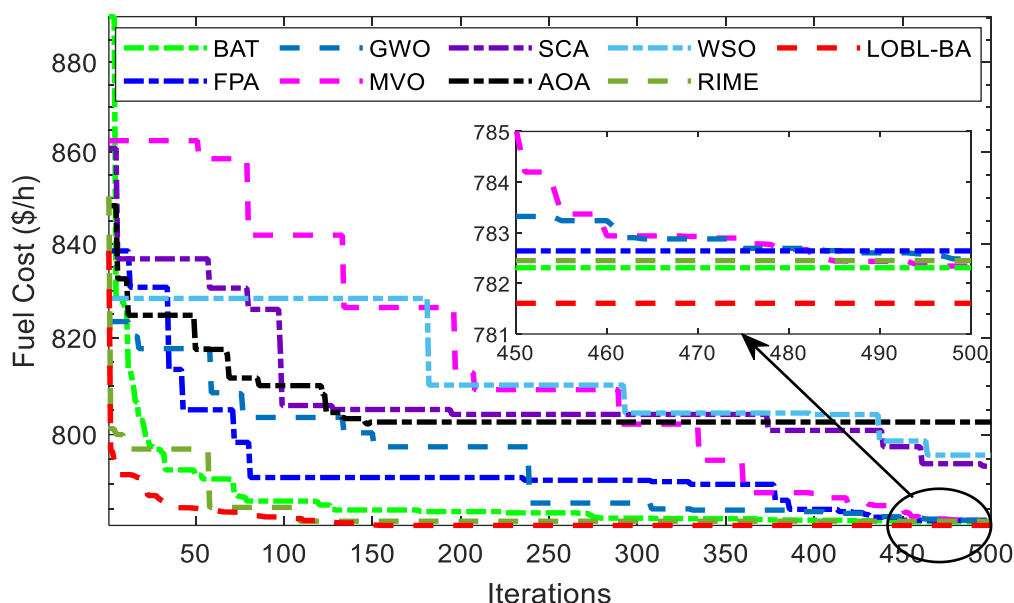
Control Variables	BWOA	FPA	SHADE-SF	MSA	GPC	CGO	ABC	SMA	ESMA	JS	LOBL-BA
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PTG1 (MW)	134.932	134.909	134.908	134.908	134.928	134.908	134.931	134.913	134.914	134.905	134.912
PTG2 (MW)	30.522	28.223	28.564	29.918	29.322	29.009	26.944	28.417	27.688	29.023	27.777
PTG3 (MW)	10.028	10.000	10.000	41.429	10.000	10.000	10.015	10.000	10.013	10.001	10.000
Pws1 (MW)	43.116	42.340	43.774	10.156	43.398	44.038	43.186	43.976	43.578	43.970	44.063
Pws2 (MW)	37.825	36.512	36.949	37.689	37.616	37.174	35.754	36.744	37.451	37.019	35.745
Pss (MW)	33.370	37.279	34.976	35.209	33.979	34.040	38.378	35.118	35.528	34.253	36.687
V1 (p.u)	1.069	1.070	1.072	1.071	1.069	1.072	1.072	1.073	1.070	1.073	1.070
V2 (p.u)	1.100	1.056	1.057	1.057	1.050	1.057	1.056	1.058	1.057	1.057	1.056
V5 (p.u)	1.096	1.027	1.035	1.079	1.036	1.035	1.035	1.037	1.034	1.035	1.039
V8 (p.u)	1.022	1.075	1.040	1.076	1.097	1.098	1.039	1.040	1.088	1.071	1.088
V11 (p.u)	1.006	1.088	1.100	1.078	1.099	1.098	1.095	1.098	1.097	1.098	1.099
V13 (p.u)	1.068	1.061	1.055	1.047	1.100	1.049	1.048	1.049	1.052	1.046	1.050

QTG1 (MVar)	-20.000	-5.548	-1.903	-3.945	2.769	-2.453	-1.230	-1.732	-6.589	-0.684	-6.293
QTG2 (MVar)	60.000	19.595	13.261	7.539	-6.702	12.081	13.010	12.900	16.436	11.012	11.428
QTG3 (MVar)	15.652	40.000	35.101	40.000	40.000	40.000	36.645	35.976	40.000	40.000	26.366
Qws1 (MVar)	35.000	16.207	23.181	35.000	27.392	22.339	23.795	24.647	21.181	22.667	40.000
Qws2 (MVar)	2.884	26.421	30.000	22.885	28.966	30.000	29.636	30.000	29.548	30.000	29.946
Qss (MVar)	25.000	20.480	17.346	15.490	25.000	15.036	15.243	15.156	16.472	14.025	15.412
Total Cost (\$/h)	784.342	782.860	782.503	782.423	782.423	782.195	782.154	781.958	781.938	781.639	781.607
Emission (t/h)	1.764	1.762	1.762	1.762	1.764	1.762	1.765	1.763	1.763	1.762	1.762
Carbon Tax (\$/h)	-	-	-	-	-	-	-	-	-	-	-
Ploss (MW)	6.401	5.864	5.770	5.908	5.843	5.769	5.808	5.768	5.772	5.774	5.784

Table 4 provides the simulation results from the literature for Case 1. In comparison with the literature, the LOBL-BA method performs better in terms of fuel cost, with the least fuel cost of 781.607 (\$/h) and identical emission of 1.762 (t/h) to SHADE-SF and CGO, the BWOA [8] method performs the worst, with the highest fuel cost of 784.342 (\$/h) from Table 4.

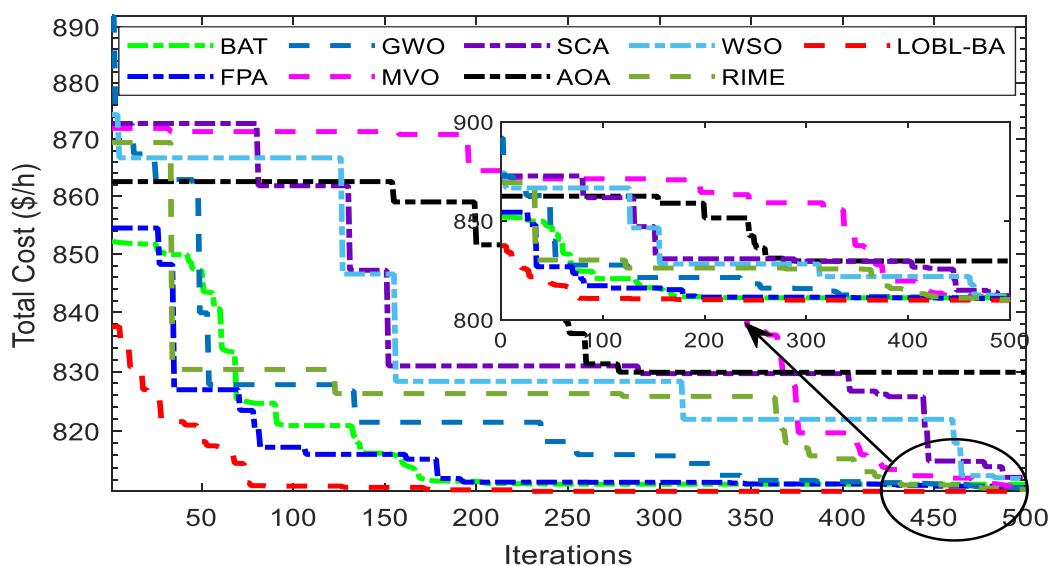
Fig. 2. The convergence of several algorithms for Case 1.



5.2. Case 2: Economic and Emission Dispatch

The proposed LOBL-BA is used to address the EED problem. The Ctax is considered as 20 (\$/tonne) [1]. The EED problem was addressed using LOBL-BA along with BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME algorithms.

Fig. 3. The convergence of several algorithms for Case 2.



VD (p.u.)	0.535	0.455	0.463	0.443	0.537	0.454	0.442	0.452	0.459	0.448	0.463
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Table 5. Simulation results of several algorithms are used for Case 2.

Control Variables	Min	Max	BA	FPA	GWO	MVO	SCA	AOA	WSO	RIME	LOBL-BA
PTG1 (MW)	50	140	123.972	122.639	123.308	123.745	105.969	63.351	113.332	123.397	123.090
PTG2 (MW)	20	80	51.241	31.131	33.834	32.145	31.469	52.023	28.860	32.552	31.761
PTG3 (MW)	10	35	30.200	10.005	10.071	10.000	10.372	13.256	10.220	10.008	10.000
Pws1 (MW)	0	75	21.637	45.996	45.255	45.328	46.173	37.562	46.701	45.661	46.064
Pws2 (MW)	0	60	28.657	39.835	38.113	41.875	42.123	21.867	39.749	36.774	38.966
Pss (MW)	0	50	33.745	37.705	38.139	35.572	35.432	39.929	39.875	40.441	38.819
V1 (p.u)	0.95	1.1	1.067	1.067	1.071	1.068	1.072	1.054	1.070	1.068	1.068
V2 (p.u)	0.95	1.1	1.055	1.058	1.058	1.054	1.016	1.050	0.950	1.005	1.057
V5 (p.u)	0.95	1.1	1.031	1.092	1.035	1.038	1.032	1.093	1.032	1.091	1.065
V8 (p.u)	0.95	1.1	1.100	1.048	1.070	1.095	1.087	1.066	1.093	1.058	1.039
V11 (p.u)	0.95	1.1	1.099	1.079	1.095	1.098	1.100	1.024	1.100	1.097	1.091
V13 (p.u)	0.95	1.1	1.094	1.037	1.043	1.063	1.059	1.050	1.075	1.092	1.066
QTG1 (MVar)	-20	150	-16.277	10.036	-2.088	-3.725	22.058	-20.000	12.182	7.695	-8.728
QTG2 (MVar)	-20	60	17.783	-20.000	13.481	4.400	-20.000	60.000	-20.000	-20.000	9.480
QTG3 (MVar)	-15	40	22.698	35.000	21.737	25.825	35.000	35.000	35.000	35.000	35.000
Qws1 (MVar)	-30	35	40.000	40.000	40.000	40.000	40.000	15.119	40.000	40.000	31.006
Qws2 (MVar)	-25	30	28.005	29.995	29.503	29.238	20.513	11.376	26.087	28.311	27.010
Qss (MVar)	-20	25	25.000	20.886	13.131	20.254	14.315	25.000	25.000	25.000	21.709
Fuel vlv cost (\$/h)			543.344	434.855	432.011	426.933	404.641	447.764	575.235	427.552	424.103
Wind Gen Cost (\$/h)			178.494	259.762	255.563	269.380	280.885	464.630	199.230	252.389	261.453
Solar Gen Cost (\$/h)			91.339	99.660	105.390	96.515	143.064	45.340	64.387	114.284	107.317
Total Cost (\$/h)			813.178	810.710	810.567	810.886	812.388	829.874	812.164	810.397	810.091
Emission (t/h)			0.911	0.918	0.899	0.903	0.900	0.891	0.893	0.896	0.870
Carbon Tax (\$/h)			17.83	17.83	17.83	17.83	17.83	17.83	17.83	17.83	17.83
Ploss (MW)			6.055	5.373	5.320	5.265	4.533	4.770	6.215	5.433	5.301
VD (p.u.)			0.560	0.501	0.444	0.503	0.471	1.922	0.417	0.542	0.498

Table 6. Simulation results from the literature show that several algorithms are used for Case 2.

Control Variables	BWOA	FPA	ABC	CGO	MSA	SMA	ESMA	SHADE SF	GPC	JS	LOBL-BA
PTG1 (MW)	123.939	124.133	123.458	123.742	123.046	123.559	123.418	123.525	124.003	123.572	123.090
PTG2 (MW)	31.558	34.226	33.069	33.684	31.947	32.704	32.899	33.047	34.008	33.163	31.761
PTG3 (MW)	10.026	10.011	10.000	10.000	10.000	10.000	10.000	10.000	10.000	10.000	10.000
Pws1 (MW)	43.522	46.668	45.988	46.360	45.406	46.018	45.878	46.021	46.395	46.081	46.064
Pws2 (MW)	38.183	38.571	38.784	39.018	38.198	38.766	38.846	38.748	39.042	38.801	38.966
Pss (MW)	41.636	35.098	37.376	35.975	40.095	37.633	37.632	37.336	35.279	37.063	38.819
V1 (p.u)	1.077	1.070	1.070	1.072	1.068	1.069	1.071	1.071	1.070	1.071	1.068
V2 (p.u)	1.060	1.055	1.057	0.952	1.055	1.056	1.057	1.057	1.054	1.057	1.057
V5 (p.u)	1.034	1.039	1.036	1.089	1.032	1.034	1.036	1.036	1.031	1.036	1.065
V8 (p.u)	1.031	1.052	1.041	1.042	1.040	1.083	1.041	1.040	1.100	1.040	1.039

V11 (p.u)	1.073	1.096	1.098	1.100	1.099	1.100	1.099	1.099	1.087	1.098	1.091
V13 (p.u)	1.057	1.054	1.056	1.062	1.100	1.054	1.053	1.056	1.100	1.056	1.066
QTG1 (MVar)	6.942	-0.379	-2.932	13.206	-6.105	-4.149	-3.048	-2.678	-0.139	-2.667	-8.728
QTG2 (MVar)	18.604	4.146	12.273	-20.000	12.982	12.035	12.620	12.319	6.648	12.354	9.480
QTG3 (MVar)	24.443	40.000	35.685	37.716	34.599	40.000	35.902	35.270	40.000	35.254	35.000
Qws1 (MVar)	22.660	25.942	22.939	35.000	19.918	21.073	23.355	22.964	19.022	22.999	31.006
Qws2 (MVar)	22.745	28.845	30.000	30.000	29.405	30.000	30.000	30.000	25.052	30.000	27.010
Qss (MVar)	20.551	17.018	17.688	20.102	25.000	16.726	16.836	17.779	25.000	17.711	21.709
Total Cost (\$/h)	812.037	811.666	811.647	811.457	810.884	810.374	810.356	810.346	810.324	810.120	810.091
Emission (t/h)	0.913	0.923	0.888	0.902	0.867	0.893	0.886	0.891	0.916	0.894	0.870
Carbon Tax (\$/h)	20.000	18.461	17.759	18.049	20.000	20.000	20.000	17.830	18.323	17.875	17.83
Ploss (MW)	5.463	5.308	5.274	5.378	5.292	5.279	5.274	5.276	5.327	5.276	5.301

VD (p.u.)	0.451	0.466	0.469	0.500	0.539	0.467	0.464	0.469	0.507	0.469	0.498
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Table 5 displays the EED problem outcomes obtained using different algorithms. The total cost will increase with the increased integration of wind and solar power, not to mention the carbon tax levied on the emissions. LOBL-BA is better in the way of total cost, with the smallest cost of 810.091 (\$/h), and the identical emissions of 0.886 (t/h) with BA and FPA. The least performance has been relative to the AOA, which had the highest total cost of 802.573 (\$/h) and emissions of 1.886 (t/h). Figure 3 shows the curve of convergence of total cost with time elapsed in various algorithms.

Table 6 provides the simulation results from the literature for Case 2. In comparison with the literature, the LOBL-BA method performs better in terms of fuel cost, with the least fuel cost of 781.607 (\$/h) and identical emission of 1.762 (t/h), the BWOA [8] method performs the worst, with the highest fuel cost of 812.037 (\$/h) from Table 6.

6. Conclusion

The proposed Lévy Opposition-Based Learning Bat Algorithm (LOBL-BA) effectively enhanced its search capability with random inertia weight, strongly balances the exploration and exploitation with Lévy opposition-based learning, and quickly converged and improved solution accuracy, and then effectively solved the ED and EED problem by minimizing the fuel cost and total cost, covering the fuel cost and emissions along with carbon tax. The LOBL-BA effectively solved the EED with security constraints for the modified IEEE-30 bus system. LOBL-BA attained the lowest fuel cost and the lowest total cost, which includes the fuel cost, carbon tax, and emissions. In comparison to traditional approaches such as BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME, along with recently published algorithms such as BWOA, FPA, SHADE-SF, MSA, GPC, CGO, ABC, SMA, ESMA, and JS, the LOBL-BA reduces the fuel cost and total cost, which includes the fuel cost and emissions along with carbon tax, by properly integrating renewable energy sources. Therefore, LOBL-BA can be considered a powerful instrument for addressing the drawbacks of the EED issue and, therefore, accelerating the shift of the energy infrastructure toward a more geothermal-friendly model. In the future, it can be extended to solve large test systems and develop multi-objective methods to solve the same and real-world problems.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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