International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(2) 2026 pp. 1932-1961
https://doi.org/10.70917/ijcisim-2026-5111
Article

Lévy Opposition-Based Learning Bat Algorithm for Solving the Economic Load Dispatch Problem

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Abstract: This paper proposes the Lévy Opposition-Based Learning-Bat Algorithm (LOBL-BA) as a solution to the Economic Load Dispatch (ELD) problem with Valve-Point Effect (VPE) and Prohibited Operating Zones (POZ). The standard Bat Algorithm (BA) suffers from slow convergence and limited exploration, making it prone to becoming trapped in local optima. To address these limitations, three enhancements are introduced. First, a random inertia weight strategy improves search capability. Second, Lévy Opposition-Based Learning (LOBL) is incorporated to balance exploration and exploitation, enabling more effective handling of complex optimization problems. Third, a Sine Function-Driven Local Search (SFDLS) mechanism refines candidate solutions and strengthens the algorithm's ability to escape local optima. The proposed LOBL-BA is thoroughly validated on 6-unit, 13-unit, 15-unit, and 40-unit power systems. The results clearly demonstrate that it achieves significantly greater fuel cost minimization for the ELD problem with VPE and POZ, with its performance benchmarked against several established algorithms, including BA, FPA, GWO, MVO, SCA, AOA, WSO, RIME, and others from the literature. Across all test cases, the proposed algorithm consistently achieves the optimal fuel cost.

Keywords: Bat Algorithm, Random Inertia Weight, Lévy Opposition-Based Learning, Sine Function-Driven Local Search, ELD Problem with VPE and POZ

1. Introduction:

The ELD problem is a critical aspect of power generation, aiming to determine the optimal power output of multiple units within a thermal power plant to meet demand at the lowest possible cost. Its primary objective is to minimize fuel consumption while satisfying system constraints, including power generation limits, transmission losses, the Valve-Point Effect (VPE), and unit capacity restrictions. As power demand continues to rise and environmental concerns intensify, optimizing power generation has become increasingly important for improving fuel efficiency and reducing operational costs.

The Valve-Point Effect (VPE) and Prohibited Operating Zones (POZ) increase the complexity of the Economic Load Dispatch (ELD) problem by introducing nonlinearity, discontinuities, and non-convexity into the fuel cost function, reflecting real steam turbine behaviour. VPE causes abrupt cost fluctuations from cyclic valve opening, producing a multimodal cost function that is far harder to optimize than standard quadratic models. Additionally, POZs represent restricted generation ranges in which units cannot operate due to physical limitations, vibration, instability, or other operational constraints. These prohibited regions create discontinuous, disconnected feasible operating spaces and further complicate the ELD problem.

Solving ELD under VPE and POZ therefore requires advanced optimization methods capable of handling nonlinear, discontinuous search spaces. Accurately modelling these constraints is vital for efficient fuel use, reliable scheduling, and minimum costs; ignoring them risks infeasible schedules, wasted fuel, and poor system performance. This is especially important for generation companies balancing economic and environmental goals, since effective

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dispatch also supports sustainability through better resource use and lower emissions. As the energy sector evolves, addressing VPE and POZ in ELD remains key to improving the efficiency, reliability, and sustainability of modern power systems.

Despite these advances, applying VPE to the ELD problem still poses significant challenges, motivating a range of research approaches. For instance, Hassan et al. [1] proposed a hybrid method combining an enhanced MRFO with GBO to achieve cost-effective ELD solutions, achieving greater accuracy, resilience, and recovery speed than traditional algorithms. Kaur and Dhillon [2] proposed HcSCA for economic generation scheduling, improving fuel-cost minimization in nonlinear, multi-constrained systems. Farhan Tabassum et al. [3] presented ESAHJ for nonconvex ELD, showing superior robustness, convergence, and cost management versus 29 competing algorithms. Alkoffash et al. [4] introduced hybrid HSSA for nonconvex ELD, outperforming 66 algorithms across small- and high-dimensional tasks. Ramli et al. [5] applied WDO to non-convex ELD, achieving better cost and power-loss reduction than PSO, MFO, and FPA in large systems. Rizk-Allah et al. [6] proposed ETSA with dynamic perturbation, surpassing TSA, GWO, and other metaheuristics in solution quality and efficiency. Iqbal et al. [7] developed hybrid MVO-SQP to reduce fuel costs and turnaround time in non-convex ELD. Luo and Yu [8] proposed RLMCS, a reinforcement-learning-enhanced cuckoo search improving accuracy, stability, and efficiency. Fu et al. [9] introduced CCAM-PDE, offering improved accuracy, faster convergence, and greater constraint sensitivity. Bhattacharjee et al. [10] developed AEO, which is more efficient, robust, and economical than competitors, especially in reducing fuel costs and penalties via chaotic sequences. Singh [11] proposed CSMA for large-scale optimization. Vedik et al. [12] introduced DSOS, outperforming other techniques in fuel consumption, convergence, robustness, and constraint handling. Al-Betar et al. [13] presented hybrid SCA-HC, combining global exploration with local search for greater efficiency in large-scale ELD. Garg et al. [14] proposed LX-BBO, outperforming conventional and nature-inspired methods in minimizing fuel cost while improving convergence and robustness for constrained ELD.

Recent ELD research has produced numerous improved algorithms. Liu et al. [15] developed an Enhanced Sine Cosine Algorithm that outperforms SCA and WOA. Al-Betar et al. [16] combined Harris Hawks Optimizer with Adaptive B-Hill Climbing, improving cost reduction and efficiency in complex ELD problems. Hassan et al. [17] proposed a hybrid global-local search algorithm that reduced costs below traditional methods; later, Hassan et al. [18] presented an improved Beluga Whale Optimization algorithm effective for large, constrained ELD problems. Yu et al. [19] introduced an antigravity-based fuzzy gravitational search algorithm balancing exploration and exploitation for complex constraints. Braik et al. [20] developed an Enhanced Chameleon Swarm Algorithm that improves exploration and avoids local optima in large, non-convex problems. Luo et al. [21] proposed ET-PDA, an event-triggered algorithm for smart grid dispatch with proven linear convergence. Seyed Garmroudi et al. [22] presented an enhanced Pelican Optimization Algorithm for large-scale dispatch optimization. Hassan et al. [23 – 24] further introduced ESNS for constrained fuel-cost minimization and LWSO, a White Shark Optimizer variant with leadership-based mutation for faster convergence. Calin and Liana [25] proposed a small-group social algorithm with superior stability and speed in large systems. Alawad et al. [26] developed a Hybrid Snake Optimizer with Dynamic Polynomial Mutation and Oppositional-Mutual Learning for faster, more stable convergence. Basetti et al. [27] introduced QOHBO, an adapted heap-based optimizer with greater cost reduction and speed. Patty et al. [28] proposed SMP-JaQA, a self-adaptive Jaya variant offering lower costs and high robustness. Finally, Spea [29] presented MRFO variants incorporating OBL and generation jumping, improving cost and constraint management over conventional MRFO.

ELD problem with VPE and POZ is fundamental to cost-effective power generation while reliably meeting electricity demand. By determining the most economical generation schedule across multiple units, it minimizes operating costs and fuel use, promoting efficient resource utilization and environmental sustainability through reduced emissions. Given the problem's complexity and nonlinearity, metaheuristic algorithms are widely used to obtain near-optimal solutions among them, the Bat Algorithm (BA) [30], inspired by bat echolocation, noted for its strong search performance. Recent research has produced several improved BA variants. This paper introduces three complementary strategies, namely Random Inertia Weight (RIW), Lévy Opposition-Based Learning (LOBL), and Sine Function-

Driven Local Search (SFDLS), which work together to refine candidate solutions, strengthen the algorithm's capacity to escape local optima, and improve overall convergence performance.

The main contributions of this work are as follows:

- A Random Inertia Weight mechanism is introduced to balance exploration and exploitation within the algorithm.
- A Lévy OBL strategy is proposed to improve the exploration-exploitation trade-off, accelerating convergence and enhancing solution accuracy and robustness.
- A Sine Function-based Local Search is employed to refine solutions and enhance global convergence toward high-quality results.

The ELD problem is formulated with ramp rate limits and prohibited operating zones.

The remainder of the article is organized as follows: Section 2 discusses the ELD problem; Section 3 presents the Bat Algorithm; Section 4 introduces the proposed Lévy-based OBL Bat Algorithm; Section 5 covers the simulation experiments and result analysis; and Section 6 concludes the article and outlines directions for future work.

2. ELD Problem

Solving the ELD problem requires minimizing fuel costs while satisfying a set of operational constraints, including both equality and inequality constraints. Accordingly, the objective function is formulated to minimize fuel cost subject to these constraints.

2.1. Objective Function (OF)

The objective is to determine the most efficient power schedule that satisfies demand at minimum cost. Accordingly, the objective function representing the fuel cost F(P) can be expressed as follows:

$$F(P) = \sum_{i=1}^{ng} a_i P_i^2 + b_i P_i + c_i \ \ (\$/h) \tag{1}$$

where ng is the total number of generators; P_i is the generating capacity of the generator set i; a_i, b_i, and c_i are the cost coefficient of the generator set i.

In practical applications, valve-point effects (VPEs) must also be taken into account; accordingly, the fuel cost function is defined as follows [17]:

$$F(P) = \sum_{i=1}^{ng} \left(a_i P_i^2 + b_i P_i + c_i\right) + \left|e_i \times \sin\left(f_i \times \left(P_i^{min} - P_i\right)\right)\right| \ \ (\$/h) \tag{2}$$

where e_i and f_i are cost coefficient of the generator set i, P_i^{min} is the minimum power generation.

2.2. Constraints Processing

In solving ELD problems, the optimization process must satisfy several equality and inequality constraints [15].

2.2.1. Equality (Power Balance) Constraint

The power balance constraint requires that total power generation, minus transmission losses, equal the load demand, expressed mathematically as:

$$\sum_{i=1}^{ng} P_i + P_D + P_L = 0 \tag{3}$$

where P_D is the total power demand, and P_L is the total power losses.

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \quad (4)$$

where B_{ij}, B_{0i}, and B_{00} are the loss coefficients

2.2.2. Inequality (Generator Power) Constraints

Each thermal generating unit's output power is bounded by upper and lower limits and must remain within this range, expressed mathematically as:

$$P_i^{min} \leq P_i \leq P_i^{max} \quad (5)$$

where, P_i, P_i^{min} and P_i^{max} are the output power, minimum and maximum allowable power generation of the ith generator, respectively.

2.2.3 Ramp Rate Limits

Ramp rate limits ensure stable operation by preventing instantaneous changes in Ramp rate limits ensure stable operation by preventing instantaneous changes in generation. In the ELD problem, they ensure that power adjustments stay within the generator's operational capabilities.

$$P_i - P_i^0 \leq UR_i \; and \; P_i^0 - P_i \leq DR_i \quad (6)$$

where "P_i^0, and P_i are the previous and current power outputs, UR_i and DR_i are the upper and lower limits of the generator i, respectively" [17]. From equations (5) and (6), the ramp rate limits are expressed as follows:

$$max(P_i^{min}, P_i^0 + UR_i) \leq P_i \leq \; max(P_i^{max}, P_i + UR_i) \quad (7)$$

2.2.4 Prohibited Operating Zones (POZs)

Prohibited operating zones (POZs) are typically excluded from the feasible operating range in the ELD problem to ensure optimal and reliable generator performance; accordingly, each unit's output power must fall outside these zones. The mathematical model of the POZs is given as follows [17]:

$$P_i^{min} \leq \; P_i \leq P_{i,1}^l \qquad P_{i,k-1}^u \leq \; P_i \leq P_{i,k}^l, k = 2, \ldots, pz_i \; P_{i,pz_i}^u \leq \; P_i \leq P_{i,1}^{max} \quad (8)$$

where $P_{i,1}^l$ and $P_{i,k}^u$ are the min and max limits of the k^{th} POZ of unit i, respectively, k is the index of POZs (pz_i).

3. Bat Algorithm

The Bat Algorithm (BA), developed by Xin-She Yang [30], is inspired by the echolocation behaviour of microbats. Bats use echolocation to detect prey, avoid obstacles, and locate their roosts in darkness: while hunting, they emit sound pulses and interpret the returning echoes to judge the size and distance of prey and navigate around obstructions. As they approach their target, they reduce the pulse loudness while increasing its frequency. This behaviour can be modelled to optimize objective functions, forming the basis of the BA optimization framework, which relies on three key parameters frequency (f), loudness (A), and pulse rate (r) applied across global and local search phases.

BA operates as a continuous, iterative process in which each bat's velocity and position are updated at every step, with each bat's position vector representing a candidate solution within the search space. Since the global optimum is unknown in advance, bats are initialized at random positions. The initialization is defined as follows [30]:

$$x_{i,j} = x_{lb} + (x_{ub} - x_{lb}) * rand \tag{9}$$

where i=1,2, ..., n; n denotes population size, j = 1, 2, ..., 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 [30]:

$$f_i = f_{min} + (f_{max} - f_{min})\beta \tag{10}$$

$$V_i^{it} = V_i^{it-1} + \left(X_i^{it} - X^*\right) * Q_i \tag{11}$$

$$X_i^{it} = X_i^{it-1} + V_i^{it} \tag{12}$$

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]:

$$X_{new} = X_{old} + \varepsilon A^{it} \tag{13}$$

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:

$$A^{it} = < A^{it} > \tag{14}$$

$$A^{it+1} = \alpha A_o^{it} \tag{15}$$

$$r_o^{it+1} = r_i^o\left(1 - exp(-\gamma \times it)\right) \tag{16}$$

$$A^{it+1} = \alpha A_o^{it} \tag{17}$$

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 governs the balance between exploration and exploitation by modulating the velocity magnitude ω. The revised equation is presented below [31]:

$$\omega = \omega_{max} - \omega_{min} * \frac{(it_{max} - it)}{A * it_{max}} + \omega_{min} * R \tag{18}$$

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

$$V_i^{it} = \omega * V_i^{it-1} + \left(X_i^{it} - X^*\right) * Q_i$$
(19)

$$X_i^{it} = X_i^{it-1} + V_i^{it}$$
(20)

4.2. Lévy Opposition-Based Learning

Many metaheuristic algorithms (MAs) initialize their solutions entirely at random. Convergence is fast when these starting solutions lie close to the global optimum but slow otherwise, underscoring the need to substantially reduce convergence time. To address this, Tizhoosh [32] introduced Opposition-Based Learning (OBL) to Mas an efficient strategy that enhances their problem-solving performance. The mathematical representation of OBL is as follows:

$$X_{op} = lb + ub - X \tag{21}$$

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

Opposite solutions may converge toward a local optimum as optimization progresses, causing other individuals to converge toward the same region and resulting in premature convergence and reduced solution accuracy. To address this issue, W. Long [33] modified OBL by introducing a random value into Equation (38), as follows:

$$X_{rop} = lb + ub - rand * X \tag{22}$$

where X_{rop} 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 (39) as follows:

$$X_{lop} = lb + ub - L\acute{e}vy(d) \cdot\!* X$$
(23)

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, once a solution is selected from the current position, a new position for each bat is generated locally through a random walk based on a sine function, as follows:

$$X = X + rand_1 * sin(rand_2 - 0.5) \cdot\!* A$$
(24)

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.

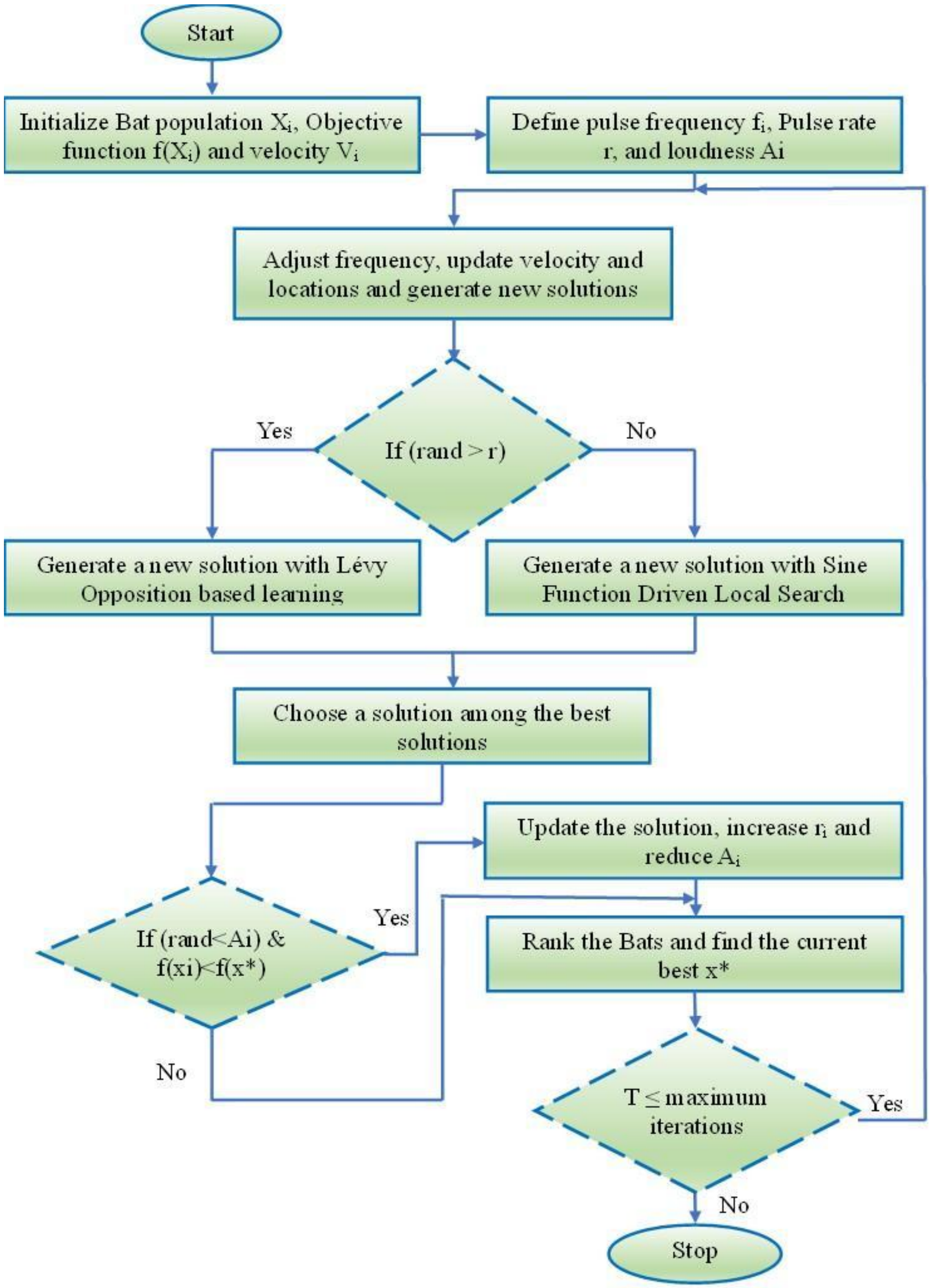

Figure 1. Flow Chart of LOBL-BA.

5. Results and Discussions

The proposed LOBL-BA was applied to ELD problems to demonstrate its superior performance across multiple aspects. For fair comparison, all algorithms were run for a maximum of 500 iterations with a population size of 50, across 30 independent runs, using MATLAB R2024a on a PC equipped with an 11th Gen Intel Core i5-11300H @ 3.10GHz processor and 8 GB RAM.

To evaluate LOBL-BA's performance on the ELD problem, it was tested on four systems 6-unit, 13-unit, 15-unit, and 40-unit with demands of 1263 MW, 1800 MW, 2630 MW, and 10500 MW, respectively [17]. Spanning small- to large-scale power systems, these test cases demonstrate the algorithm's effectiveness across varying problem sizes.

5.1. Case 1

In this case, the proposed LOBL-BA, along with BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME algorithms are used to address the ELD problem for a 6_unit test system with a load demand of 1263 MW. The cost coefficients with ramp rate limits, POZ and power losses, were obtained from [17].

Table 1: The results attained by LOBL-BA and other algorithms for case 1.

Units (MW)	**BA**	**FPA**	**GWO**	**MVO**	**SCA**	**AOA**	**WSO**	**RIME**	**LOBL-BA**
PG1	441.569	452.162	444.928	453.533	439.895	441.138	445.854	450.207	450.066
PG2	170.513	171.595	172.685	177.24	171.921	168.773	177.581	174.318	171.98
PG3	257.864	262.527	265	265	265	265	261.049	265	265
PG4	144.384	141.281	144.385	131.218	138.942	142.44	140.673	135.589	137.559
PG5	170.187	162.816	160.889	166.422	167.675	167.317	162.964	166.249	166.42
PG6	90.6802	84.9043	87.3269	82.0471	91.8912	90.6299	87.0555	83.9941	84.2549
TPG	1275.2	1275.28	1275.21	1275.46	1275.32	1275.3	1275.18	1275.36	1275.28
TPL	12.1982	12.2845	12.2145	12.4598	12.3244	12.2983	12.1761	12.3565	12.2804
TC ($/h)	15441.9	15442	15442.3	15442.3	15442	15442.4	15440.7	15441.1	15440.4

* TPG is total power generation, TPL is total power losses, TC is total cost.

Table 1 displays the total costs for case 1 using the proposed LOBL-BA, along with BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME. LOBL-BA exhibits the best performance, with the lowest total cost of 15,440.419 $/h and the lowest average cost of 15,441.724 $/h, indicating optimal cost efficiency; on the other hand, AOA shows the worst performance with the highest total cost of 15,442.439 $/h this indicates that AOA incurs the highest expenses, making it the least cost-efficient algorithm, and the BA shows the highest average cost of 15,448.267 $/h in this regards BA not able provide consistent results.

Table 2 presents the results attained by LOBL-BA and from the literature includes GA, CBA, PSO, NPSO-LRS, MABC, MSSA, ST-IRDPSO, DEa, DEb, MCSA, HHS, SOH-PSO, MTS, SDO, ESSDO, ESCSDO10, and HGS. Table 2 emphasizes the significant performance of LOBL-BA and other established algorithms in optimizing the generating units. In a direct comparison with other recently published methods, such as GA, CBA, PSO, NPSO-LRS, MABC, MSSA, ST-IRDPSO, DEa, DEb, MCSA, HHS, SOH-PSO, MTS, SDO, ESSDO, ESCSDO10, HGS, the LOBL-BA algorithm stands out, achieving the lowest fuel cost of 15,440.419 $/h and the lowest average cost of 15,441.724 $/h.

Table 2: The results attained by LOBL-BA and existing algorithms in the literature for case 1.

Methodology	PG1	PG2	PG3	PG4	PG5	PG6	TPL	Total Cost ($/h)
GA [34]	474.807	178.636	262.209	134.283	151.904	74.1812	13.0217	15459.0000
CBA [35]	447.419	172.826	264.076	139.247	165.653	86.7652	12.984	15450.2381
PSO [34]	447.497	173.322	263.475	139.059	165.476	87.128	12.9584	15450.0000
NPSO-LRS [36]	446.96	173.394	262.344	139.512	164.709	89.0162	12.9361	15450.0000
MABC [37]	447.504	173.319	263.462	139.065	165.473	87.135	12.9582	15449.8995
MSSA [38]	447.503	173.319	263.463	139.066	165.473	87.1349	12.958	15449.8995
ST-IRDPSO [39]	447.513	173.298	263.467	139.036	165.484	87.1605	12.958	15449.8945
DEa [40]	447.744	173.407	263.411	139.076	165.364	86.944	12.957	15449.7660
DEb [41]	448.27	172.96	263.44	139.3	165.28	86.68	12.98	15449.5826
MCSA [42]	444.637	174.641	265	139.225	165.712	86.6807	12.9576	15449.1672
HHS [43]	447.496	173.314	263.445	139.055	165.475	87.125	12.95	15449.0000
SOH-PSO [44]	438.21	172.58	257.42	141.09	179.37	86.88	12.55	15446.0200
MTS [45]	448.128	172.808	262.593	136.961	168.203	87.3304	13.0205	15450.0600
SDO [17]	446.727	173.145	262.788	143.492	163.921	85.3497	12.422	15444.1863
ESSDO [17]	446.712	173.152	262.792	143.49	163.911	85.3656	12.4219	15444.1863
ESCSDO10 [17]	446.712	173.145	262.802	143.491	163.918	85.3543	12.422	15444.1863
HGS [17]	446.744	174.251	261.785	143.833	162.069	86.7068	12.3885	15444.2596
BA	441.5695	170.5133	257.8641	144.3841	170.1870	90.6802	12.1982	15441.8583
FPA	452.1619	171.5947	262.5272	141.2806	162.8158	84.9043	12.2845	15442.0074
GWO	444.9280	172.6853	265.0000	144.3848	160.8894	87.3269	12.2145	15442.2894

MVO	453.5327	177.2397	265.0000	131.2183	166.4221	82.0471	12.4598	15442.3465
SCA	439.8949	171.9213	265.0000	138.9422	167.6747	91.8912	12.3244	15441.9824
AOA	441.1380	168.7733	265.0000	142.4397	167.3174	90.6299	12.2983	15442.4388
WSO	445.8539	177.5806	261.0491	140.6730	162.9639	87.0555	12.1761	15440.6906
RIME	450.2065	174.3178	265.0000	135.5893	166.2488	83.9941	12.3565	15441.1287
LOBL-BA	450.0664	171.9798	265.0000	137.5594	166.4200	84.2549	12.2804	15440.4190

DEa refers to [43] and DEb refers to [44] references respectively.

Table 3: Statistical results for LOBL-BA vs. existing algorithms from the literature, Case 1.

Methodology	**Best**	**Worst**	**Avg**	**Std**
GA [34]	15,459	15,524	15,469	NR
CBA [35]	15,450.24	15,518.66	15,454.76	2.965
PSO [34]	15,450	15,492	15,454	NR
NPSO-LRS [36]	15,450	15,454	15,452	NR
MABC [37]	15,449.90	15,449.90	15,449.90	6.04E-8
MSSA [38]	15,449.90	15,453.55	15,449.94	0.3647
ST-IRDPSO [39]	15,449.89	NR	15,450.70	1.416
DEa [40]	15,449.77	15,449.87	15,449.78	NR
DEb [41]	15,449.58	15,449.65	15,449.62	NR
MCSA [42]	15,449.17	15,449.39	15,449.24	0.2681
HHS [43]	15,449.00	15,453.00	15,450.00	NR
SOH-PSO [44]	15,446.02	15,609.64	15,497.35	NR
MTS [45]	15,450.06	15,453.64	15,451.17	NR
GAAPI [49]	15449.78	15449.85	15449.81	NR
DE [40]	15449.766	15449.777	15449.874	NR
Jaya [46]	15446.5675	15573.5151	15489.7034	13.3122
Jaya-M [46]	15446.0196	15498.5242	15464.8797	10.9328
Jaya-SM [46]	15445.8001	15468.923	15459.4744	8.4657
Jaya-SML [46]	15445.1682	15450.6497	15447.291	6.2214
SA [45]	15461.1	15545.5	15488.98	28.3678
TS [45]	15454.89	15498.05	15472.56	13.7195
SSGA [47]	15,447	15,470	15,450	7.458

FA [48]	15450.509	15458.4427	15452.531	2.048
CMFA [48]	15449.8994	15449.8994	15449.8994	8.96E-06
SDO [17]	15444.18631	15444.18633	15444.18632	3.42E-06
ESSDO [17]	15444.18631	15444.18632	15444.18632	3.04E-06
ESCSDO10 [17]	15444.18631	15444.18632	15444.18632	4.03E-06
BA	15441.8583	15460.6939	15448.2674	5.56E+00
FPA	15442.0074	15454.6974	15443.6036	3.07E+00
GWO	15442.2894	15445.8313	15443.9932	1.03E+00
MVO	15442.3465	15447.1438	15444.3589	1.17E+00
SCA	15441.9824	15447.4280	15443.6133	1.13E+00
AOA	15442.4388	15447.0795	15444.4985	1.14E+00
WSO	15440.6906	15444.1666	15442.3599	9.55E-01
RIME	15441.1287	15451.0057	15444.1471	2.09E+00
LOBL-BA	15440.4190	15443.5727	15441.7240	9.01E-01

DE[a] refers to [40] and DEb refers to [41] references respectively.

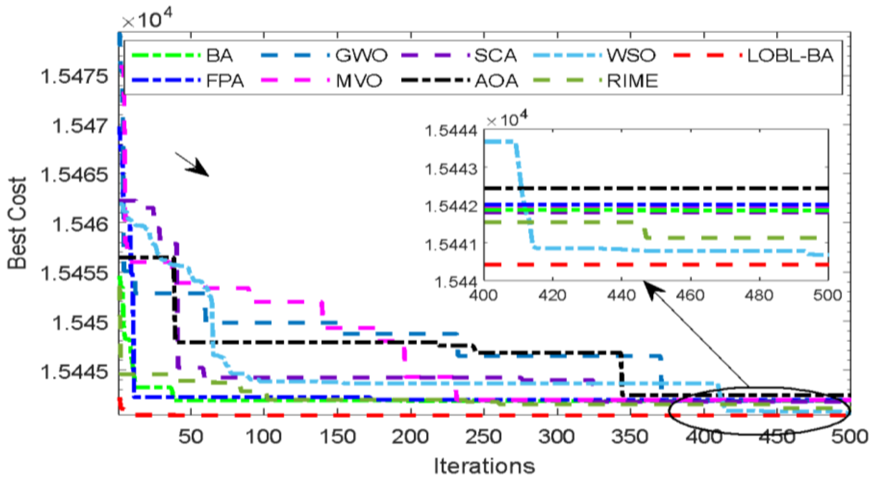

Figure 2(a): Convergence of different algorithms for a case 1.

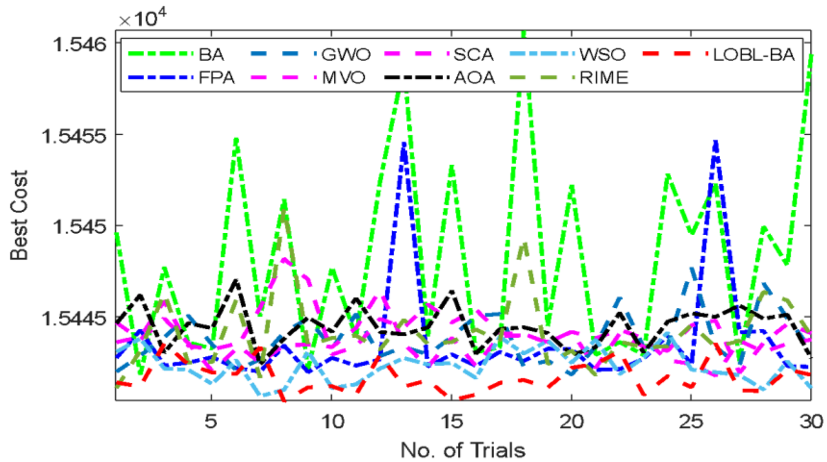

Figure 2(b): Fuel cost results from various algorithms over 30 trials for a case 1.

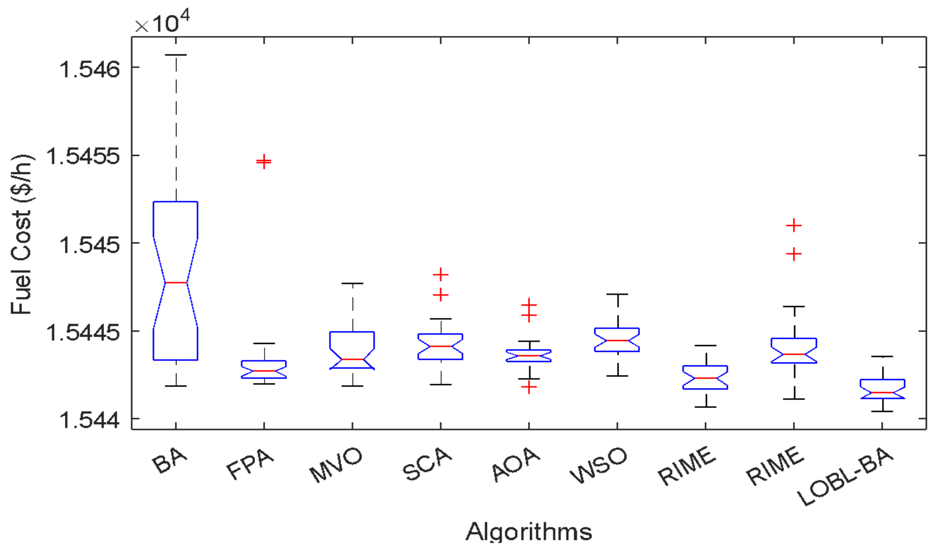

Figure 2(c): Box plot of fuel cost ($/h) for different algorithms for a case 1.

Table 3 presents the statistical results attained by LOBL-BA and existing algorithms in the literature across on 30 independent runs. The findings suggest that the LOBL-BA algorithm exhibits the most robust stability, as LOBL-BA attained the lowest Std. Dev., value of 9.01E-01, compared to BA, PSO, DE, GWO, MVO, SCA, AOA, WSO, and RIME, and other recently published methods like GA, CBA, PSO, NPSO-LRS, MSSA, ST-IRDPSO, DEa, DEb, MCSA, HHS, SOH-PSO, MTS, SDO, ESSDO, ESCSDO10, and HGS. The MABC has the lowest Std. Dev. i.e., 6.04E-8, which is lower than the LOBL-BA Std. Dev. i.e., 9.01E-01, even though MABC is not able to find a global solution. The LOBL-BA demonstrates superior effectiveness in resolving the ELD problem. Figure 2(a) illustrates the reduction in total cost over time for different optimization algorithms. Figure 2(b) presents the total cost results from 30 trials, while Figure 2(c) shows a box plot of total cost for various algorithms.

5.2. Case 2

In this case, the proposed LOBL-BA, along with BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME algorithms are used to address the ELD problem for a 13_unit test system with a load demand of 1800 MW. The fuel cost coefficients with valve-point effects and without power losses, were obtained from [17].

Table 4 displays the total and average costs for case 2 using the proposed LOBL-BA, along with BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME. LOBL-BA exhibits the best performance, with the lowest total cost of

17,988.174 $/h and the lowest average cost of 18,024.344 $/h, indicating optimal cost efficiency; on the other hand, AOA shows the worst performance with the highest total cost of 18,056.017 $/h this indicates that AOA incurs the highest expenses, making it the least cost-efficient algorithm, and the GWO shows the highest average cost of 18,141.711 $/h in this regards GWO not able provide consistent results.

Table 5 presents the results attained by LOBL-BA and from the literature includes SDO, ESSDO, ESCSDO10, HGS, TLBO, and NN-EPSO. Table 5 emphasizes the significant performance of LOBL-BA and other established algorithms in optimizing the generating units. In a direct comparison with other recently published methods, such as SDO, ESSDO, ESCSDO10, HGS, TLBO, and NN-EPSO, the LOBL-BA algorithm stands out, achieving the lowest fuel cost of 17,988.174 $/h and the lowest average cost of 18,024.344 $/h.

Table 6 presents the statistical results attained by LOBL-BA and existing algorithms in the literature across on 30 independent runs. The findings suggest that the LOBL-BA algorithm exhibits the most robust stability, as LOBL-BA attained the lowest Std. Dev., value of 15.41, compared to BA, PSO, DE, GWO, MVO, SCA, AOA, WSO, and RIME, and other recently published methods like SDO, ESSDO, ESCSDO10, HGS, TLBO, and NN-EPSO. The LOBL-BA demonstrates superior effectiveness in resolving the ELD problem. Figure 3(a) illustrates the reduction in total cost over time for different optimization algorithms. Figure 3(b) presents the total cost results from 30 trials, while Figure 3(c) shows a box plot of total cost for various algorithms.

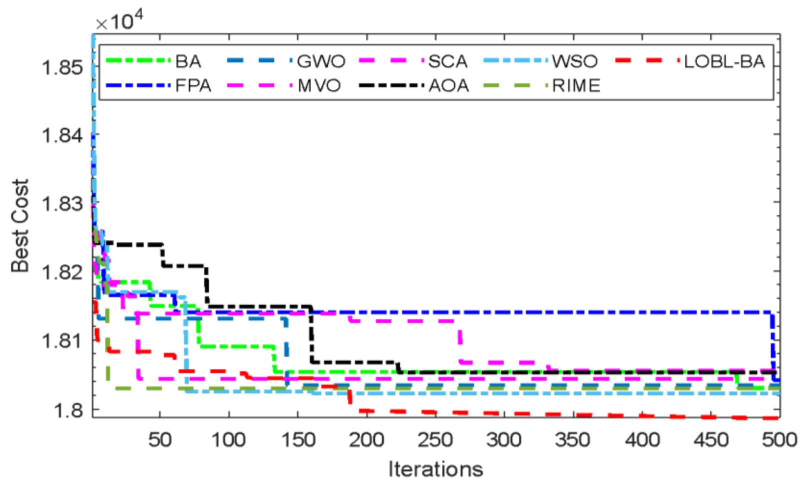

Figure 3(a): Convergence of different algorithms for a case 2.

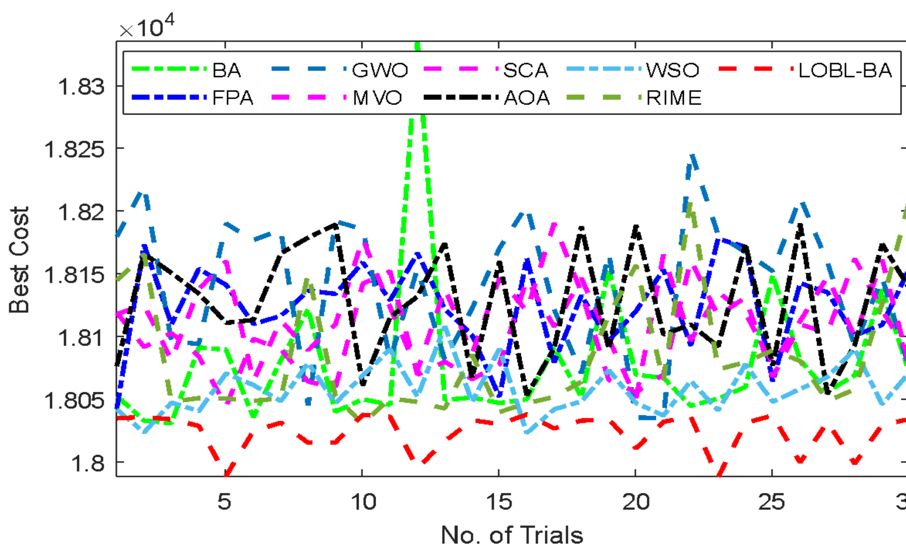

Figure 3(b): Fuel cost results from various algorithms over 30 trials for case 2.

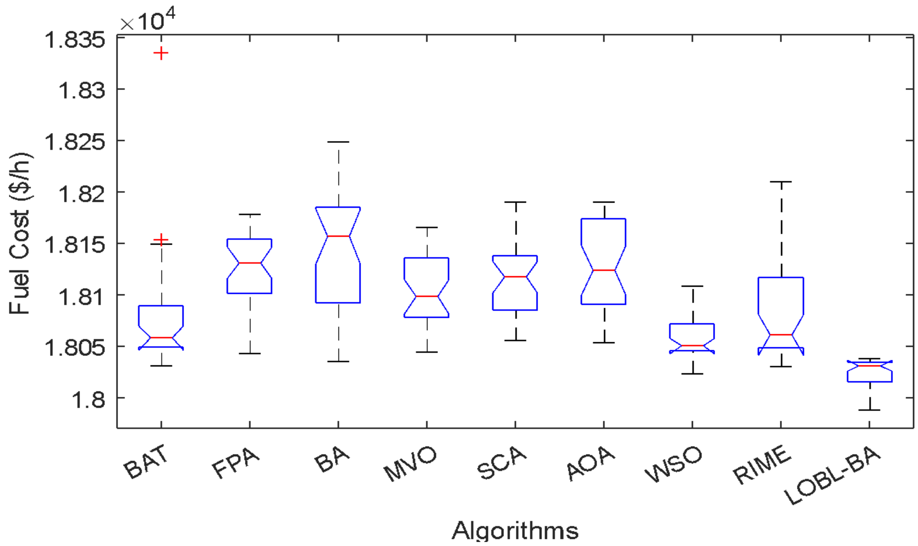

Figure 3(c): Box plot of fuel cost ($/h) for different algorithms for a case 2.

Table 4: The results attained by LOBL-BA and other algorithms for case 2.

Units (MW)	**BA**	**FPA**	**GWO**	**MVO**	**SCA**	**AOA**	**WSO**	**RIME**	**LOBL-BA**
PG1	626.4039	718.4542	481.6216	717.9211	807.3192	722.4649	628.6269	717.9901	628.1919
PG2	221.6003	230.4659	45.4723	223.4587	292.7333	227.1055	295.4839	224.6253	224.3917
PG3	299.2941	301.0798	320.9015	308.6201	149.9476	300.4296	226.3622	307.3846	298.4509
PG4	60	60	76.05288	60	60	60	159.52698	60	158.9653
PG5	60	60	131.42098	60	60	60	60	60	60.000022
PG6	60	60	139.44053	60	60	60	60	60	60.00003
PG7	110.00524	60	77.256837	60	60	60	60	60	60
PG8	60	60	120.74961	60	60	60	60	60	60
PG9	112.69638	60	63.733598	60	60	60	60	60	60
PG10	40	40	110.2322	40	40	40	40	40	40
PG11	40	40	61.121561	40	40	40	40	40	40.000175

PG12	55	55	78.418592	55	55	55	55	55	55
PG13	55	55	93.577802	55	55	55	55	55	55
TPG	1800	1800	1800	1800	1800	1800	1800	1800	1800
TC ($/h)	18031.296	18042.882	18035.43	18044.635	18056.017	18053.536	18023.471	18030.545	17988.1741

Table 5: The results attained by LOBL-BA and existing algorithms in the literature for case 2.

Units (MW)	**SDO [17]**	**ESSDO [17]**	**ESCSDO10 [17]**	**HGS [17]**	**TLBO [50]**	**LOBL-BA**
PG1	448.799	448.799	538.5587	360.8537	448.7988	628.1919
PG2	152.9354	152.9302	75.6427	360	224.6004	224.3917
PG3	224.3995	224.4018	224.3995	224.4438	149.6106	298.4509
PG4	159.7331	109.8673	109.8666	180	109.8659	158.9653
PG5	60.00013	109.8665	109.8666	129.6487	109.8664	60.000022
PG6	159.7331	109.8668	109.8666	60	109.8891	60.00003
PG7	109.8665	159.7331	109.8666	112.2345	109.8607	60
PG8	109.8669	109.8665	109.8666	60	109.8962	60.0000
PG9	109.8666	109.8688	109.8666	60	109.9019	60
PG10	40.00002	40.00002	40	40	77.3953	40
PG11	77.39991	40.00002	77.39996	40	77.4043	40.000175
PG12	55	92.39986	92.39991	117.8193	92.4209	55
PG13	92.39992	92.40009	92.39991	55	70.4896	55
TPG	1800.00008	1799.9999	1800.00028	1800	1800	1800
TPL	0.00008	-0.00001	0.00028	0	0	0
Total Cost ($/h)	18041.4861	18028.5646	18028.1888	18552.1857	18115.0000	17988.1741

Table 6: Statistical results for LOBL-BA vs. existing algorithms from the literature for case 2.

Methodology	**Best**	**Worst**	**Avg**	**Std**
SDO [17]	18041.4900	18160.1800	18092.7900	26.0367
ESSDO [17]	18028.5600	18186.7000	18090.5000	32.1778
ESCSDO10 [17]	18028.1900	18184.3500	18106.8700	40.5607
HGS [17]	18552.1900	19091.2600	18816.5000	179.7230
BA	18031.2958	18335.0925	18078.9113	58.5607
FPA	18042.8818	18178.3729	18125.0819	35.6043
GWO	18035.4302	18248.4004	18141.7109	58.1798
MVO	18044.6350	18165.5588	18103.0617	34.1707

SCA	18056.0167	18190.5912	18114.9650	35.8607
AOA	18053.5364	18190.2854	18127.3698	45.4596
WSO	18023.4708	18108.7544	18058.8079	20.4756
RIME	18030.5448	18210.2179	18084.8712	50.9628
LOBL-BA	17988.1741	18038.2528	18024.3439	15.4117

5.3. Case 3

In this case, the proposed LOBL-BA, along with BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME algorithms are used to address the ELD problem for a 15_unit test system with a load demand of 2630 MW. The fuel cost coefficients, POZ, ramp-rate limits, and power losses, were obtained from [17].

Table 7 displays the total and average costs for case 3 using the proposed LOBL-BA, along with BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME. LOBL-BA exhibits the best performance, with the lowest total cost of 32,681.615 $/h and the lowest average cost of 32,682.492 $/h, indicating optimal cost efficiency; on the other hand, SCA shows the worst performance with the highest total cost of 32,723.591 $/h this indicates that AOA incurs the highest expenses, making it the least cost-efficient algorithm, and the RIME shows the highest average cost of 32,845.295 $/h in this regards RIME not able provide consistent results.

Table 8 presents the results attained by LOBL-BA and from the literature includes SDO, ESSDO, ESCSDO10, HGS, APSO, CPSO2, EO, and EO-SCA. Table 8 emphasizes the significant performance of LOBL-BA and other algorithms in optimizing the generating units. In a direct comparison with other recently published methods, such as SDO, ESSDO, ESCSDO10, HGS, APSO, CPSO2, EO, and EO-SCA, the LOBL-BA algorithm stands out, achieving the lowest fuel cost of 32,681.615 $/h and the lowest average cost of 32,682.492 $/h.

Table 9 presents the statistical results attained by LOBL-BA and existing algorithms in the literature across on 30 independent runs. The findings suggest that the LOBL-BA algorithm exhibits the most robust stability, as LOBL-BA attained the lowest Std. Dev., value of 0.708, compared to BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME, and other recently published methods like IAEDP, Jaya-M, Jaya-SM, Jaya-SML, TS, DSPSO-TS, BF-NM, SDO, ESSDO, ESCSDO10, and HGS. HGS. The TLBO has the lowest Std. Dev. i.e., 0.0000, which is lower than the LOBL-BA Std. Dev. i.e., 0.7080, even though TLBO is not able to find a global solution. The Std. Dev. of TLBO is the lowest among the compared algorithms, followed in increasing order by CCSO, then GABC. The LOBL-BA demonstrates superior effectiveness in resolving the ELD problem. Figure 4(a) illustrates the reduction in total cost over time for different optimization algorithms. Figure 4(b) presents the total cost results from 30 trials, while Figure 4(c) shows a box plot of the objective function for various algorithms.

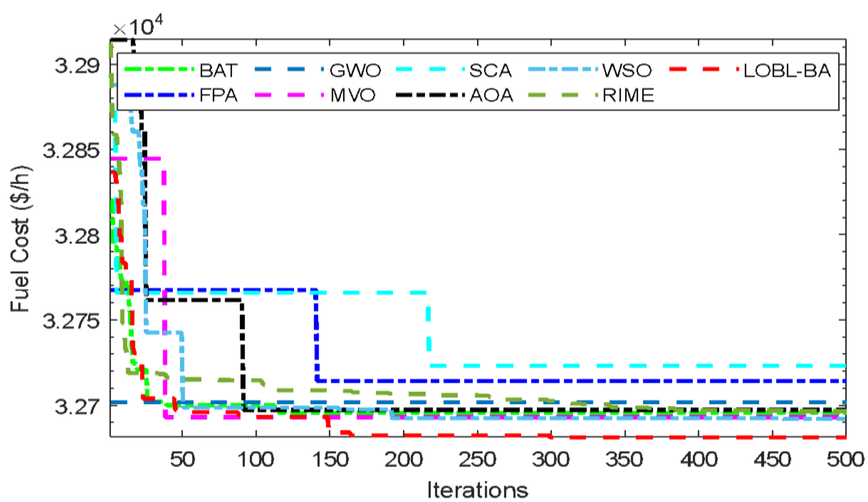

Figure 4(a): Convergence of different algorithms for a case 3.

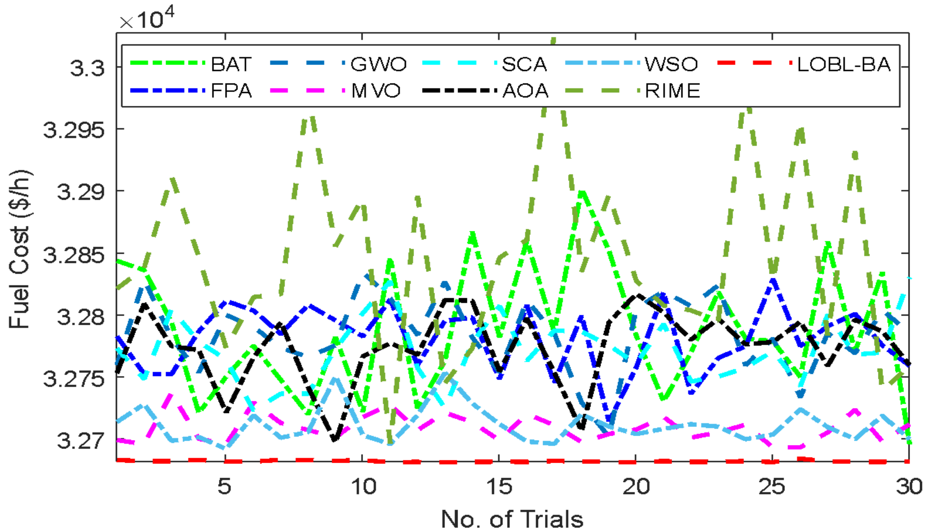

Figure 4(b): Fuel cost results from various algorithms over 30 trials for case 3.

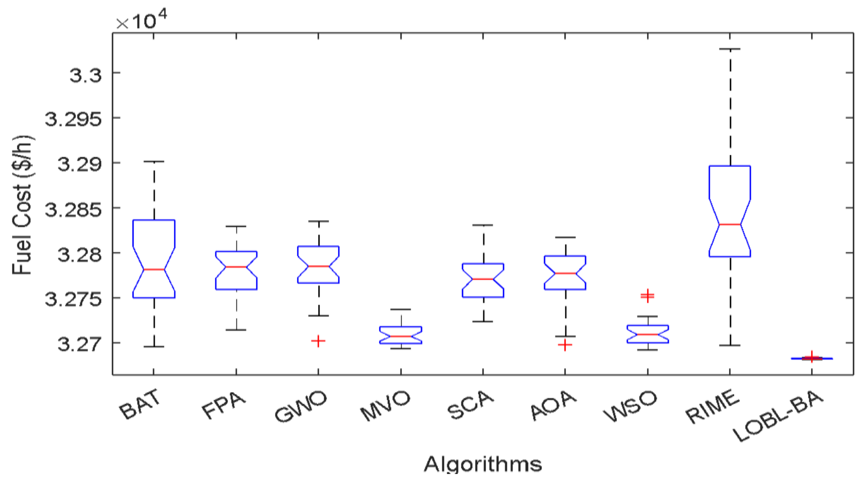

Figure 4(c): Box plot of fuel cost ($/h) for different algorithms for a case 3.

Table 7: The results attained by LOBL-BA and other algorithms for case 3.

Units (MW)	**BA**	**FPA**	**GWO**	**MVO**	**SCA**	**AOA**	**WSO**	**RIME**	**LOBL-BA**
PG1	454.9410	448.2650	454.9410	454.4806	452.8245	453.0137	454.9745	454.9976	454.8719
PG2	380	380	380	380	380	380	380	380	380
PG3	130	130	130	130	130	130	130	130	130
PG4	130	130	130	130	130	130	130	130	130
PG5	170	170	170	170	170	170	170	170	170
PG6	460	460	460	460	460	460	460	460	460

PG7	430	430	430	430	430	430	430	430	430
PG8	104.9866	60	104.98662	60	68.7200	100.1425	71.6409	105.2612	70.5157
PG9	25	77.6012	25	70.1007	25	31.7820	57.9829	25.2774	58.1411
PG10	160	145.1837	160.0000	160	156.2929	160	160	159.4632	160
PG11	80	80	80	80	80	80	80	80	80
PG12	80	80	80.0000	80	80	80	80	79.4586	79.9778
PG13	25	25	25	25	25	25	25	25	25
PG14	15	15	15.0000	15	48.5946	15	15	15	15
PG15	15	28.0864	15	15	22.0316	15	15	15.4708	15.0064
TPG	2659.9276	2659.1363	2659.9276	2659.5813	2658.4635	2659.9382	2659.5983	2659.9289	2658.5129
TPL	29.9276	29.1363	29.9276	29.5813	28.4635	29.9382	29.5983	29.9289	28.5129
Total Cost ($/h)	32695.9687	32714.6736	32695.9687	32693.4244	32723.5905	32697.6591	32692.4710	32696.8856	32681.6148

Table 8: The results attained by LOBL-BA and existing algorithms in the literature for case 3.

Methodology	**SDO [17]**	**ESSDO [17]**	**ESCSDO10 [17]**	**HGS [17]**	**APSO [51]**	**CPSO2 [52]**	**EO [53]**	**EO-SCA [54]**	**LOBL-BA**
PG1	455	454.9999	455	455	455	450.02	455	455	454.8719
PG2	379.9996	379.9992	379.9996	380	380.01004	454.06	380	380	380
PG3	129.9995	130	129.9999	130	130	124.81	130	129.99	130
PG4	130	129.9999	130	130	126.52284	124.81	130	130	130
PG5	169.9999	170	170	169.9999	170.01312	151.06	170	170	170
PG6	459.9999	460	460	460	460	460	460	460	460
PG7	429.9984	429.9998	430	430	428.28356	434.57	430	430	430
PG8	67.74251	70.71708	70.25793	60	60	148.46	60	67.91	70.5157
PG9	61.83312	58.87155	59.33272	69.55549	25	63.59	69.871	62.38	58.1411

PG10	159.9982	159.9986	159.9956	160	159.78932	101.12	160	160	160
PG11	79.99983	79.99998	80	80	80	28.655	80	80	80
PG12	79.99986	80	80	80	80	20.914	80	79.99	79.9778
PG13	25.00081	25.00042	25.00012	25	33.70376	25.002	25	25	25
PG14	15.00454	15.00197	15.00058	15	55	54.414	15.206	15	15
PG15	15.00102	15.00174	15.00171	15	15	20.624	15.191	15	15.0064
TPG	2659.57719	2659.59014	2659.58816	2659.55539	2658.3226	2662.1	2660.268	2660.27	2658.5129
TPL	29.57719	29.59014	29.58816	29.55539	28.36552996	32.1303	30.2707	30.295	28.5129
Total Cost ($/h)	32692.41306	32692.40489	32692.40133	32692.64264	32742.7774	32,834	32701.18	32700.51	32681.6148

Table 9: Statistical results for LOBL-BA vs. existing algorithms from the literature for case 2.

Methodology	**Best**	**Worst**	**Avg**	**Std**
EO [53]	32701.18	32701.51	32701.31	NR
FA [55]	32704.5	33,175	32856.1	NR
MPSO-GA [56]	32,702	32755.19	32701.31	NR
EO-SCA [54]	32700.51	32701.05	32702.74	NR
PSOSIF [57]	32,706.88	32,709.92	32,707.79	3.04
GAAPI [49]	32,732.95	32,756.01	32,735.06	NR
FA [55]	32,704.45	33,175.00	32,856.10	NR
EPSO [58]	32,704.83	32,762.01	32,725.37	NR
IAEDP [59]	32,698.20	32,823.78	32,750.22	29.2989
EMA [60]	32,704.45	32,704.45	32,704.45	NR
GABC [61]	32,706.66	32706.81	32,706.69	0.035838
TLBO [62]	32,697.22	32,697.22	32,697.22	0.0000
Jaya [46]	32712.6458	32822.9993	32743.4613	47.0256
Jaya-M [46]	32707.0312	32743.6808	32714.4386	12.0972
Jaya-SM [46]	32706.983	32728.2292	32709.0463	8.7817
Jaya-SML [46]	32706.3578	32707.2925	32706.6764	2.3244
TS [63]	32917.87	33245.54	33066.76	66.82
DSPSO-TS [63]	32715.06	32730.39	32724.63	8.4
BF-NM [64]	32784.5024	NR	32976.81	85.77

CSO [65]	32709.36	32722.55	32712.49	4.56
CCSO [65]	32706.64	32706.64	32706.64	0.0007
SDO [17]	32692.41	32740.32	32732.64	17.4465
ESSDO [17]	32692.4	32740.33	32725.92	22.4866
ESCSDO10 [17]	32692.4	32740.36	32730.71	19.64
HGS [17]	32692.64	32725.4	32697.3	8.948
PSO	32695.9687	32902.0142	32788.6175	52.8414
DE	32714.6736	32829.2450	32781.2095	27.1484
BA	32702.0453	32834.9265	32784.5756	31.4010
GWO	32693.4244	32737.5405	32709.3268	11.4521
MVO	32723.5905	32830.8973	32771.6127	27.3997
SCA	32697.6591	32817.4459	32774.3092	29.8595
AOA	32692.4710	32753.6908	32711.6392	14.7506
WSO	32696.8856	33027.1289	32845.2951	78.2231
LOBL-BA	32681.6148	32684.6239	32682.4922	0.7080

5.4. Case 4

In this case, the proposed LOBL-BA, along with BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME algorithms are used to address the ELD problem for a 40_unit test system with a load demand of 10500 MW. The fuel cost coefficients with valve-point effects and without power losses, were obtained from [17].

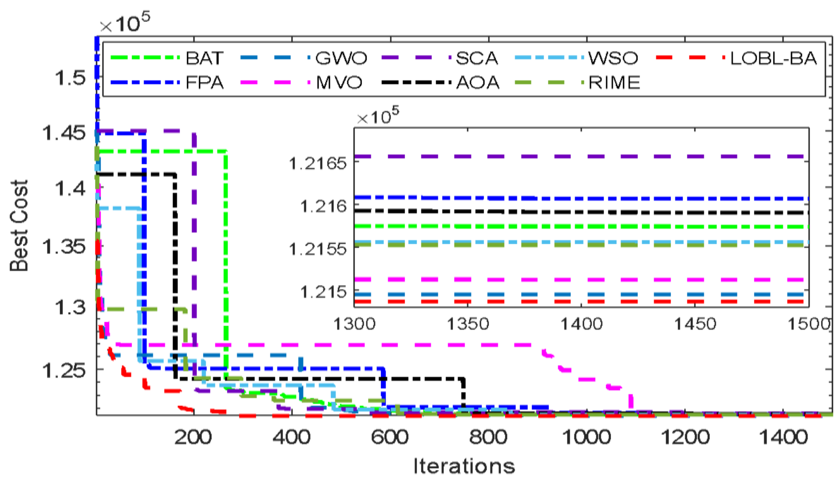

Figure 5(a): Convergence of different algorithms for a case 4.

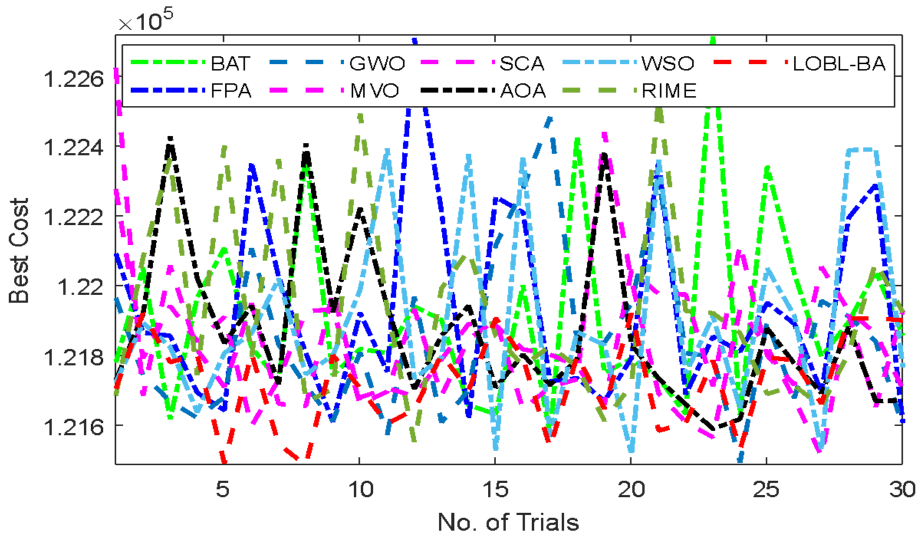

Figure 5(b): Fuel cost results from various algorithms over 30 trials for case 4.

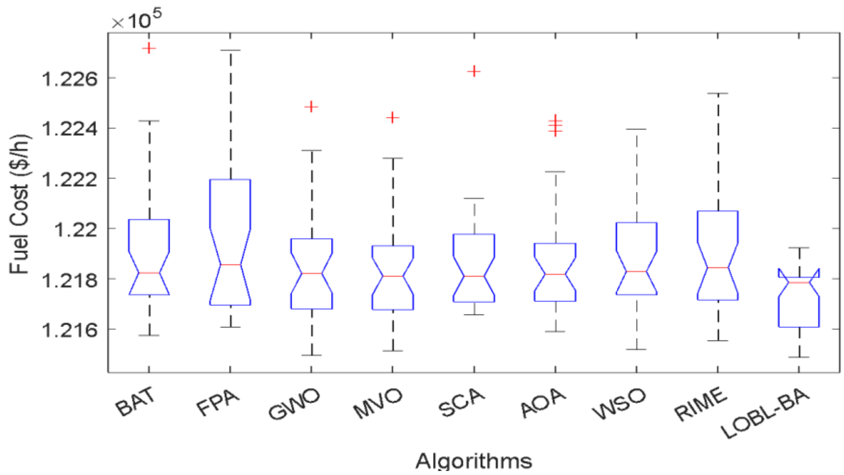

Figure 5(c): Box plot of fuel cost ($/h) for different algorithms for a case 4.

Table 10: The results attained by LOBL-BA and other algorithms for case 4.

Unit (MW)	**BA**	**FPA**	**GWO**	**MVO**	**SCA**	**AOA**	**WSO**	**RIME**	**LOBL-BA**
PG1	113.9809	111.7732	110.8116	111.3270	111.2374	113.9785	110.8078	111.3616	111.4074
PG2	110.8153	113.3542	112.6288	111.8295	113.9984	113.9994	112.5371	113.3313	111.0620
PG3	97.4059	119.9999	97.3854	97.9208	119.9827	100.5623	97.7625	119.9604	97.4047
PG4	179.7410	179.7462	179.7316	179.7335	179.7340	181.0940	179.7266	179.7391	179.7371
PG5	87.8944	89.0839	89.3714	92.3148	97.0000	96.9821	87.8000	96.9973	96.9992

PG6	139.7532	139.9512	140.0000	139.9974	139.9913	139.9997	139.9138	139.9996	140.0000
PG7	299.9868	299.9161	299.9993	299.8049	261.3747	299.9722	299.0832	260.1706	299.9996
PG8	284.6283	285.9473	285.5897	284.6298	285.8625	287.0914	284.7021	284.6168	284.6460
PG9	284.6927	299.9224	284.6510	285.8777	286.3105	287.2708	284.5996	296.4689	284.6375
PG10	204.8012	130.0013	130.0040	130.0597	130.0081	130.6326	130.3095	130.0000	130.0013
PG11	94.0003	94.0008	94.0572	94.2198	94.0187	94.0193	94.0026	94.0182	94.0005
PG12	168.8005	94.0386	94.0222	94.0100	94.0054	94.0013	94.0453	94.0021	94.0006
PG13	125.0002	214.7623	125.0000	125.0311	125.0001	125.0027	125.0191	125.0004	125.0000
PG14	304.5218	304.5393	394.2743	394.2750	394.2859	394.5945	394.4465	394.2800	394.2793
PG15	394.2788	394.2797	394.2754	394.3571	304.5201	394.3257	394.2834	394.2808	394.2787
PG16	394.2452	394.3004	394.2805	394.2792	484.0426	394.3000	394.3164	394.2645	394.2799
PG17	489.2863	489.3199	489.2838	489.3109	489.4487	489.4504	489.2788	489.2992	489.2796
PG18	489.2341	489.2834	489.2795	489.3214	489.3079	489.3133	489.5089	489.2914	489.2806
PG19	511.2798	511.2748	511.2794	511.2885	511.4269	511.3424	511.3195	511.2834	511.2794
PG20	511.2797	511.5188	511.2832	511.6992	511.2792	511.2901	511.2798	511.3369	511.2825
PG21	523.2842	523.2840	523.2935	523.2878	523.2784	523.3154	523.2685	523.2816	523.2829
PG22	523.2797	523.3062	523.2794	523.2795	524.0406	523.5552	524.6017	523.3219	523.2800
PG23	523.2791	523.2954	523.2802	523.6490	523.3047	523.4706	523.2795	523.2852	523.2800
PG24	523.2791	523.6662	523.2973	524.7253	523.3196	523.4046	523.4998	523.3582	523.2829
PG25	523.2922	523.4487	523.2801	523.3443	523.3540	523.3188	523.2800	523.2932	523.2793
PG26	523.2841	524.6692	523.2792	523.3142	523.3418	523.3015	523.2847	523.2988	523.2795

PG27	10.0016	10.0126	10.0014	10.0318	10.0592	10.0057	10.0018	10.0166	10.0000
PG28	10.0078	10.0601	10.1085	10.0000	10.0387	10.0015	10.0022	10.0006	10.0015
PG29	10.0359	10.3540	10.0012	10.0612	10.0140	10.1839	10.0433	10.0095	10.0000
PG30	87.8360	92.5107	93.6516	87.9338	96.9988	96.9919	95.3871	91.3272	88.1898
PG31	189.9984	189.9444	189.9954	189.9983	190.0000	189.9985	189.9964	189.9961	189.9990
PG32	189.9999	189.8993	189.9981	189.9999	190.0000	189.9982	189.8177	189.9998	189.9999
PG33	189.9993	189.9947	190.0000	189.9904	189.9988	189.9972	189.9891	190.0000	189.9953
PG34	164.8525	164.9070	199.9886	199.9988	199.9981	173.9990	199.8754	199.9969	199.9999
PG35	183.5027	199.7479	200.0000	199.8014	200.0000	199.9519	199.9997	199.9830	199.9966
PG36	199.5404	193.5597	200.0000	199.9689	199.9986	199.9997	199.9319	199.8686	199.9989
PG37	109.6519	109.9999	109.9986	110.0000	109.9737	109.9967	109.7438	110.0000	109.9992
PG38	109.9833	110.0000	109.9823	109.9633	109.9999	109.9918	109.9766	109.9679	109.9976
PG39	109.9870	109.9768	109.9955	109.9699	109.9641	109.9996	109.9906	110.0000	109.9999
PG40	509.2788	510.3497	509.3611	509.3950	509.4819	509.2961	509.2883	509.2925	509.2822
TPL	-3.17E-04	-9.04E-06	-2.08E-04	-2.01E-05	-7.47E-05	-4.06E-04	-4.11E-04	-8.60E-06	-4.89E-04
Total Cost	121574.36	121607.39	121495.16	121512.66	121656.50	121590.98	121516.88	121553.03	121486.81

Table 11: The results attained by LOBL-BA and existing algorithms in the literature for case 4.

Unit (MW)	**EBWO [67]**	**BWO [67]**	**FOX [67]**	**SOA [67]**	**SCSO [67]**	**SMA [46]**	**SDO [17]**	**ESSDO [17]**	**ESCSDO [17]**	**HGS [17]**	**LOBL-BA**
PG1	110.8227	113.0447	113.9983	108.3213	111.9387	112.3525	112.1391	111.3958	110.8002	114	111.4074
PG2	113.0463	111.6908	113.9893	96.64839	111.7449	112.4689	113.106	111.7094	110.7814	114	111.0620
PG3	97.40076	118.7495	120	94.66741	119.0468	97.4915	97.40064	97.40771	97.3987	60.1394	97.4047

PG4	179.7333	175.3644	130.1123	176.2129	181.267	179.7416	179.7355	179.7576	179.7312	179.7998	179.7371
PG5	87.81169	97	97	85.84437	85.25916	93.71706	87.80159	89.18163	87.79114	97	96.9992
PG6	140	140	140	112.2232	124.1194	139.9995	105.421	105.5467	139.9984	140	140.0000
PG7	300	295.5326	248.4128	259.7063	183.1686	260.4362	259.6137	259.6439	259.5963	300	299.9996
PG8	284.64	293.8739	290.0736	284.6061	294.4216	289.743	284.6095	284.5999	284.5963	300	284.6460
PG9	284.5992	300	299.77	266.9254	285.9682	296.0535	284.5989	284.6077	284.5915	300	284.6375
PG10	130	130	204.8026	240.6309	130.2536	130.0189	204.8536	130.0001	130.0107	130	130.0013
PG11	94.00002	94	168.7965	243.376	134.3844	168.7887	168.8005	94.00019	239.0063	94.00006	94.0005
PG12	94.00004	94	168.8108	291.4729	316.2222	168.7212	168.8032	168.801	166.3011	94	94.0006
PG13	125	125	304.5214	304.5738	394.2806	125.0003	304.5121	394.275	214.7574	125	125.0000
PG14	484.0394	404.2393	394.2786	304.3852	394.2758	394.2872	394.2813	394.2988	304.5057	394.2847	394.2793
PG15	394.2793	299.4391	304.5188	304.5596	304.5512	304.5919	304.5089	304.5235	394.2829	394.2796	394.2787
PG16	304.5195	382.5056	394.2859	393.892	304.5917	394.3118	304.5268	394.2794	394.2769	394.2794	394.2799
PG17	489.2793	500	309.881	453.8946	489.298	489.2915	489.3018	489.2851	489.276	489.3126	489.2796
PG18	489.2793	484.9316	310.1625	489.4224	489.2917	489.881	489.2864	489.3087	489.2794	489.2963	489.2806
PG19	511.2794	512.7894	511.289	511.2903	511.273	511.2385	511.2827	511.3006	511.2789	511.2809	511.2794
PG20	511.2798	503.7622	511.3617	424.0771	421.5424	511.2866	511.3339	511.28	511.2788	511.3354	511.2825
PG21	523.2784	536.5517	523.3476	523.4744	523.2835	523.3004	523.3314	523.2836	523.2804	523.5524	523.2829
PG22	523.2811	515.5569	549.9879	523.3381	523.566	523.2929	523.2799	523.2759	523.2774	523.366	523.2800
PG23	523.2839	545.3899	532.1728	523.5299	523.2902	523.3215	523.2755	523.2844	523.2791	539.7297	523.2800
PG24	523.2793	533.83	523.3539	523.2311	440.7299	523.2599	523.4085	523.2795	523.2744	523.8539	523.2829

PG25	523.2846	533.8145	549.9994	523.2777	523.4239	523.3046	523.2736	523.3598	523.2783	523.3009	523.2793
PG26	523.2787	534.5109	523.7803	523.2307	523.4425	523.2675	523.2832	523.3029	523.2836	523.3843	523.2795
PG27	10	10	10.0003	30.5968	10.06509	10.00489	10.06301	10.01909	10.00249	10	10.0000
PG28	10	10	10.00231	30.83167	12.52982	10	10.00807	10.01497	10.00074	10	10.0015
PG29	10	10	10.02122	38.66068	10.2097	10.00001	10.00798	10.00053	10.00303	10	10.0000
PG30	94.02475	94.33285	97	81.12339	88.27368	92.73674	89.64376	90.34668	87.79601	97	88.1898
PG31	189.9997	190	189.9993	159.8499	186.5191	189.9981	161.123	161.6513	189.9963	190	189.9990
PG32	190	186.1501	189.9997	150.3682	189.9529	190	189.9989	189.9978	189.9999	190	189.9999
PG33	190	190	190	159.8171	189.7575	190	189.9791	161.145	189.9845	190	189.9953
PG34	200	195.9569	199.999	179.3837	165.493	195.8292	164.7992	164.8925	164.8044	172.5026	199.9999
PG35	199.9998	200	200	169.1827	191.9234	200	164.9028	164.919	164.8001	200	199.9966
PG36	200	191.7499	200	164.914	197.7798	200	164.8301	164.9784	164.7969	200	199.9989
PG37	110	106.685	110	74.30234	101.5418	89.89076	109.9967	95.76652	89.09699	110	109.9992
PG38	110	110	109.9995	90.15813	99.41214	91.73751	97.59832	109.9943	89.11364	110	109.9976
PG39	109.9995	110	109.9991	72.50001	100.6187	109.9905	109.9998	109.9976	89.11416	110	109.9999
PG40	511.2795	512.5753	511.2786	511.3659	511.2862	511.2371	511.2801	511.2872	511.2784	511.3023	509.2822
TPG	10500	10493.03	10477.01	10499.87	10500	10500.59	10500	10500	10500	10500	10500
Cost($/h)	121600.9	122875.8	123745.7	125704.4	123633.3	121658.67	121750.18	121873.64	121626.97	121869.54	121486.81

Table 10 displays the total and average costs for case 4 using the proposed LOBL-BA, compared with BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME. LOBL-BA exhibits the best performance, with the lowest total cost of 1,21,486.8 $/h and the lowest average cost of 1,21,730.2 $/h, indicating optimal cost efficiency; on the other hand, AOA shows the worst performance with the highest total cost of 1,26,487.71 $/h and the highest average cost of 1,29,811.1 $/h; this indicates that AOA incurs the highest expenses, making it the least cost-efficient algorithm.

Table 11 presents the results attained by LOBL-BA and from the literature includes EBWO, BWO, FOX, SOA, SCSO, SMA, SDO, ESSDO, ESCSDO10, and HGS. Table 11 emphasizes the significant performance of LOBL-BA and other established algorithms in optimizing the generating units. In a direct comparison with other recently published methods, such as EBWO, BWO, FOX, SOA, SCSO, SMA, SDO, ESSDO, ESCSDO10, and HGS, the LOBL-BA algorithm stands out, achieving the lowest fuel cost of 1,21,486.8 \$/h and the lowest average cost of 1,21,730.2 \$/h.

Table 12 presents the statistical results attained by LOBL-BA and existing algorithms in the literature across on 30 independent runs. The findings suggest that the LOBL-BA algorithm exhibits the most robust stability, as LOBL-BA attained the lowest Std. Dev., value of 136.496, compared to BA, PSO, DE, GWO, MVO, SCA, AOA, WSO, and RIME, and other recently published methods like PSO, SOA, PPSO, PSO, TLBO, FOX, SCSO, SSA, MPA, BWO, MGMPA, SA, HSSA, ESSDO, HGS, SDO, ESCSDO10, EBWO, and CTLBO. The LOBL-BA demonstrates superior effectiveness in resolving the ELD problem. Figure 5(a) illustrates the reduction in total cost over time for different optimization algorithms. Figure 5(b) presents the total cost results from 30 trials, while Figure 5(c) shows a box plot of total cost for various algorithms.

Table 12: The statistical results by LOBL-BA and algorithms in the literature for case 4.

Methodology	**Best**	**Worst**	**Avg**	**Std**
PSO [68]	126487.71	130049.36	129613.92	2363.06
SOA [67]	125704.40	127019.50	128066.90	667.16
PPSO [68]	125503.09	129631.35	127886.04	1033.37
PSO [66]	124959.12	131637.50	127495.43	1470.00
TLBO [66]	124517.27	128207.06	126581.56	1060.00
FOX [67]	123745.70	125954.30	129811.10	1391.51
SCSO [67]	123633.30	125219.70	128464.70	1092.27
SSA [68]	123565.75	127442.23	125408.20	905.64
MPA [68]	123180.98	126614.40	124750.53	927.37
BWO [67]	122875.80	123398.60	123858.90	240.70
MGMPA [68]	122634.69	125523.19	123939.11	755.10
SA [66]	122261.96	124749.98	123672.38	593.00
HSSA [4]	121960.27	NA	122239.53	NA
ESSDO [17]	121873.60	123301.80	122380.50	449.99
HGS [17]	121869.50	124042.90	122751.20	496.81
SDO [17]	121750.20	123222.70	122460.10	405.02
ESCSDO10 [17]	121626.97	123128.90	122351.70	412.30
EBWO [67]	121600.90	122012.60	122180.90	163.42
CTLBO [66]	121553.83	122116.18	121790.23	150.00
BA	121574.4	122718	121907.2	269.9301
FPA	121607.4	122711.4	121931	279.8432
GWO	121495.2	122485.2	121847.9	232.8816
MVO	121512.7	122441.3	121818.9	200.9531
SCA	121656.5	122626.3	121858.7	201.0568
AOA	121591	122429.2	121867.9	227.1393

WSO	121516.9	122394.5	121901	279.5093
RIME	121553	122539	121919.2	272.2289
LOBL-BA	121486.8	121922.6	121730.2	136.4963

6. Conclusions

The proposed LOBL-BA algorithm has demonstrated strong effectiveness in solving the ELD problem, particularly within power generation systems. Incorporating random inertia weight, LOBL, and sine function-driven local search is recommended, as these components enhance the algorithm's search capability, balance exploration and exploitation, prevent entrapment in local optima, and ensure faster convergence. LOBL-BA consistently achieved superior fuel cost minimization results, including 15,440.419 $/h for the 6-unit system, 17,988.174 $/h for the 13-unit system, 32,681.615 $/h for the 15-unit system, and 121,486.8 $/h for the 40-unit system, along with strong computational efficiency and robustness compared to established algorithms such as BA, FPA, GWO, MVO, SCA, AOA, WSO, and RIME. Although minor inconsistencies emerged in certain test cases, LOBL-BA outperformed competing methods in most scenarios, confirming its suitability for both small- and large-scale power system optimization. Future work may extend the algorithm to more complex, dynamic ELD problems involving real-time variations, uncertainties, and multi-objective functions like cost-emission minimization. Combining LOBL-BA with other modern techniques could further boost global search performance. Applying it to multi-objective optimization also offers a promising path toward sustainable, efficient power solutions.

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