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Evolutionary Learning Based Optimization for Solving Non-convex Optimal Power Flow Problems: A Modern Teaching–Learning-Based Optimization Algorithm

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Abstract:

Optimal power flow (OPF) is one of the fundamental and complex problems in power system planning and operation, which requires efficient and flexible optimization methods due to its nonlinear characteristics, multiple constraints, and multi-objective nature. In this paper, a new meta-heuristic algorithm named evolutionary learning based optimization (ELBO) is presented, which is an extended and improved version of the teaching learning based optimization (TLBO) algorithm. In the design of ELBO, an evolutionary step with a trigonometric mutation mechanism is added to the TLBO training process to reduce premature convergence and maintain population diversity in the search space. The proposed algorithm has been evaluated in two main areas: first, a set of CEC2014 benchmark test functions and several real engineering optimization problems were first used. In these experiments, ELBO was able to show superior performance over modified versions of TLBO and other reference algorithms in accuracy, convergence speed, and stability. Second, in solving several OPF optimization problems on standard 30- and 57-bus test networks, in all of which the ELBO algorithm has been able to provide more accurate, more stable, and faster convergence rates than other methods. These results confirm the effectiveness and high power of ELBO in solving complex and real problems in the fields of electrical engineering and optimization, and introduce it as an innovative and powerful tool.

Key words: OPF problem, a trigonometric TLBO, evolutionary–learning-based optimization, non-smooth cost functions.

1. Introduction

One of the key concerns of the energy industry is the efficient functioning of power networks. Solving the Optimal Power Flow (OPF) issue for control variable optimization is one of the main techniques available for achieving this aim. Finding the ideal value for these parameters to ensure correct, safe, and cost-effective functioning in the power system under various circumstances is the fundamental goal of OPF. However, OPF often consists of uneven and non-derivative parts that are non-convex and particularly non-linear. So, the classical methods do not have the necessary power to find its appropriate solutions. So, the need for a powerful optimization method to achieve this goal has always been felt and explored [1-5].

Recently, met-heuristic optimization methods have attracted considerable interest for their efficacy and adaptability in addressing intricate optimization challenges [6-10].

Recently, MetaHuristic (MH) algorithms are used in different problems like Harris Hawks Optimization (HHO) in feature extraction [11], Grasshopper Optimization Algorithm (GOA), combination of Whale Optimization Algorithm (WOA) and Moth-Flame Optimization (MFO) and combination of HHO and Arithmetic Optimization Algorithm (AOA) in image

segmentation [12-14] and combination of Aquila Optimizer (AO) and WOA (AWOA), also multi-objective MFO has been successfully applied for scheduling problem [15, 16].

These algorithms draw inspiration from natural events, biological processes, or physical systems, and seek to provide near-optimal solutions within a feasible computing timeframe [17-21]. Examples of these very new met-heuristic algorithms include: MEO [22], PMW [23], potter optimization algorithm (POA) [24], carpet weaving optimization (CWO) [25], Jaya optimization method [26], sled dog optimizer (SDO) [27], fossa optimization algorithm (FOA) [28], addax optimization algorithm (AOA) [29], dollmaker optimization algorithm (DOA) [30], sculptor optimization algorithm (SOA) [31], Rao optimization methods [32], war strategy optimization (WSO) [33], flow direction algorithm (FDA) [34], hippopotamus optimization (HO) [35], past present future (PPF) [36], convex combination search (CCS) [37], draco lizard optimizer (DLO) [38], white-faced capuchin optimizer (WFCO) [39], information acquisition optimizer (IAO) [40], and lungs performance-based optimization (LPO) [41]. The adaptability of these algorithms has resulted in their widespread use across several scientific and technical fields, including structural engineering, feature selection, energy systems optimization, wireless sensor networks, and machine learning [42-46]. The OPF issue is designed to enhance the generation of power generators, primarily aiming to reduce fuel expenses. Contemporary issues need a wider viewpoint, integrating supplementary goals such as pollution reduction, power loss minimization, and system stability enhancement [47-51]. Current methodologies often encounter difficulties in attaining an equitable trade-off among these goals owing to early convergence, restricted exploration within search areas, or prohibitive computing expenses[52-56].

In recent decades, there was an ever-increasing trend towards proposing new nature-inspired algorithms for optimizing different mixed constrained benchmark functions including engineering design and operation problems [57-61]. OPF, as a major problem in operating the energy transmission networks, is one of the problems being the subject of many applications of these algorithms [62]. A number of the proposed nature-inspired approaches which were used for solving OPF problems are moth swarm algorithm (MSA) and its enhanced version [63], [64], artificial bee colony (ABC) [65], modified honey bee mating optimization (MHBMO) [66], social spider optimization (SSO) [67], adaptive group search optimization (AGSO) [68], chaotic ABC [69], an improved colliding bodies optimization (ICBO) [70], a new parallel genetic algorithm (EPGA) [71], multi-objective DE algorithm [72], differential evolution (DE) [73], a modified bacteria foraging [74], a multi-objective particle swarm optimization (PSO) [75], tabu search (TS) [76], modified ABC algorithm [77], an enhanced self-adaptive DE [78], glowworm swarm optimization [79], a new and powerful adaptive modified Jaya optimizer [80], an new improved adaptive DE [81], an improved Jaya optimizer based on quasi-oppositional method [82], chaotic invasive weed optimization (CIWO) algorithms [83], grey wolf optimizer (GWO) [84], improved artificial bee colony (IABC) [85], multi-objective electromagnetism-like algorithm (MOELA) [86], differential search algorithm (DSA) [87], a hybrid PSO and SFLA algorithm [88], BAT search algorithm [89], a new differential-based harmony search algorithm [90], interior search algorithm (ISA) [91], ant lion algorithm (ALA) [82], an improved strength Pareto evolutionary algorithm [93], modified pigeon-inspired optimization algorithm [94], TLBO algorithm enhanced with Lévy mutation (LTLBO) [95], a sine-cosine algorithm [96], tree-seed algorithm [97], etc., which attested to the efficiency of using naturalistic approaches to address OPF issues.

To evaluate the uniqueness and efficacy of the optimization methods presented in the literature, a succinct overview is offered. The uniqueness of current optimization methods in the new papers is in their varied methodologies for tackling non-convex and intricate optimization challenges. Algorithms such as PSO, DE, TLBO, and other optimization methods have significant qualities, including flexibility, exploration proficiency, and convergence efficiency. Notwithstanding these features, prevalent disadvantages are also apparent:

- Sensitivity to Decision Variables: Numerous methods depend on meticulous parameter adjustment, impacting their generalizability across various challenges.
- Imbalanced Search Mechanisms: Certain algorithms favor either local exploitation or global exploration, resulting in inferior outcomes across varied problem domains.
- Elevated computing Expenses: Intricate issues of greater magnitude need more computing resources and time.
- Restricted Generalizability: The majority of algorithms demonstrate proficiency in addressing certain issue areas but often lack wider application.

This research explicitly tackles these difficulties via the ELBO algorithm. The suggested ELBO algorithm resolves these concerns by amalgamating the advantages of TLBO and DE, including an innovative trigonometric mutation approach for enhancing equilibrium and computing efficiency, as corroborated by comparative analyses.

Optimization issues often include several attributes, including changing settings, intricate restrictions, and multiple objectives. These traits are intrinsically linked. In dynamic situations, restrictions and goals may change over time, requiring adaptable and resilient optimization methods. The equilibrium between exploitation and exploration in search methods is crucial when addressing dynamic changes. Recent progress in metaheuristic optimization has shown considerable promise in tackling these difficulties. Research, including [98], [99], underscores the need of integrating flexibility and resilience mechanisms inside optimization algorithms. Furthermore, the amalgamation of hybrid methodologies, including the fusion of teaching-learning paradigms with evolutionary techniques, has shown potential in

enhancing solution quality and convergence. Our suggested ELBO algorithm enhances these gains by including a unique trigonometric mutation process, particularly designed to tackle dynamic restrictions and augment the method's overall flexibility. The incorporation of extensive trials and benchmark comparisons using the CEC 2014 functions additional substantiates its efficacy, as elaborated in the following sections.

Rao et al. suggested a novel and potent algorithm in 2011 and 2012 in different applications, drawing inspiration from the way a teacher and students learned together in a demonstration class [100], [101], [102], [103]. In [104], an evaluation of the applications of the TLBO method and an instructional guide for novices to address both restricted and unconstrained optimization issues were examined. In the recent years, this simple algorithm have absorbed many applications in different respects and numerous improved types have been proposed for TLBO [105]. But, this method has been well established in the articles that TLBO sometimes converges to the optimal local solutions [95]. In contrast, evolutionary algorithms have good power in escaping local optima but along with low convergence speed. Therefore, we decided to design an evolutionary TLBO algorithm for various OPF functions, which has been created via hybridizing TLBO and differential evolution (DE) with trigonometric mutations is and is called evolutionary-studying-based optimization algorithm (ELBO). It is verified by the obtained optimal results that, the new suggested hybridization optimizer considerably enhances the efficacy of the TLBO algorithm in effectively avoiding convergence to local optima.

This study's principal contributions, which answer the stated gaps and requirements, are as follows:

- **Mitigating Parameter Sensitivity:** The use of a trigonometric mutation method in the ELBO algorithm diminishes reliance on exact parameter calibration, hence improving its versatility across various issue contexts.
- **Minimizing the Difficulty of Computing:** With its novel algorithmic designs, the suggested solution improves computing efficiency, making it practical for complicated and large-scale tasks.
- **Reconciling Exploration with Exploitation:** The hybridization of TLBO and DE creates a strong search mechanism that successfully balances global exploration with local exploitation, leading to enhanced optimization outcomes.
- **Enhanced Resilience and Flexibility:** ELBO integrates mechanisms to adjust to dynamic limitations and evolving goals, as shown by comprehensive benchmarking using CEC 2014 functions.
- Comprehensive Verification: Thorough comparison assessments confirm the ELBO's effectiveness, establishing it as a better option to current approaches for addressing OPF and associated optimization challenges.

This study's principal contributions, which answer the stated gaps and requirements, consist of the following: (1) mitigating parameter sensitivity: The use of a trigonometric mutation method in the ELBO algorithm diminishes reliance on exact parameter calibration, hence improving its versatility across various issue contexts, (2) minimizing the difficulty of computing: With its novel algorithmic designs, the suggested solution improves computing efficiency, making it practical for complicated and large-scale tasks, (3) reconciling exploration with exploitation: The hybridization of TLBO and DE creates a strong search mechanism that successfully balances global exploration with local exploitation, leading to enhanced optimization outcomes, (4) enhanced resilience and flexibility: ELBO integrates mechanisms to adjust to dynamic limitations and evolving goals, as shown by comprehensive benchmarking using CEC 2014 functions, and (5) comprehensive verification: Thorough comparison assessments confirm the ELBO's effectiveness, establishing it as a better option to current approaches for addressing OPF and associated optimization challenges.

The work is divided into four pieces. Part II presents the formulation of the goal functions. The principles and structure of TLBO and the suggested ELBO algorithm are presented in section III. Section IV is dedicated to reporting the results of simulations and discussing the findings. Finally, section V presents the paper's findings.

2. OPF issue

This problem has a global constrained objective functions. The general formulation of this issue has been known as [83]:

$$\text{The objective function: } Min\ J(x, u) \tag{1}$$

$$\text{The equality constraints: } g(x, u) = 0 \tag{2}$$

$$\text{The inequality constraints: } h(x, u) \leq 0 \tag{3}$$

Where, u represents the set of control variables (also called decision variables) of the system and x are independent variables which are called state variables. The inequality constraints pertaining to the physical limits of the power system on the control and state variables. In general, the optimization variables of the OPF include generating units' active power outputs of all buses except the reference bus, generator buses' voltage magnitudes, transformers' tap adjustments, and compensations by reactive power compensators. Also, the state variables of this problem incorporate voltage phase angles in all buses, voltage magnitudes in load buses, maximum transmission capacity of branches, reactive generations of the generating units and active power output of the reference bus.

A. Problem constraints

This issue includes different $g(x, u)$ and $h(x, u)$ limitations related to generators and network, that as follows [40]:

1. $g(x, u)$ ***constraints***

The network generation power unit's limitations of network buses are specified as limits:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left[B_{ij} * \sin(\delta_i - \delta_j) + G_{ij} * \cos(\delta_i - \delta_j) \right] = 0 \quad (4)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} * \sin(\delta_i - \delta_j) - B_{ij} * \cos(\delta_i - \delta_j) \right] = 0 \quad (5)$$

In the above equations, j and i show the indices of bus numbers, V_j and V_i represent the voltage magnitudes; Q_{Gi}, P_{Gi} show the reactive and real power outputs of generators, respectively; Q_{Di}, P_{Di} show the reactive and active power demands, respectively; B_{ij}, G_j show the susceptance and conductance of the branch between buses i and j, respectively; δ_{ij} shows the angular differences of voltages between these busses; and NB denotes the number of buses.

2. $h(x, u)$ ***constraints***

This vector comprises the following collections of inequality constraints [40]:

i. Constraints pertaining to the generating units: voltage magnitudes and power outputs of generating buses are constrained in their corresponding ranges as for $i=1,2,...,NG$:

$$\begin{aligned} V_{Gi}^{\min} &\le V_{Gi} \le V_{Gi}^{\max} \\ P_{Gi}^{\min} &\le P_{Gi} \le P_{Gi}^{\max} \\ Q_{Gi}^{\min} &\le Q_{Gi} \le Q_{Gi}^{\max} \end{aligned} \quad (6)$$

Where, V_{Gi}^{min} and V_{Gi}^{max} denote the permissible voltage magnitude limitations of ith network's unit; P_{Gi}^{min} and P_{Gi}^{max} the permissible range of generation active power via ith generator; and Q_{Gi}^{min} and Q_{Gi}^{max} define the permissible range of generation reactive power via ith generator.

ii. Adjustments of the taps on transformers: The taps of transformers may be modified within their allowable range as:

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i = 1,...,NT \quad (7)$$

Where, $T_i^{\min}$ and $T_i^{\max}$ show the permissible range for adjusting the taps of ith transformer.

iii. Volt-ampere Reactive(VAR) compensating unit limitations: the outputs of these devices are limited as follows:

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, \quad i = 1,...,NC \quad (8)$$

The allowed range of VAR injection with a compensating unit is determined by the values of $Q_{Ci}^{\min}$ and $Q_{Ci}^{\max}$.

iv. Security restrictions: the permissible range of load buses' voltage ($V_{Li}^{\min}$ to $V_{Li}^{\max}$) and transmission power magnitudes are considered as:

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}, \quad i = 1,2,..., NPQ \quad (9)$$

$$S_{li} \le S_{li}^{\max}, \quad i = 1,2,..., NTL \quad (10)$$

Where, respectively, S_{li} and $S_{li}^{\max}$ stand for the apparent power across the ith transmission line and its upper limit. The optimization technique takes into account the allowable ranges of the decision variables. The penalty factors method is a common approach for dealing with constraints in constrained optimization problems. It involves converting the constrained objective function into an unconstrained one by incorporating penalized values of violated constraints into the objective function. This results in the formation of an augmented objective function [106]. This method is used here as:

$$\begin{aligned} J = &\sum_{i=1}^{NG} F_i(P_{Gi}) + \lambda_P (P_{G1} - P_{G1}^{\lim})^2 + \lambda_V \sum_{i=1}^{NPQ} (V_{Li} - V_{Li}^{\lim})^2 \\ &+ \lambda_Q \sum_{i=1}^{NG} (Q_{Gi} - Q_{Gi}^{\lim})^2 + \lambda_S \sum_{i=1}^{NTL} (S_{li} - S_{li}^{\lim})^2 \end{aligned} \quad (11)$$

Where, λ_Q, λ_V, λ_P, and λ_S show the penalty factors; and x^{lim} shows an auxiliary variable which is defined in the following equation:

$$x^{\lim} = \begin{cases} x^{\min}; & x < x^{\min} \\ x^{\max}; & x > x^{\max} \\ x & x^{\min} \le x \le x^{\max} \end{cases} \quad (12)$$

3. Evolutionary-studying-based optimization algorithm (ELBO)

A. TLBO

TLBO [101], [102], [103] was developed based on the pedagogical principles of teaching and learning in a classroom setting. In the classroom, the instructor endeavors to enhance the collective knowledge of the pupils via instruction. Students also endeavor to enhance their knowledge by engaging in the exchange of information with one another. TLBO has garnered significant interest in several fields owing to its simplicity, absence of algorithm-specific parameters, and strong convergence characteristics. In the last ten years, TLBO has shown exceptional adaptability in addressing intricate optimization challenges. This method has been extensively used across several scientific disciplines and diverse issues, including: for extensive distribution of integrated electrical power and thermal energy [107], for addressing intricate optimization challenges [108], [109], [110], multi-objective OPF [111], biomedical polishing applications by optimizing the design of a 3D-manufactured monolithic stage [112], a combined heat with power (CHP) system's optimisation via the use of a dispatching forecast [113], microgrid energy optimization [114], accurately forecasting the academic success of individuals [115], architectures of convolutional neural networks optimally designed for picture categorization [116], for DHFSP, the scheduling issue of distributed hybrid flow shops [117], and improving transformer failure diagnosis precision [118].

The TLBO method involves the modeling of two processes, with the following steps:

Initially, a set of beginning points is formed within the permissible range of variables. The point that yields the best solution is designated as the teacher, while the other points are designated as the pupils. Subsequently, the instructional and educational procedure, comprising of two stages involving the instructor and the learner (student), commences and is iterated until convergence is attained. The modeling of these two stages is as follows:

1. Teaching phase

The teacher's instruction is intended to enhance the collective knowledge of the students in the class, specifically the average knowledge (X_{mean}). Hence, the aforementioned process is represented by the following connection:

$$X_{new} = X_i + r*(X_{teacher} - (T_F * X_{mean})) \tag{13}$$

The variables X_i and X_{new} represent the status of the *i*th student before and after the instruction, respectively. $X_{teacher}$ represents the status of the teacher, X_{mean} represents the average status of the class, and "*r*" represents a random number between 0 and 1. T_F is a stochastic variable that may take on the values of either 1 or 2, and it represents the pace at which the pupil learns. The equation for obtaining T_F is as follows:

$$T_F = round\,(r) + 1 \tag{14}$$

2. Learning phase

Each student randomly selects another student (for example *ii*th student) in the learning phase to exchange information, and the student with lower knowledge learns from the alternative. The method is stated in the following manner:

$$X_{new} = \begin{cases} X_i + r*(X_{ii} - X_i) & \text{if } \mathrm{Cost}(X_{ii}) < \mathrm{Cost}(X_i) \\ X_i + r*(X_i - X_{ii}) & Else. \end{cases} \tag{15}$$

In Eq.(15), *j* represents the student picked at random. For a minimization problem, the inverse relationship between the objective function $\mathrm{Cost}(X_i)$ and a student's knowledge indicates that as the objective function $\mathrm{Cost}(X_i)$ decreases, the student's knowledge increases. In both teacher and student phases, a new point is accepted if the answer is better.

B. Proposed algorithm: ELBO

At first for proposed ELBO, we have combined the two teaching and learning phases of TLBO. Thus, with an equal number of populations, the number of objective function evaluations in each iteration is halved. Now, instead of the learning phase, we can add a new phase called the students' evolutionary phase to the algorithm, by adding which the importance of objective function assessments of the resultant ELBO would be the same as the original TLBO.

1. Studying (teaching-learning) phase

As mentioned, in the proposed ELBO algorithm, the two optimization phases of TLBO are combined, as follows:

$$X_{new} = \begin{cases} X_i + r1*(X_{teacher} - T_F X_{mean}) \\ \qquad + r2*(X_{ii} - X_i) \quad \text{if } \mathrm{Cost}(X_{ii}) < \mathrm{Cost}(X_i) \\ X_i + r1*(X_{teacher} - T_F X_{mean}) \\ \qquad + r2*(X_i - X_{ii}) \quad Else \end{cases} \tag{16}$$

2. Students' trigonometric evolution phase:

In the differential evolution algorithm, to update each member, for example the *i*th member, the member is considered as a donor and then it is transferred to a new position by creating a scaled deviation as a sum of one or two differentials (depending on mutation type). In a trigonometric mutation, three different members *k*1, *k*2 and *k*3 are randomly selected and the center of the hyper geometric triangle composed by them is considered as a donor. Also, the deviation applied to the donor is defined as the sum of the differential vectors connecting these three members, with an appropriate scaling. Thus, the evolutionary action for the *i*th member is performed as follows [119]:

$$X_{new,j}=\begin{cases}X_{k3j}+F(X_{k1j}-X_{k2j}), & \text{if } rand(0,1)\le Cr \text{ and } rand(0,1)\le Mt\\ TM_j, & \text{if } rand(0,1)\le Cr \text{ and } rand(0,1)>Mt\\ X_{ij}, & \text{if } rand(0,1)>Cr\end{cases} \tag{17}$$

Where, *Mt* is the ratio of trigonometric mutation; and *TM* represents the vector of trigonometric mutation. With a lot of simulations and also according to the reference [76], the value of *Mt* in all simulations was considered to be 0.95, which yielded very good results. In the relation (17), the worth of the crossover coefficient *Cr* and the scaling index *F* are selected equal to 0.85 and 0.99, respectively. The trigonometric mutation vector *TM* is obtained as follows [119]:

$$\begin{aligned}TM=&\frac{(X_{k1}+X_{k2}+X_{k3})}{3}+(t2-t1)*(X_{k1}-X_{k2})\\&+(t3-t2)*(X_{k2}-X_{k3})+(t1-t3)*(X_{k3}-X_{k1})\end{aligned} \tag{18}$$

In the above relation, the coefficients *t*1 to *t*3 are calculated as follows:

$$t1=\frac{|\text{Cost}(X_{k1})|}{|\text{Cost}(X_{k1})|+|\text{Cost}(X_{k2})|+|\text{Cost}(X_{k3})|} \tag{19}$$

$$t2=\frac{|\text{Cost}(X_{k2})|}{|\text{Cost}(X_{k1})|+|\text{Cost}(X_{k2})|+|\text{Cost}(X_{k3})|} \tag{20}$$

$$t3=\frac{|\text{Cost}(X_{k3})|}{|\text{Cost}(X_{k1})|+|\text{Cost}(X_{k2})|+|\text{Cost}(X_{k3})|} \tag{21}$$

Choosing the coefficients of the differentials as *t2-t1*, *t3-t2* and *t1-t3* has two advantages. First, it ensures that the sets of deviation vectors tend to move toward better objective functions. On the other hand, more the values of the deviate from the objective function of the two members whose difference is considered, the greater the value of their difference multiplied by the coefficient and the greater their effect in the next situation.

Fig. 1 displays the flowchart of the final ELBO algorithm proposal.

Size of control parameters selected in the proposed process of ELBO (F = 0.99, Cr = 0.85, Mt = 0.95) were established via meticulous testing and validation against established benchmarks and practical applications. These values were obtained with the help of the results obtained in [119] and comprehensive simulations, which consistently validated their efficacy.

Although these parameter choices worked well in many problem domains, the degree to which they are sensitive can change depending on the optimization challenge at hand. Future study may investigate adaptive and self-adaptive methodologies for parameter optimization, using knowledge from the comprehensive literature on this subject. The strategies shown in references [120], [121], [122] may serve as a basis for creating a completely self-adaptive ELBO algorithm, therefore augmenting its flexibility and resilience.

3. Illustrative example of the ELBO optimization technique:

The Rastrigin function is a prominent benchmark in optimization, distinguished through its complex and multimodal characteristics. The Rastrigin function has been delineated as:

$$f(X)=\sum_{i=1}^{D}X_i^2-10*\cos(2*\pi*X_i)+10*D \tag{22}$$

In this equation, the index D represents the dimension of the function, which in this example is a number equal to 5. Although these parameter choices worked well in many problem domains, the degree to which they are sensitive can change depending on the optimization challenge at hand. Also, the range of variables of this function, i.e. X_i with i=1 to D, is between -5 and 5, which indicates the range of changes in the control parameters. Also, the population (N) and number of iterations of the optimization cycle of the desired algorithm are chosen to be 10 and 100, respectively.

a) Procedures of the suggested optimization technique:

Arbitrary starting points: X= {X_1= [-3.0, 2.5, 0.7, -4.1, 3.2], …, X_N}.

b) Phase of studying (teaching-learning):

- Students position mean: X_{mean}= [1.5, -2.0, 0.2, 1.0, -1.8].
- $X_{teacher}$= [-0.8, 0.5, 0.1, -1.5, 0.0].

- Every student acquires knowledge and education from another students and teacher.
- Generating new students by:

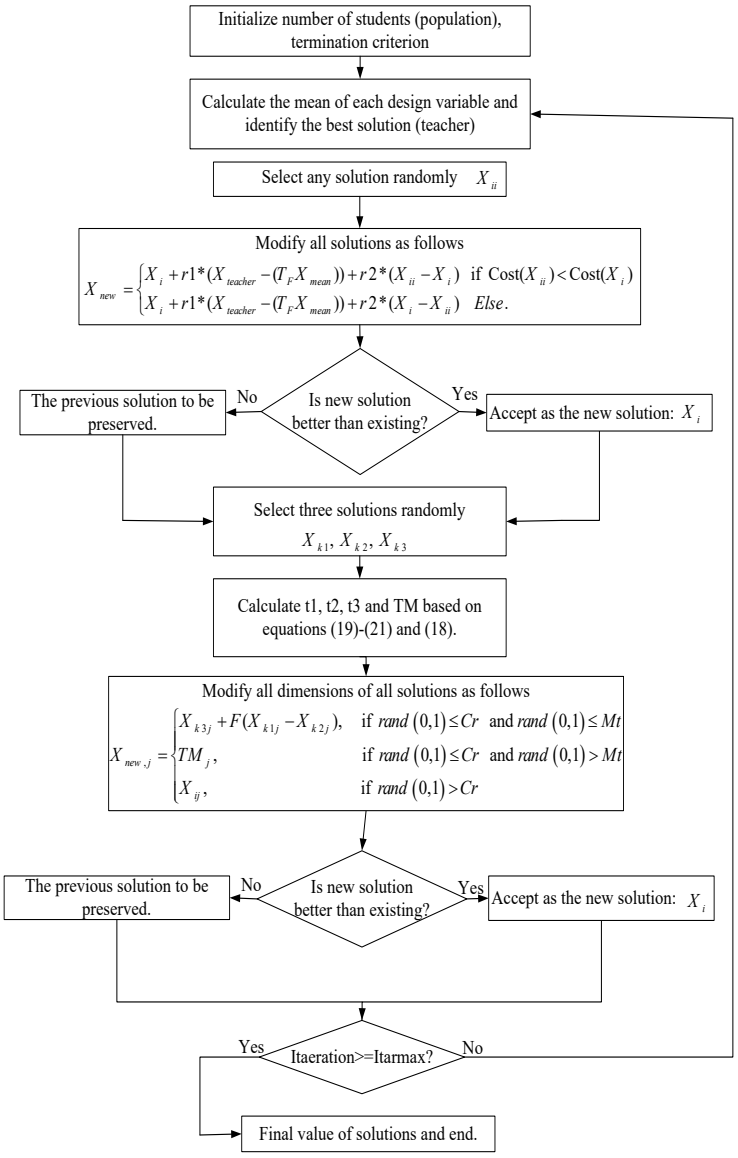


Figure 1. Flowchart of ELBO.

$$X_{new} = \begin{cases} X_i + r1*(X_{teacher} - T_F X_{mean}) \\ \qquad + r2*(X_{ii} - X_i) \quad \text{if } \text{Cost}(X_{ii}) < \text{Cost}(X_i) \\ X_i + r1*(X_{teacher} - T_F X_{mean}) \\ \qquad + r2*(X_i - X_{ii}) \quad Else \end{cases} \tag{23}$$

- Students have been revised just when their cost enhances.

c) Students' trigonometric evolution phase:

- Choose three arbitrary students X_{k1}, X_{k2}, and X_{k3}.
- Points for update:

$$TM = \frac{(X_{k1} + X_{k2} + X_{k3})}{3} + (t2 - t1)*(X_{k1} - X_{k2}) + (t3 - t2)*(X_{k2} - X_{k3}) + (t1 - t3)*(X_{k3} - X_{k1}) \tag{24}$$

d) Expense Assessment:

- The Rastrigin function is used to compute the cost. The optimal member for the iteration is the one with the lowest cost.

e) Generations:

- Keep going until you reach convergence.

f) Outcomes:

- Initial expenditure for Iteration=1: $f(X_{best}$ or $X_{teacher}) = 85.4$.
- The best solution produced at the end of the algorithm execution for Iteration=100, $f(X_{best}$ or $X_{teacher}) = 5.2$
- Enhancement: 93.9% decrease in expenditure.

This numerical example illustrates the efficacy and resilience of the ELBO method in addressing intricate optimization challenges.

Table 1 shows the outcomes for iterations or generations 1, 30, 70, and 100, including the locations and objective function values of the first student and the best member or teacher. The effectiveness and behavior of the suggested algorithm are shown in this thorough example. For simplicity and better demonstration of the workflow, the dimension of the test function has been chosen to be 3 for the results shown in Table 1, but the remaining conditions are the same as the workflow above.

Table 1. The results of the illustrative example for ELBO.

Generations	First member (student) position	$f(X_1)$	Teacher position	$f(X_{best}$ or $X_{teacher})$
1	[2.38, 5.97, -3.15]	72.880	[1.15, -2.14, -0.7]	27.050
30	[3.01, 1.88, -1.78]	26.916	[1.0, -1.92, -0.96]	7.288
70	[1.04, 1.89, -0.85]	12.205	[-1.07, -1.1, -0.98]	6.497
100	[0.96, 1.87, -0.95]	9.250	[-1.07, -1.08, -0.99]	5.270

C. The computational complexity of the proposed optimization technique

The computational cost of the proposed ELBO method is determined by its two primary phases: the students' trigonometric development phase and the integrated teaching-learning phase.

In the teaching-learning phase, the optimization process involves evaluating the objective function for each population member once, resulting in a complexity of O(N) for a single iteration, where N is the population size.

During the trigonometric evolution phase of the pupils, the trigonometric mutation process necessitates the selection of three random individuals, k_1, k_2, and k_3, from the population to calculate the centroid of the geometric triangle produced by these individuals. This phase encompasses vector operations like scaling, addition, and subtraction, all of which exhibit a linear computing cost in relation to the population size. Consequently, the complexity of this phase is O(N) every iteration. The computational cost of executing the ELBO method for I iterations is given as: O(T)=O($I \cdot N$), where I denotes the number of iterations and N signifies the population size. In summary, the suggested ELBO algorithm exhibits linear computational cost per iteration, enhancing search efficiency and convergence via its trigonometric mutation technique. This guarantees that the computational load stays feasible for real optimization challenges.

In contrast to the original TLBO, ELBO preserves computational complexity in a linear fashion, with integrating improvements that boost convergence characteristics and solution variety. Moreover, in comparison to other metaheuristics such as DE and PSO, ELBO attains competitive computing efficiency while including sophisticated mechanisms for exploration and exploitation.

These characteristics provide ELBO a scalable and efficient solution for intricate optimization challenges, as shown by tests conducted in both large-scale (like 118-bus test network) and small-scale (mechanical engineering issues) contexts.

D. A comparative study between ELBO and popular optimization algorithms

Optimization is a fundamental and extensively used subject across several domains of engineering and technology. Optimization algorithms are formulated to address intricate issues and identify the optimal solutions for diverse challenges. Simultaneously, the introduction and examination of novel approaches to enhance efficiency, precision, and computing speed is vital. This portion of the essay examines a comparison analysis between the suggested ELBO approach and commonly used optimization methods. This section thoroughly assesses the efficacy of LPO in comparison to other established algorithms using the thirty CEC2014 functions of several kinds of multimodal, including compositional, hybrid, simple, and multimodal [123], which have been effectively used in many studies. The dimension of all test functions is 30 and the number of function evolutions fitting times is 300,000 in the experiments selected in this section. The selected population for each the proposed algorithm is 60 and each test function is executed 30 independent times.

D.1. First comparative study

This paragraph aims to assess the suggested method's performance relative to the original TLBO algorithm and also a simplified example of the proposed algorithm called DETLBO to thoroughly discern its strengths and limitations. DETLBO is similar to the proposed ELBO method, with the difference that in the second phase or the students' evolution phase, a simple evolutionary algorithm model is used, and in fact, the *TM* vector or trigonometric evolution is removed,

and the value of the *Cr* and *F* coefficients are the same as in the proposed method, and the same mutation model used in the proposed algorithm is also used in this algorithm. In fact, to better understand the performance of trigonometric mutation in the students' evolution phase optimization on the proposed algorithm, we have also simulated this new algorithm.

Based on the average of the obtained best solutions (Mean) and the best solution attained across these runs (Best) as well as the standard deviation (Std.) of the optimization best solutions for each CEC2014 function across 30 separate runs, Table 2 displays the simulation results of the studied optimization methods. Furthermore, each algorithm's rank is given for every problem, followed by the algorithm's mean rank and final rank. For all indexes (Best, Std., and Mean), the suggested ELBO method consistently produces the best results across the majority of test functions. In the majority of test functions, the DETLBO method performs better than the baseline TLBO method, demonstrating the enhancements made to DETLBO. Table 2's findings demonstrate ELBO's advantage in terms of robustness and convergence over a broad variety of test functions. Also in the last row is the average execution time of 30 test functions. In fact, the execution time of the entire algorithm for 30 test functions and independent execution of each test function 30 times is added together and divided by the number of tested functions and this average value is obtained in seconds. It must be noted that the execution time of these three optimization algorithms is almost the same because they use almost the same optimization process.

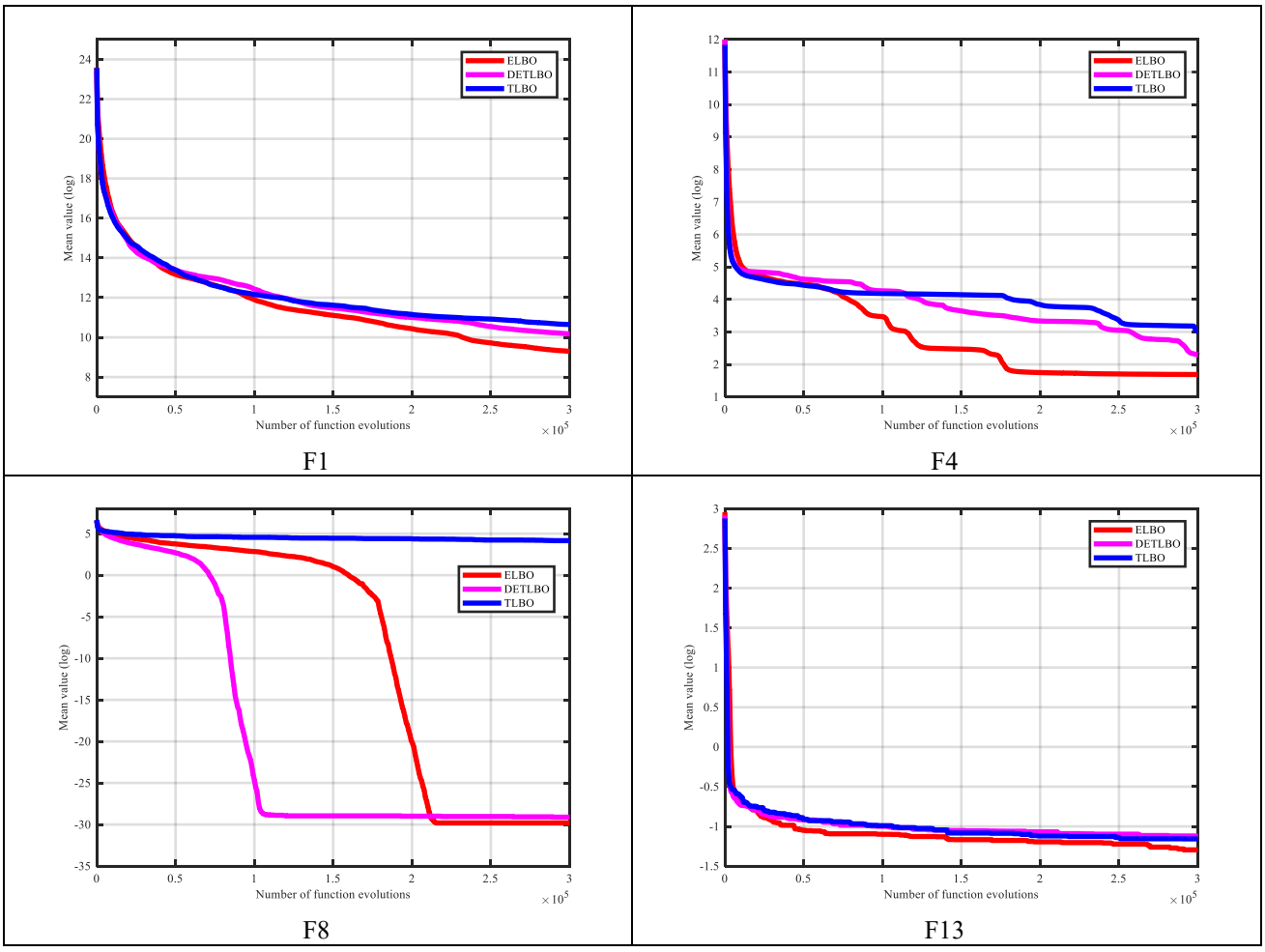
The algorithms' convergence properties for a few chosen CEC2014 optimization functions are shown in Fig. 2. The following are important insights: For the majority of test functions, ELBO exhibits quicker and more consistent convergence, and, ELBO typically performs better than DETLBO and TLBO, despite the fact that all three algorithms have significant convergence properties.

Win: The number of times the model outperformed other models (or the number of times it won)

Table 2. The optimal results via the different algorithms on CEC2014.

Function		DETLBO	TLBO	ELBO	DETLBO	TLBO	ELBO	DETLBO	TLBO	ELBO
		Mean Win	Mean Win	Mean Win	Std. Win	Std. Win	Std. Win	Best Win	Best Win	Best Win
F1	Unimodal	2.616E+04 2	4.206E+04 3	1.087E+04 1	1.610E+04 2	3.832E+04 3	7.483E+03 1	3.879E+03 2	5.668E+03 3	1.239E+03 1
F2		1.042E-13 2	2.736E-13 3	4.026E-14 1	3.702E-14 2	2.459E-13 3	1.464E-14 1	5.684E-14 2	8.527E-14 3	2.842E-14 1
F3		3.482E-13 2	5.891E+01 3	3.316E-13 1	2.335E-13 2	9.570E+01 3	1.649E-13 1	1.705E-13 2	2.728E-03 3	1.137E-13 1
F4	Simple Multimodal	9.939E+00 2	2.032E+01 3	5.411E+00 1	2.078E+01 2	3.036E+01 3	1.826E+01 1	5.196E-02 2	8.941E-02 3	2.449E-04 1
F5		2.042E+01 1	2.089E+01 3	2.044E+01 2	4.748E-02 2	5.029E-02 3	4.190E-02 1	2.033E+01 1	2.081E+01 3	2.037E+01 2
F6		1.106E+01 2	1.659E+01 3	4.627E+00 1	1.507E+00 2	5.466E+00 3	1.467E+00 1	3.061E+00 2	1.339E+01 3	1.585E+00 1
F7		2.067E-02 2	2.152E-02 3	2.747E-13 1	1.959E-02 3	1.432E-02 2	1.024E-13 1	2.274E-13 2	4.547E-13 3	1.137E-13 1
F8		2.274E-13 2	6.404E+01 3	1.137E-13 1	4.848E-14 2	1.577E+01 3	0.000E+00 1	1.137E-13 1.5	3.590E+01 3	1.137E-13 1.5
F9		7.085E+01 2	1.008E+02 3	6.106E+01 1	6.652E+00 2	4.774E+01 3	5.324E+00 1	4.944E+01 2	6.093E+01 3	2.487E+01 1
F10		1.595E+01 2	2.828E+03 3	7.642E+00 1	4.327E+00 2	3.441E+02 3	3.217E+00 1	1.099E+01 2	2.505E+03 3	1.041E-01 1
F11		3.332E+03 1	6.462E+03 3	3.744E+03 2	4.725E+02 3	3.055E+02 1	3.212E+02 2	2.401E+03 1	6.074E+03 3	2.993E+03 2
F12		6.580E-01 1	2.231E+00 3	6.941E-01 2	7.561E-02 1	2.318E-01 3	1.056E-01 2	5.050E-01 2	1.890E+00 3	4.876E-01 1
F13		3.261E-01 3	3.142E-01 2	2.738E-01 1	5.479E-02 3	4.826E-02 2	3.581E-02 1	2.245E-01 2	2.714E-01 3	2.013E-01 1
F14		2.650E-01 2	2.715E-01 3	2.606E-01 1	6.651E-02 2	6.731E-02 3	3.420E-02 1	2.158E-01 3	1.852E-01 2	1.707E-01 1
F15		7.199E+00 2	7.547E+00 3	6.991E+00 1	1.034E+00 2	4.914E+00 3	6.567E-01 1	5.476E+00 2	5.609E+00 3	2.220E+00 1
F16		1.096E+01 2	1.171E+01 3	1.071E+01 1	3.640E-01 2	4.465E-01 3	2.854E-01 1	1.035E+01 2	1.094E+01 3	1.006E+01 1
F17	Hybrid	3.006E+03 3	2.466E+03 2	7.658E+02 1	1.496E+03 3	1.486E+03 2	4.518E+02 1	1.142E+03 2	1.217E+03 3	1.799E+02 1
F18		9.186E+01 2	9.212E+02 3	2.623E+01 1	4.556E+01 2	1.399E+03 3	1.092E+01 1	3.534E+01 2	1.302E+02 3	8.276E+00 1
F19		6.249E+00 2	6.549E+00 3	4.902E+00 1	9.744E-01 1	1.244E+00 2	1.330E+00 3	5.049E+00 3	4.582E+00 2	2.604E+00 1

Function		DETLBO	TLBO	ELBO	DETLBO	TLBO	ELBO	DETLBO	TLBO	ELBO
		Mean Win	Mean Win	Mean Win	Std. Win	Std. Win	Std. Win	Best Win	Best Win	Best Win
F20		1.709E+02 2	2.164E+02 3	1.592E+01 1	8.787E+01 2	4.234E+02 3	5.246E+00 1	2.086E+01 2	6.238E+01 3	1.024E+01 1
F21		6.263E+02 2	8.520E+02 3	2.862E+02 1	1.644E+02 2	3.921E+02 3	1.116E+02 1	2.290E+02 2	6.177E+02 3	2.837E+01 1
F22		1.582E+02 3	1.067E+02 1	1.169E+02 2	6.332E+01 2	6.598E+01 3	5.869E+01 1	5.888E+01 3	2.761E+01 1	3.644E+01 2
F23	Composition	3.152E+02 2	3.152E+02 2	3.152E+02 2	1.952E-12 2	4.341E-12 3	4.268E-13 1	3.152E+02 2	3.152E+02 2	3.152E+02 2
F24		2.336E+02 2	2.362E+02 3	2.282E+02 1	6.473E+00 3	5.283E+00 2	4.910E+00 1	2.256E+02 3	2.252E+02 2	2.231E+02 1
F25		2.064E+02 2	2.085E+02 3	2.042E+02 1	3.087E+00 2	4.402E+00 3	1.396E+00 1	2.026E+02 1.5	2.032E+02 3	2.027E+02 1.5
F26		1.087E+02 3	1.003E+02 1.5	1.003E+02 1.5	2.877E+01 3	1.179E-01 2	6.235E-02 1	1.002E+02 2	1.002E+02 2	1.002E+02 2
F27		4.560E+02 2	5.616E+02 3	3.828E+02 1	5.892E+01 2	1.135E+02 3	5.841E+01 1	3.918E+02 2	4.561E+02 3	3.010E+02 1
F28		9.175E+02 2	9.860E+02 3	8.254E+02 1	9.169E+01 2	1.815E+02 3	4.199E+01 1	7.724E+02 2	8.687E+02 3	7.172E+02 1
F29		7.520E+02 1	1.146E+06 3	7.929E+02 2	2.102E+01 1	3.239E+06 3	1.587E+02 2	7.228E+02 3	6.519E+02 2	4.495E+02 1
F30		3.001E+03 2	3.716E+03 3	2.732E+03 1	1.292E+03 2	1.618E+03 3	1.219E+03 1	1.466E+03 2	1.916E+03 3	7.961E+02 1
Rank mean /Total rank		2.000/2	2.7833/3	1.2167/1	2.1/2	2.7333/3	1.1667/1	2.0667/2	2.7333/3	1.2/1
Mean Time (s)		DETLBO =93.25			TLBO =91.38			ELBO =88.22		



F1 F4

F8 F13

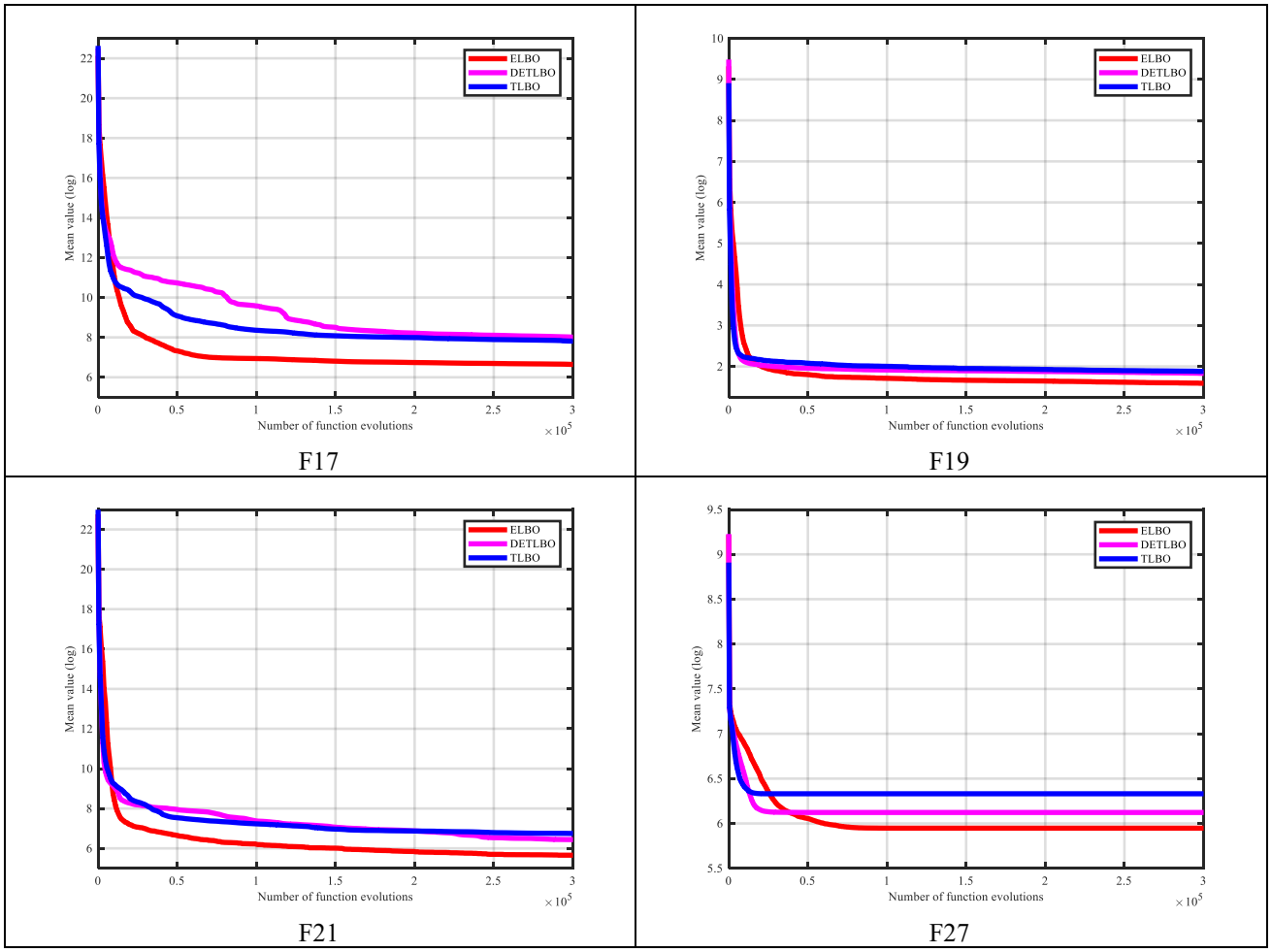


Figure 2. Convergence characteristics of sample test functions such as F1, F4, F8, F13, F17, F19, F21, and F27 by the proposed algorithms.

D.2. A comparative study with other algorithms

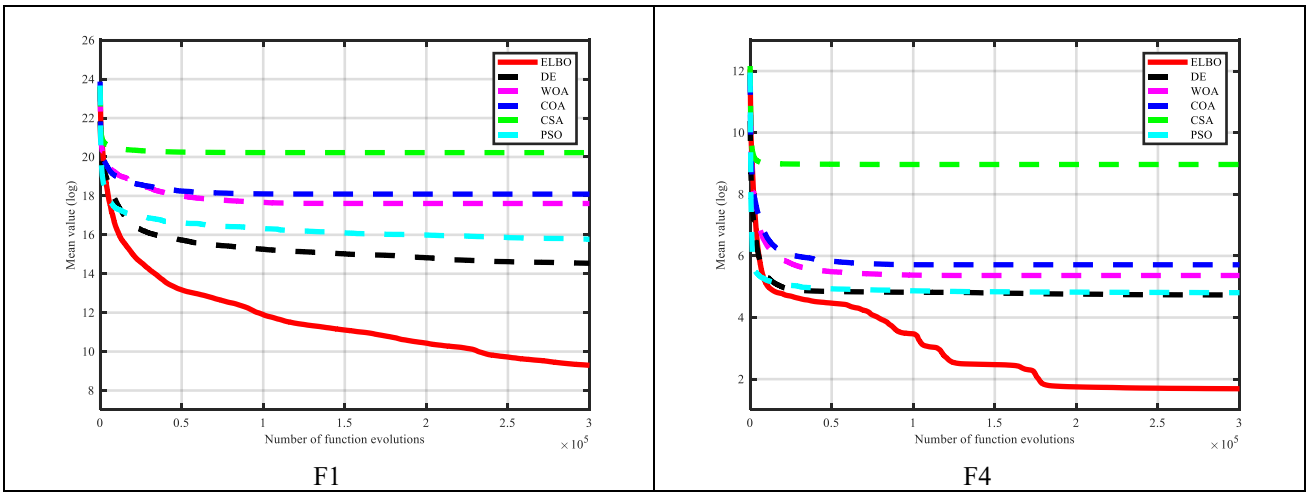
A comparison of a number of optimization methods over 30 test functions is shown in Table 3, including PSO [124], [125], crow search algorithm (CSA) [126], coati optimization algorithm (COA) [127], WOA [128], DE [129], [130], with the suggested ELBO algorithm. It should be noted that the selection of control parameters in the correct algorithms is based on the original reference introducing the desired algorithm. In the table, "+" shows when the ELBO algorithm performed better than alternative approaches, "=" indicates equal the power of optimization, as well as "-" indicates a loss. It is clear from the one row left to the end that ELBO outperformed the other options in practically every test function, proving its excellence and dependability. Furthermore, the convergence behavior of the algorithms for certain functions is depicted in Fig. 3. The convergence curves unequivocally demonstrate that, in comparison to the other algorithms, ELBO not only finds the ideal solution more quickly but also retains a better degree of precision and stability. ELBO reliably finds the best answer with the least amount of computation for functions such as F1 and F4.

All things considered, these findings demonstrate the ELBO algorithm's resilience and effectiveness in resolving challenging optimization issues, surpassing more conventional techniques such as PSO, and DE in based on convergence speed and solution quality.

Table 3. The optimal results via the different algorithms on CEC2014.

Function		DE	WOA	COA	CSA	PSO	ELBO
		Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std.
F1	Unimodal	2.061E+06 3.999E+05 +	4.442E+07 2.753E+07 +	7.187E+07 3.769E+07 +	6.063E+08 1.062E+08 +	7.043E+06 2.261E+06 +	1.087E+04 7.483E+03
F2		1.707E+05 5.604E+04 +	2.402E+07 2.551E+07 +	1.380E+09 1.317E+09 +	5.207E+10 6.373E+09 +	1.289E+05 9.131E+04 +	4.026E-14 1.464E-14
F3		8.156E+02 4.429E+02 +	6.055E+04 5.152E+04 +	5.321E+04 2.819E+04 +	7.835E+04 2.164E+04 +	3.349E+02 1.478E+02 +	3.316E-13 1.649E-13
F4	Simple Multimodal	1.135E+02 2.953E+01 +	2.135E+02 4.232E+01 +	3.024E+02 1.484E+02 +	7.835E+03 1.921E+03 +	1.223E+02 3.117E+01 +	5.411E+00 1.826E+01
F5		2.047E+01 3.172E-02 +	2.048E+01 1.740E-01 +	2.050E+01 1.676E-01 +	2.082E+01 1.430E-01 +	2.083E+01 8.560E-02 +	2.044E+01 4.190E-02
F6		1.749E+01 3.570E+00 +	3.544E+01 3.550E+00 +	3.467E+01 4.439E+00 +	3.261E+01 2.114E+00 +	1.486E+01 4.080E+00 +	4.627E+00 1.467E+00
F7		3.512E-01 7.718E-02 +	1.410E+00 5.691E-01 +	1.034E+01 1.410E+01 +	4.857E+02 7.172E+01 +	4.890E-01 1.654E-01 +	2.747E-13 1.024E-13
F8		6.544E+01 1.289E+01 +	1.786E+02 5.368E+01 +	1.945E+02 5.109E+01 +	2.503E+02 1.678E+01 +	7.594E+01 1.910E+01 +	1.137E-13 0.000E+00
F9		7.342E+01 1.274E+01 +	2.241E+02 4.850E+01 +	2.314E+02 3.943E+01 +	2.623E+02 2.077E+01 +	9.791E+01 2.665E+01 +	6.106E+01 5.324E+00
F10		2.179E+03 4.625E+02 +	3.985E+03 4.749E+02 +	4.398E+03 6.557E+02 +	6.065E+03 6.072E+02 +	1.281E+03 4.335E+02 +	7.642E+00 3.217E+00
F11		3.820E+03 2.548E+02 +	5.539E+03 6.324E+02 +	4.672E+03 6.339E+02 +	6.339E+03 4.353E+02 +	3.757E+03 6.578E+02 +	3.744E+03 3.212E+02
F12		7.500E-01 1.014E-01 +	1.512E+00 5.315E-01 +	1.652E+00 2.457E-01 +	1.656E+00 5.621E-01 +	1.246E+00 4.180E-01 +	6.941E-01 1.056E-01
F13		3.309E-01 5.597E-02 +	4.670E-01 7.789E-02 +	6.929E-01 4.405E-01 +	6.708E+00 2.740E-01 +	3.648E-01 9.421E-02 +	2.738E-01 3.581E-02
F14		2.988E-01 3.399E-02 +	2.862E-01 2.434E-02 +	2.784E-01 4.958E-02 +	1.793E+02 3.840E+01 +	2.830E-01 3.928E-02 +	2.606E-01 3.420E-02
F15		8.079E+00 2.639E+00 +	8.058E+01 3.436E+01 +	1.433E+02 1.269E+02 +	6.203E+04 4.457E+04 +	1.476E+01 2.323E+00 +	6.991E+00 6.567E-01
F16		1.196E+01 7.158E-01 +	1.262E+01 7.529E-01 +	1.247E+01 6.306E-01 +	1.236E+01 3.710E-01 +	1.138E+01 5.437E-01 +	1.071E+01 2.854E-01
F17	Hybrid	1.856E+05 9.437E+04 +	9.278E+06 5.447E+06 +	9.031E+06 6.199E+06 +	1.612E+07 1.428E+07 +	6.984E+05 4.929E+05 +	7.658E+02 4.518E+02
F18		4.396E+02 5.062E+02 +	8.170E+03 7.516E+03 +	1.199E+07 3.169E+07 +	6.863E+08 7.873E+08 +	3.999E+03 5.014E+03 +	2.623E+01 1.092E+01
F19		1.273E+01 1.687E+00 +	7.514E+01 6.180E+01 +	1.082E+02 5.751E+01 +	2.214E+02 6.787E+01 +	9.607E+00 2.077E+00 +	4.902E+00 1.330E+00
F20		4.059E+02 3.812E+02 +	4.456E+04 3.359E+04 +	3.431E+04 1.147E+04 +	2.796E+04 1.069E+04 +	3.434E+02 8.049E+01 +	1.592E+01 5.246E+00
F21		7.946E+04 3.470E+04 +	9.882E+05 9.136E+05 +	5.018E+06 4.705E+06 +	1.918E+06 2.324E+06 +	1.721E+05 8.013E+04 +	2.862E+02 1.116E+02

Function		DE	WOA	COA	CSA	PSO	ELBO
		Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std.
F22		4.659E+02 7.846E+01 +	7.737E+02 2.243E+02 +	8.286E+02 3.754E+02 +	8.985E+02 2.261E+02 +	3.635E+02 1.689E+02 +	1.169E+02 5.869E+01
F23	Composition	3.153E+02 8.461E-03 =	3.321E+02 4.358E+00 +	3.520E+02 1.603E+01 +	5.524E+02 8.492E+01 +	3.153E+02 4.292E-02 =	3.152E+02 4.268E-13
F24		2.354E+02 1.600E+00 +	2.325E+02 2.047E+00 +	2.353E+02 6.096E+00 +	2.713E+02 9.053E+00 +	2.401E+02 4.093E+00 +	2.282E+02 4.910E+00
F25		2.113E+02 4.565E+00 +	2.213E+02 2.164E+01 +	2.181E+02 1.783E+01 +	2.252E+02 3.721E+00 +	2.106E+02 2.370E+00 +	2.042E+02 1.396E+00
F26		1.303E+02 4.818E+01 +	1.146E+02 3.767E+01 +	1.432E+02 5.313E+01 +	1.058E+02 1.326E+00 +	1.802E+02 4.215E+01 +	1.003E+02 6.235E-02
F27		5.464E+02 1.940E+02 +	1.109E+03 2.963E+02 +	1.063E+03 3.797E+02 +	8.926E+02 1.784E+02 +	5.738E+02 1.896E+02 +	3.828E+02 5.841E+01
F28		3.151E+03 8.491E+02 +	2.102E+03 4.996E+02 +	2.392E+03 6.766E+02 +	2.809E+03 4.965E+02 +	2.030E+03 1.049E+03 +	8.254E+02 4.199E+01
F29		1.274E+03 3.613E+02 +	5.945E+06 5.539E+06 +	8.901E+06 6.384E+06 +	8.830E+07 4.213E+07 +	1.457E+06 4.603E+06 +	7.929E+02 1.587E+02
F30		2.811E+03 5.698E+02 +	8.246E+04 6.146E+04 +	1.097E+05 5.195E+04 +	5.255E+05 4.801E+05 +	2.968E+03 1.058E+03 +	2.732E+03 1.219E+03
+/-/=		29/0/1	30/0/0	30/0/0	30/0/0	29/0/1	-----
Mean Time (s)		90.19	202.47	174.30	125.67	96.53	88.22



F1 F4

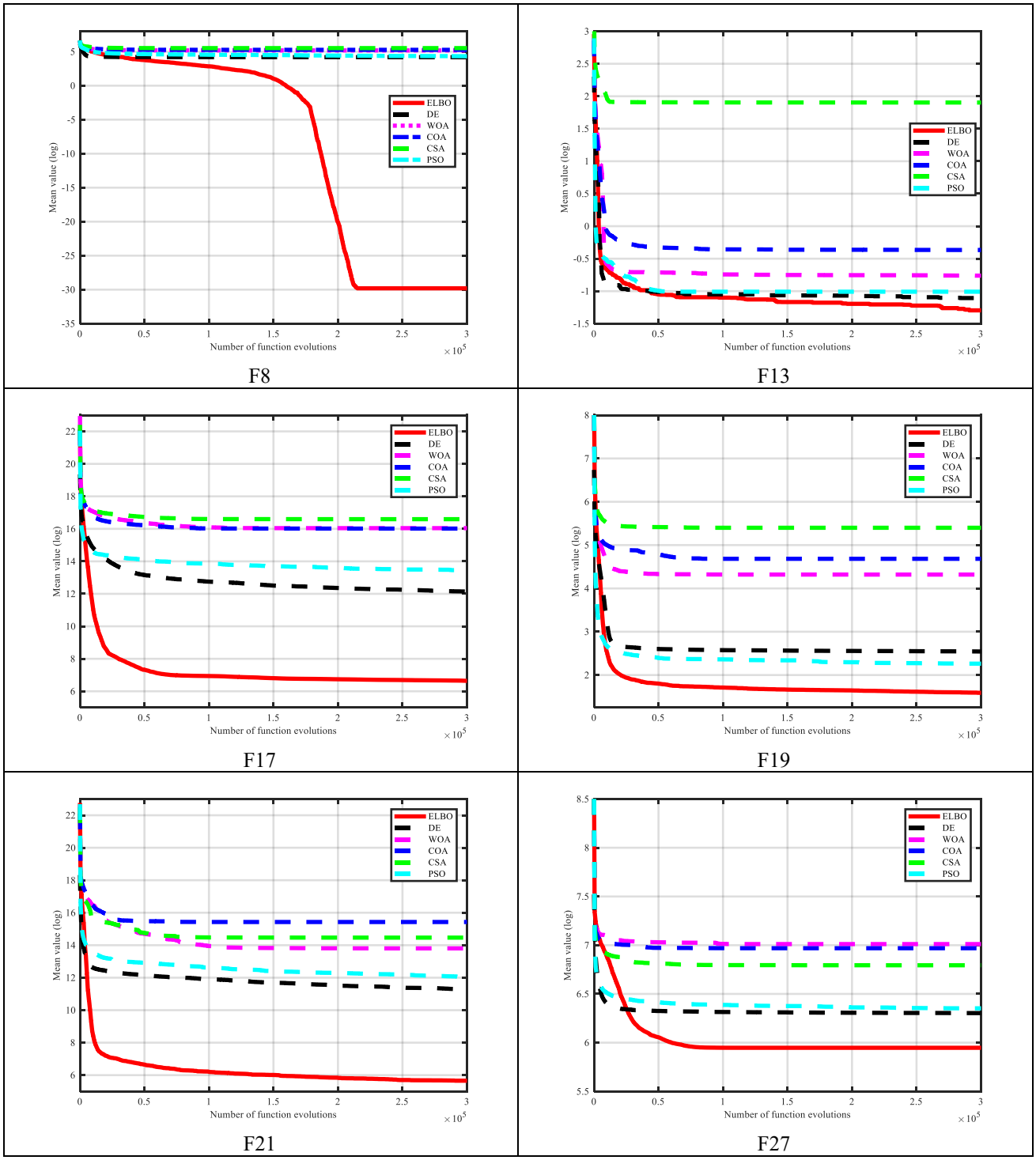


Figure 3. Convergence characteristics of sample test functions by the optimization algorithms.

C. 3. A comparative study with other results

Table 4 compares ELBO, and some recent optimization methods with a dimension of 30 applied to the CEC-2014 functions [131]. The list of algorithms includes SOS [132], [133], m-SCA (a hybrid sine-cosine algorithm (SCA)) [134], MG-SCA (a memory-guided SCA) [135], TOGPEAE (grey prediction evolutionary algorithm based on the TOBL) [136],

NIWTLBO (a TLBO nonlinear control parameters) [137], MFO [135], [138], CS [139], [97], LJA (Jaya with Levy flight) [140], MTLBO (a modified TLBO) [137], [141], and CMA-ES [142], [143]. Performance indicators including Std., Mean and wins for each function are taken into account in the comparison. Notably, the suggested ELBO method continuously performs better than others in terms of the stability and quality of the solutions. ELBO's robustness and dependability are demonstrated by the substantially lower mean values it obtains with little standard deviation for functions such as F1 and F2. Furthermore, the "+/-/=" numbers at the last row of the chart demonstrate ELBO's dominance across the majority of the test functions. These findings demonstrate ELBO's advantage over both conventional and modern approaches in managing intricate and varied optimization challenges.

Table 4. A comparison of ELBO with other results.

Function	SOS	MG-SCA	m-SCA	TOGPEAE	NIWTLBO	MFO	CS	LJA	MTLBO	CMA-ES	ELBO
	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. Winner	Mean Std. ---
F1	6.95E+07 2.92E+07 +	2.92E+07 2.07E+07 +	2.26E+07 6.35E+06 +	6.54E+06 3.49E+06 +	4.95E+05 3.70E+05 +	3.50E+07 2.49E+07 +	7.59E+07 9.77E+07 +	6.31E+07 1.87E+07 +	6.46E+07 4.03E+07 +	9.42E+04 7.89E+04 +	1.087E+04 7.483E+03
F2	3.61E+09 7.76E+08 +	2.26E+09 1.69E+09 +	8.11E+07 5.59E+07 +	1.79E+07 2.26E+07 +	1.78E+02 2.49E+02 +	1.95E+07 5.49E+07 +	1.36E+10 8.42E+09 +	4.77E+09 6.03E+08 +	1.18E+09 1.52E+09 +	2.55E+10 3.85E+09 +	4.026E-14 1.464E-14
F3	2.38E+04 1.35E+04 +	1.77E+04 6.63E+03 +	2.59E+04 6.43E+03 +	5.47E+03 4.07E+03 +	2.52E+01 5.73E+01 +	3.10E+04 1.36E+04 +	8.99E+04 4.98E+04 +	6.91E+04 1.07E+04 +	4.68E+00 1.73E+01 +	1.45E+04 5.66E+03 +	3.316E-13 1.649E-13
F4	4.10E+02 6.58E+01 +	2.76E+02 6.55E+01 +	1.83E+02 2.58E+01 +	1.44E+02 4.37E+01 +	9.32E+01 3.17E+01 +	2.03E+02 6.69E+01 +	1.14E+03 1.13E+03 +	4.08E+02 5.38E+01 +	3.85E+02 1.17E+02 +	2.52E+03 5.36E+02 +	5.411E+00 1.826E+01
F5	2.06E+01 6.32E−02 +	2.04E+01 1.44E−01 =	2.09E+01 7.07E−02 +	2.05E+01 3.56E−01 +	2.09E+01 4.68E–02 +	2.00E+01 2.28E−03 -	2.04E+01 1.75E−01 =	2.09E+01 4.97E–02 +	2.09E+01 5.60E–02 +	2.00E+01 2.63E-05 -	2.044E+01 4.190E-02
F6	2.33E+01 1.55E+00 +	1.94E+01 2.89E+00 +	1.46E+01 3.35E+00 +	2.16E+01 3.46E+00 +	2.88E+01 3.01E+00 +	3.23E+01 3.27E+00 +	2.40E+01 3.33E+00 +	3.39E+01 1.29E+00 +	2.42E+01 2.27E+00 +	4.09E+01 2.13E+00 +	4.627E+00 1.467E+00
F7	3.33E+01 6.92E+00 +	1.99E+01 1.18E+01 +	2.01E+00 4.62E−01 +	1.40E+00 3.12E−01 +	3.15E−01 1.42E+00 +	1.79E+00 2.19E+00 +	1.17E+02 6.91E+01 +	1.58E+01 2.80E+00 +	6.00E+01 2.36E+01 +	2.31E+02 2.83E+01 +	2.747E-13 1.024E-13
F8	8.16E+01 6.84E+00 +	1.07E+02 2.14E+01 +	1.10E+02 1.24E+01 +	5.89E+01 1.80E+01 +	1.42E+02 1.96E+01 +	1.71E+02 3.46E+01 +	1.43E+02 3.81E+01 +	2.24E+02 9.93E+00 +	1.16E+02 2.46E+01 +	2.83E+02 2.21E+01 +	1.137E-13 0.000E+00
F9	1.69E+02 1.75E+01 +	1.39E+02 2.56E+01 +	1.31E+02 9.81E+00 +	7.22E+01 2.17E+01 +	1.72E+02 2.15E+01 +	2.80E+02 5.16E+01 +	2.23E+02 6.06E+01 +	2.61E+02 1.47E+01 +	1.25E+02 2.89E+01 +	3.28E+02 7.65E+01 +	6.106E+01 5.324E+00
F10	1.38E+03	2.82E+03	3.58E+03	3.79E+03 1.91E+03	3.15E+03 4.38E+02	2.66E+03	3.47E+03	5.68E+03	2.87E+03	2.61E+02	7.642E+00

	1.96E+02 +	6.83E+02 +	4.72E+02 +	+	+	5.34E+02 +	8.85E+02 +	3.95E+02 +	6.57E+02 +	1.06E+02 +	3.217E+00
F11	4.48E+03 4.10E+02 +	3.30E+03 6.26E+02 -	4.93E+03 4.71E+02 +	4.53E+03 1.45E+03 +	3.05E+03 7.21E+02 -	4.13E+03 5.35E+02 +	4.15E+03 6.90E+02 +	6.88E+03 3.12E+02 +	3.28E+03 5.48E+02 -	1.69E+02 1.98E+02 -	3.744E+03 3.212E+02
F12	8.29E−01 1.44E−01 +	6.33E−01 3.36E−01 -	1.76E+00 2.89E−01 +	7.74E−01 1.10E+00 +	1.93E+00 6.19E−01 +	5.11E−01 2.56E−01 -	4.33E−01 2.64E−01 -	2.49E+00 2.73E−01 +	2.50E+00 2.66E−01 +	3.03E-01 2.18E+00 -	6.941E-01 1.056E-01
F13	7.79E−01 1.48E−01 +	5.51E−01 8.94E−02 +	3.86E−01 5.92E−02 +	4.93E−01 1.15E−01 +	5.93E−01 1.44E−01 +	4.81E−01 1.17E−01 +	2.21E+00 1.34E+00 +	1.08E+00 1.19E−01 +	1.77E+00 9.83E−01 +	5.51E+00 3.07E-01 +	2.738E-01 3.581E-02
F14	9.76E+00 3.87E+00 +	2.34E+00 3.31E+00 +	2.65E−01 2.94E−02 +	2.63E−01 5.02E−02 +	2.91E−01 1.67E−01 +	3.08E−01 5.64E−02 +	3.54E+01 2.47E+01 +	4.33E+00 1.70E+00 +	2.04E+01 8.51E+00 +	7.53E+01 8.08E+00 +	2.606E-01 3.420E-02
F15	2.50E+02 2.05E+02 +	8.72E+01 1.01E+02 +	1.52E+01 1.47E+00 +	2.43E+01 7.54E+00 +	1.74E+02 2.96E+02 +	9.80E+01 3.02E+01 +	2.23E+05 5.77E+05 +	5.05E+01 9.36E+00 +	1.20E+03 1.46E+03 +	1.02E+04 3.24E+04 +	6.991E+00 6.567E-01
F16	1.13E+01 3.70E−01 +	1.16E+01 6.91E−01 +	1.20E+01 2.89E−01 +	1.23E+01 6.54E−01 +	1.16E+01 4.92E−01 +	1.27E+01 5.01E−01 +	1.27E+01 5.33E−01 +	1.28E+01 1.78E−01 +	1.11E+01 7.48E−01 +	1.38E+01 5.31E−01 +	1.071E+01 2.854E-01
F17	5.68E+06 3.70E+06 +	9.56E+05 7.62E+05 +	5.99E+05 3.59E+05 +	7.12E+04 5.59E+04 +	2.52E+04 3.08E+04 +	1.48E+06 1.21E+06 +	3.39E+06 4.07E+06 +	2.63E+06 9.76E+05 +	6.56E+05 1.24E+06 +	5.49E+03 3.62E+03 +	7.658E+02 4.518E+02
F18	4.95E+05 2.26E+05 +	1.48E+05 9.00E+05 +	1.61E+05 8.25E+04 +	3.07E+03 3.05E+03 +	2.06E+03 2.34E+03 +	7.67E+03 6.70E+03 +	5.19E+06 3.61E+07 +	1.26E+07 1.06E+07 +	1.92E+04 8.10E+04 +	1.52E+09 3.93E+08 +	2.623E+01 1.092E+01
F19	3.80E+01 2.93E+01 +	2.28E+01 1.43E+01 +	1.93E+01 5.95E+00 +	1.60E+01 1.80E+01 +	2.30E+01 1.40E+01 +	5.33E+01 3.63E+01 +	7.36E+01 5.32E+01 +	3.78E+01 3.45E+01 +	8.02E+01 3.50E+01 +	2.98E+02 4.25E+01 +	4.902E+00 1.330E+00
F20	1.59E+04 1.09E+04 +	4.24E+03 3.82E+03 +	1.22E+04 3.70E+03 +	3.31E+03 3.67E+03 +	3.75E+02 1.56E+02 +	3.93E+04 2.20E+04 +	5.67E+04 4.34E+04 +	9.92E+03 3.69E+03 +	2.72E+02 1.21E+02 +	4.61E+03 3.88E+03 +	1.592E+01 5.246E+00
F21	7.86E+05 6.12E+05 +	2.35E+05 2.39E+05 +	1.10E+05 5.66E+04 +	1.73E+04 1.74E+04 +	1.44E+04 8.91E+03 +	3.54E+05 3.48E+05 +	7.83E+05 1.18E+06 +	6.94E+05 2.03E+05 +	3.18E+04 2.86E+04 +	6.86E+03 2.76E+03 +	2.862E+02 1.116E+02
F22	5.36E+02 1.74E+02 +	3.39E+02 1.78E+02 +	2.57E+02 5.71E+01 +	6.87E+02 1.65E+02 +	6.41E+02 2.93E+02 +	9.47E+02 3.31E+02 +	8.67E+02 2.29E+02 +	5.47E+02 1.05E+02 +	5.32E+02 2.09E+02 +	1.61E+03 2.92E+02 +	1.169E+02 5.869E+01
F23	3.32E+02 4.05E+00 +	3.29E+02 4.03E+00 +	3.21E+02 1.58E+00 +	2.16E+01 3.46E+00 -	2.00E+02 0.00E+00 -	3.29E+02 7.51E+00 +	3.71E+02 3.98E+01 +	3.43E+02 3.41E+00 +	3.53E+02 1.98E+01 +	5.79E+02 4.94E+01 +	3.152E+02 4.268E-13
F24	2.66E+02	2.00E+02	2.00E+02	3.17E+02 1.93E+00	2.00E+02 1.99E−05	2.78E+02	2.76E+02	2.57E+02	2.00E+02	2.12E+02	2.282E+02

	4.05E+00 +	1.56E−03 -	4.29E−02 -	+	-	3.11E+01 +	2.73E+01 +	4.04E+00 +	7.93E−04 -	7.49E+00 -	4.910E+00
F25	2.16E+02 2.60E+00 +	2.11E+02 2.82E+00 +	2.01E+02 3.19E+00 -	2.09E+02 7.21E+00 +	2.00E+02 0.00E+00 -	2.23E+02 9.39E+00 +	2.14E+02 7.65E+00 +	2.16E+02 2.58E+00 +	2.04E+02 7.51E+00 =	2.12E+02 2.97E+00 +	2.042E+02 1.396E+00
F26	1.01E+02 1.22E−01 +	1.01E+02 1.53E−01 +	1.00E+02 5.40E−02 =	1.04E+02 1.83E+01 +	1.90E+02 3.03E+01 +	1.00E+02 1.63E−01 =	1.03E+02 1.50E+00 +	1.01E+02 1.02E−01 +	1.41E+02 4.93E+01 +	1.25E+02 5.51E+01 +	1.003E+02 6.235E-02
F27	5.03E+02 1.48E+02 +	8.19E+02 9.17E+01 +	4.33E+02 2.01E+01 +	9.26E+02 8.92E+01 +	5.24E+02 2.76E+02 +	4.27E+02 1.96E+01 +	9.21E+02 2.23E+02 +	9.86E+02 2.48E+02 +	9.40E+02 2.48E+02 +	1.07E+03 2.30E+02 +	3.828E+02 5.841E+01
F28	1.33E+03 1.36E+02 +	9.68E+02 1.06E+02 +	1.05E+03 2.74E+02 +	1.58E+03 2.22E+02 +	1.88E+03 3.98E+02 +	3.49E+03 5.48E+02 +	1.12E+03 1.57E+02 +	1.13E+03 6.63E+01 +	2.36E+03 5.34E+02 +	2.79E+03 5.92E+02 +	8.254E+02 4.199E+01
F29	1.11E+05 1.14E+05 +	1.19E+06 3.25E+06 +	4.44E+04 1.77E+04 +	2.09E+03 5.16E+02 +	9.18E+05 3.58E+06 +	5.44E+05 2.61E+06 +	3.06E+06 3.62E+06 +	9.82E+05 2.07E+06 +	5.45E+06 1.21E+07 +	3.52E+04 5.34E+03 +	7.929E+02 1.587E+02
F30	3.73E+04 2.12E+04 +	1.92E+04 8.25E+03 +	3.48E+04 1.05E+04 +	1.09E+04 6.80E+03 +	2.93E+03 7.84E+02 +	2.49E+04 2.26E+04 +	5.89E+04 5.40E+04 +	1.09E+04 4.24E+03 +	8.61E+04 6.81E+04 +	6.48E+05 1.31E+05 +	2.732E+03 1.219E+03
+/-/=	30/0/0	26/3/1	27/2/1	29/1/0	26/4/0	27/2/1	28/1/1	30/0/0	27/2/1	26/4/0	-----

E. A comparative study of ELBO for the Engineering Optimization

This section evaluates the efficacy of the ELBO algorithm in addressing engineering optimization challenges, hence affirming its performance in practical applications. This work addresses the constraints of the optimization issue with the static penalty method [144]:

$$\partial(X) = f(X) \pm \left[\sum_{i=1}^{m} k_i \cdot \max\left(0, t_i(X)\right)^{\emptyset} + \sum_{j=1}^{n} b_j \cdot \left|S_j(X)\right|^{\gamma} \right] \tag{25}$$

Where, $\partial(X)$ is the objective function, and k_i and b_i represent two substantial penalty values. S_j (X) and t_i (X) delineate the constraints of the task. The specified exponents $\emptyset$ and γ belong to the set $\{1, 2\}$.

E.1. Gear train optimal design

Finding the four-gear sequence with the fewest teeth that minimizes the ratio of the follower shaft's and input shaft's angular velocities is the objective here. Remember that changing n_A (x_1), n_B (x_2), n_D (x_3) and n_F (x_4) has no effect on the values of the objective function and the side constraints (where i=1, 2, 3, 4). Hence, there are several global minima in the issue. All design variables are given integer values between 12 and 60 before the objective function is evaluated. See Fig. 4 for the gear train diagram related to this design problem. The goal here is to find a way to maximize the gear ratio's total cost [145].

Keeping to a minimum:

$$f\left(X\right) = \left(\frac{1}{6.931} - \left(x_2 x_3\right)\left(x_1 x_4\right)^{-1} \right)^2 \tag{26}$$

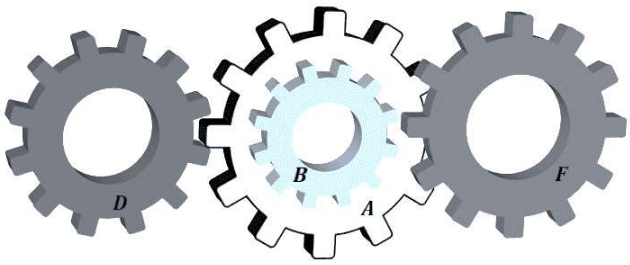


Figure 4. The gear train diagram.

Table 5 demonstrates that, in comparison to GOA and BES, ELBO has found a global optimal solution ***X*** **=< 49, 16, 19, 43 >**. For this kind of job, the best methods were LPO, CSA, mGWO, and UPSO, as shown in Table 5; however, LPO announced higher Worst, Mean, and Std.

Table 5. The optimal solutions for the problem.

Methods	Best	Mean	Worst	Std.
GOA [146]	2.308E-11	2.096E-08	1.110E-07	2.596E-08
UPSO	**2.700857E-12**	3.80562E-8	N.A.	1.09E-7
mGWO [147]	**2.7009E-12**	N.A.	N.A.	N.A.
BES [146]	1.166E-10	1.590E-03	4.563E-02	8.327E-03
CSA	**2.700857E-12**	2.059327E-9	3.184738E-8	5.0598E-9
ELBO	**2.700857E-12**	**8.3495E-10**	**4.7163E-9**	**3.15E-9**

E.2. Welded beam optimal design

As shown in Fig. 5, the main objective of this issue is to find the optimal values for the bar thickness (b), bar height (t), weld thickness (h), and length of the connected component of the bar (l) in order to minimize fabrication cost. The variables can't be legitimate until all seven conditions are satisfied. If you want to know how this problem is mathematically stated, read the original paper [148], [149]:

Keeping to a minimum:

$$f\left(X\right)=1.10471x_2x_1^2+0.04811x_3x_4\left(14+x_2\right) \tag{27}$$

By considering:

$$g_1\left(X\right)=\tau\left(x\right)-\tau_{\max}\le 0, \tag{28}$$

$$g_2\left(X\right)=-\sigma_{\max}+\sigma\left(x\right)\le 0, \tag{29}$$

$$g_3\left(X\right)=-x_4+x_1\le 0, \tag{30}$$

$$g_4\left(X\right)=0.04811\left(14+x_2\right)\times\left(x_3x_4\right)+0.10471x_1^2-5\le 0, \tag{31}$$

$$g_5\left(X\right)=-x_1+0.125\le 0, \tag{32}$$

$$g_6\left(X\right)=-\delta_{\max}+\delta\left(x\right)\le 0, \tag{33}$$

$$g_7\left(X\right)=-P_c\left(x\right)+P\le 0, \tag{34}$$

Where

$$\tau(x)=\sqrt{\left(\tau'\right)^2+2\tau'\tau''\frac{x_2}{2R}+\left(\tau''\right)^2} \tag{35}$$

$$\tau'=\frac{P}{\sqrt{2}x_1x_2},\tau''=\frac{MR}{J}, \tag{36-37}$$

$$M=P\left(L+\frac{x_2}{2}\right),R=\sqrt{\frac{x_2^2}{4}+\left(\frac{x_1+x_3}{2}\right)^2},\ \delta(x)=\frac{4PL^3}{Ex_3^3x_4} \tag{38-40}$$

$$J=2\left[\left\{\frac{x_2^2}{12}+\left(\frac{x_1+x_3}{2}\right)^2\right\}\times\sqrt{2}x_1x_2\right],\sigma(x)=\frac{6PL}{x_4x_3^2}, \tag{41-42}$$

$$P_c(x)=\frac{4.013E\sqrt{\frac{x_4^6x_3^2}{36}}}{L^2}\left(1-\frac{x_3}{2L}\sqrt{\frac{E}{4G}}\right), \tag{43}$$

σ_{max} =30,000, E = 30e6 psi, τ_{max} =13,000 psi, G=12e6 psi, L =14 in, psi P = 6,000 lb.

δ_{max} =0.25 in, $0.1\le x_1,x_4\le 2$, $0.1\le x_2,x_3\le 10$.

By applying it to the issue of designing welded beams, we have evaluated ELBO against other common optimization approaches. Table 6 shows that out of all the algorithms we looked at, the ELBO produces the best results. Consequently, the issue is clearly one that the ELBO can optimally solve. Keep in mind that the sum of all computations is shown in Table 7.

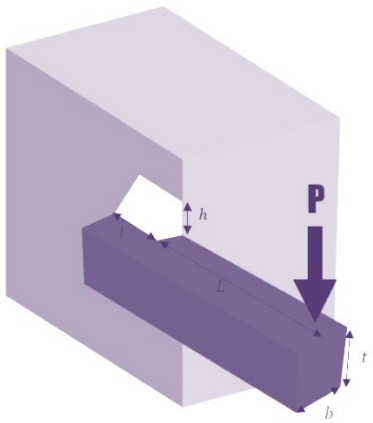


Figure 5. The welded beam.

Table 6. The optimal solutions for the methods.

Methods	Best	Mean	Worst	Std.
SFO [150]	1.73231	N.A.	N.A.	N.A.
EPSO [151]	1.7248530	1.7282190	1.7472200	5.62E-03
CPSO [152]	1.728024	1.748831	1.782143	1.2926E-02
BIANCA [153]	1.725436	1.752201	1.793233	2.3001E-02
HSA-GA [154]	2.2500	2.26	2.28	7.80E-03
UPSO [155]	1.92199	2.83721	N.A.	6.83E-01
IPSO [156]	2.3810	2.3819	N.A.	5.23E-03
HMS [157]	1.7255	N.A.	N.A.	N.A.
CDE [158]	1.73346	1.768158	1.824105	2.2194E-02
GA4 [159]	1.728226	1.792654	1.993408	7.47E-02

BFOA [160]	2.3868	2.4040	N.A.	1.60E-02
TEO [161]	1.725284	1.768040	1.931161	5.8166E-02
RAER [162]	2.3816	N.A.	2.38297	3.4E-04
EO [163]	1.724853	1.726482	1.736725	3.257E-03
AD-IFA [164]	1.81	2.40	N.A.	0.50
GWO [165]	1.72624	N.A.	N.A.	N.A.
ELBO	1.7248523	1.725938	1.7333927	8.16E-07

Table 7. The optimal results for the problem.

Parameters	ELBO
x_1	0.2057296
x_2	3.47048867
x_3	9.036624
x_4	0.20572964
$g_1(X)$	-2.2647E-07
$g_2(X)$	-3.1927E-07
$g_3(X)$	0.0
$g_4(X)$	-3.4325
$g_5(X)$	-0.0809
$g_6(X)$	-0.2358
$g_7(X)$	-1.109E-06
Best	1.7248523

E.3. Tension/compression spring optimal design

The optimization considers the tension and compression of the load on a spring, as seen in Fig. 6. The objective is to decrease the mass of the spring's reactive volume when exposed to tensile or compressive forces [158]. Assumed design parameters include the wire diameter ($x3$), winding diameter ($x2$), and quantity of active spring coils ($x1$); the spring volume need optimization to resolve the issue [158].

$$f\left(X\right)=\left(x_3+2\right)x_2x_1^2 \tag{44}$$

Subject to:

$$g_1\left(X\right)=1-\frac{x_2^3x_3}{71,785x_1^4}\le 0, \tag{45}$$

$$g_2\left(X\right)=\frac{4x_2^2-x_1x_2}{12,566\left(x_1^3x_2-x_1^4\right)}+\frac{1}{5,108x_1^2}-1\le 0, \tag{46}$$

$$g_3\left(X\right)=1-\frac{140.45x_1}{x_2^2x_3}\le 0, \tag{47}$$

$$g_4\left(X\right)=\frac{x_1+x_2}{1.5}-1\le 0. \tag{48}$$

$$2\le x_3\le 15,\ 0.25\le x_2\le 1.3,\ 0.05\le x_1\le 2. \tag{49}$$

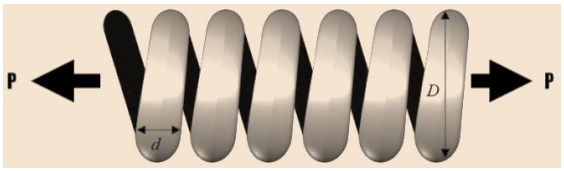


Figure 6. The tension/compression spring.

Table 8 presents the outcomes of several meta-heuristic methodologies. The cost function was similarly reduced by the ELBO algorithm for the issue. Upon examining the data in Table 8, it is evident that the outcomes of the majority of the assessed heuristics closely resemble those of constraint correction and mathematical optimization. One model variable yields somewhat different results, however. Moreover, there exists significant overlap in the cost function values between the benchmarks documented in the literature and the examined heuristics. Consequently, it would be erroneous to claim that the suggested ELBO is the superior optimization method among those we evaluated. ELBO attains a success rate in trials comparable to that of the traditional algorithms GA and PSO. Consequently, ELBO has attained the highest ranking in the data shown in Table 9.

Table 8. The optimal solutions for the problem.

Methods	Best	Mean	Worst	Std.
CDE [158]	0.012670	0.012703	0.012790	2.07E-05
GA4 [159]	0.012681	0.012742	0.012973	9.5E-05
CPSO [153]	0.0126747	0.012730	0.012924	5.19E-05
CVI-PSO [150]	0.0126655	0.012731	0.0128426	5.58E-05
SFFA [166]	0.0126660517	0.0127072216	0.0127680353	2.57941E-05
UPSO [189]	0.01312	0.02294	N.A.	7.2E-03
INFO [167]	0.012666	N.A.	N.A.	N.A.
MFO [168]	0.012753902	0.014023657	0.017236590	0.001390
GA3 [169]	0.0127048	0.012769	0.012822	3.93E-05
(l + λ)-ES [148]	0.012689	0.013165	N.A.	3.9E-04
HGA [127]	0.012668	0.013481	0.016155	N.A.
MVO [168]	0.012816930	0.014464372	0.017839737	0.001622
TDO [171]	0.012671024	0.012681410	0.012701561	0.00002042
DDAO [172]	0.0129065	0.0151829	0.0173199	1.26E-03
EO [163]	0.012666	0.013017	0.013997	3.91E-04
SCA [168]	0.012709667	0.012839637	0.012998448	0.000078
SDO [173]	0.0126663	0.0126724	0.0126828	6.1899E-06
mGWO [147]	0.012668	N.A.	N.A.	N.A.
BFOA [160]	0.012671	0.012759	N.A.	1.36E-04
ELBO	0.0126652	0.012668935	0.0126775	3.41E-06

Table 9. The optimal results for the problem.

Parameters	**ELBO**
x_1	0.051662352
x_2	0.356077462
x_3	11.326603
$g_1(X)$	-3.9018E-11
$g_2(X)$	-1.9527E-11
$g_3(X)$	-4.05249
$g_4(X)$	-0.72817
Best	0.0126652

4. Results of numerical optimization

With the intention of verification of the functionality and efficacy of ELBO algorithm, it is used for optimizing power flow in IEEE 30- (the first system) and 57-bus (the second system), and 118-bus (the three system) networks. All simulations were carried out using MATLAB 7.6.

Penalty values in (11) are selected as λ_P =5000000, $\lambda_V = \lambda_Q$ =5000000 and λ_S =1000000. For every instance, each algorithm was executed thirty times. For the 30-bus system, the maximum number of iterations (Itermax) and the population value are 400 and 30, respectively, while for the 57-bus system, they are 600 and 60. To investigate the efficiency of ELBO, eleven types have been considered as follows:

The initial network's case studies included:

• Cutting the fuel cost
• Cutting fuel cost functions piecewise quadratic.
• Cutting down on emissions.
• Reducing the actual power outage
• Reducing the actual power loss and fuel expenditure; minimizing the non-smooth fuel cost
• Cutting down on fuel costs, pollutants, voltage variation, and losses.

The considered Cases for the second network:

- Minimizing the fuel cost
- Minimizing the voltage deviation and fuel cost
- Minimizing the fuel cost, emissions, voltage deviation and losses

A. The first network

The limits for the control variables, generator data and bus data of the first network have been given in [174], [175], [176]. This system, which is shown in Fig. 7, has generation units at the buses 1, 2, 5, 8, 11 and 13 and P_D= 283.4 MW. The load buses' voltage restrictions are set at 1.06 and 0.94 p.u., respectively [177], [178].

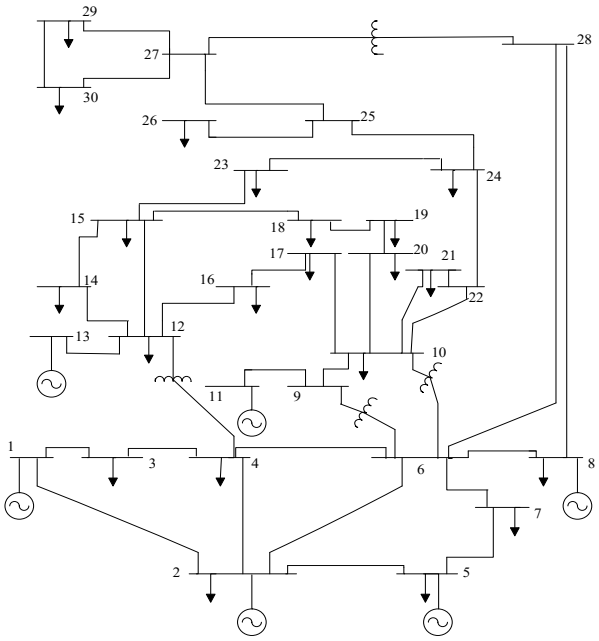


Figure 7. The IEEE 30-bus network.

All the obtained optimal results by ELBO for all the problems of this network have been given in the Supplementary Material's Table S.1.

1. Minimizing the fuel cost

In practical power systems, generating units use fossil fuel resources such as natural gas and oil. The expenses related to these fuels may be stated in the following manner:

$$J = \sum_{i=1}^{NG} F_i(P_{Gi}) = \sum_{i=1}^{NG} (\alpha_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad (50)$$

The variables α_i, b_i and c_i indicate the cost coefficients of the ith unit, whereas NG represents the number of generating units. These values are provided in reference [176]. Comparison of fuel cost minimum, Emission, Power losses, and V.D., of TLBO and ELBO algorithms are summarized in Table 10 and these results have been compared with other algorithms have been achieved in the recent studies.

As this table illustrates well, ELBO is a suitable and reliable algorithm for optimizing this basic fuel cost function compared to other algorithms. The convergence characteristic of this problem by basic fuel cost function compared to basic fuel cost function has been given in Fig. 8. Based on Fig. 8, it can be seen that the suggested method exhibits a favorable and efficient rate of convergence.

2. Minimizing the units fuel cost take into account multi-fuel sources

In real power systems, some generators are powered by multiple fuels, leading to a piecewise quadratic objective function. Therefore, this OPF problem for these systems can be modeled as follows [179]:

$$F(P_{Gi}) = \begin{cases} \alpha_{i1} + b_{i1}P_{Gi} + c_{i1}P_{Gi}^2 & P_{Gi}^{\min} \le P_{Gi} \le P_{Gi1} \\ \alpha_{i2} + b_{i2}P_{Gi} + c_{i2}P_{Gi}^2 & P_{Gi1} \le P_{Gi} \le P_{Gi2} \\ \dots & \\ \alpha_{ik} + b_{ik}P_{Gi} + c_{ik}P_{Gi}^2 & P_{Gik-1} \le P_{Gi} \le P_{Gi}^{\max} \end{cases} \quad (51)$$

Where, k represents the fuel type.

Typically in most previous articles, these conditions are considered only for the first and the second generators, as modeled below:

Table 10. Comparison of the best outcomes using algorithms.

Method	Fuel cost ($/h)	Emission (t/h)	Power losses (MW)	V.D. (p.u.)
ELBO	800.4791	0.3661	9.0189	0.9060
TLBO	800.515	0.3668	9.1056	0.9763
MSA [63]	800.5099	0.36645	9.0345	0.90357
MFO [63]	800.6863	0.36849	9.1492	0.75768
FPA [63]	802.7983	0.35959	9.5406	0.36788
MHBMO [66]	801.985	-	9.49	-
IEP [180]	802.46	-	-	-
ARCBBO [181]	800.5159	0.3663	9.0255	0.8867
MICA-TLA [106]	801.0488	-	9.1895	-
GWO [84]	801.41	-	9.30	-
DE [176]	802.39	-	9.466	-
SFLA-SA [182]	801.79	-	-	-
SKH [183]	800.5141	0.3662	9.0282	-
Jaya [184]	800.4794	-	9.06481	0.1273
TS [76]	802.29	-	-	-
MGBICA [185]	801.1409	0.3296	-	-
ABC [65]	800.660	0.365141	9.0328	0.9209
EP [186]	803.57	-	-	-
MPSO-SFLA [88]	801.75	-	9.54	-
PSOGSA [187]	800.49859	-	9.0339	0.12674
AGSO [68]	801.75	0.3703	-	-

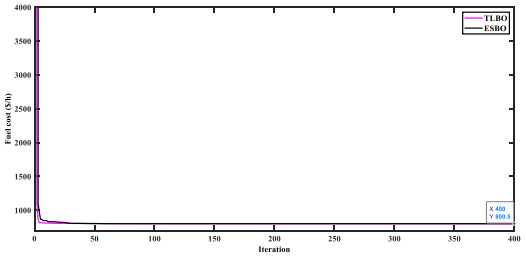


Figure 8. Convergence of TLBO and ELBO.

$$J=\left(\sum_{i=1}^{2}\alpha_{ik}+b_{ik}P_{Gi}+c_{ik}P_{Gi}^{2}\right)+\left(\sum_{i=3}^{NG}\alpha_{i}+b_{i}P_{Gi}+c_{i}P_{Gi}^{2}\right) \quad (52)$$

The data of the units having multi-fuel types were extracted from [176]. The fuel cost, emissions, system losses, and V.D. of TLBO and ELBO algorithms are compared in Table 11. These results are then contrasted with the findings from current research. The table demonstrates that ELBO has a suitable level of optimization capability in comparison to other methods. Furthermore, based on the information shown in Fig. 9, it can be seen that this algorithm is capable of attaining the ultimate optimum solution within the suitable amount of repetitions.

Table 11. Comparison of the best outcomes using algorithms.

Algorithm	**Fuel cost ($/h)**	Emission (t/h)	Power losses (MW)	V.D. (p.u.)
ELBO	**646.4612**	0.2835	6.7321	0.9066
TLBO	648.8523	0.2840	7.2096	0.7060
MSA [63]	646.8364	0.28352	6.8001	0.84479
MFO [63]	649.2727	0.28336	7.2293	0.47024
FPA [63]	651.3768	0.28083	7.2355	0.31259
MDE [176]	647.846	-	7.095	-
IEP [180]	649.312	-	-	-
GABC [188]	647.03	-	6.8160	0.8010
MICA-TLA [106]	647.1002	-	6.8945	-
SSO [67]	663.3518	-	-	-
LTLBO [95]	647.4315	0.2835	6.9347	0.8896
MPSO-SFLA [88]	647.55	-	-	-

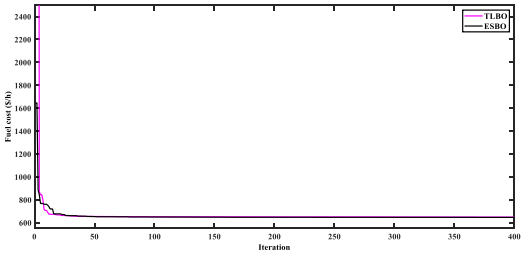


Figure 9. Convergence of TLBO and ELBO.

3. Minimizing the emission

Today, one of the most significant issues in the energy generation units using fossil fuels is the emission of various pollutants due to the burning of these fuels by generation units. For this reason, in recent optimization papers, the amount of emissions is considered as a separate function (as in the present study) or in combination with other functions. This work examines the emission function in the following manner**:**

$$F_{\mathrm{OPF4}}=\sum_{i=1}^{NG}F_{Ei}(P_{Gi})=\sum_{i=1}^{NG}\left(\alpha_{i}+\beta_{i}P_{Gi}+\gamma_{i}P_{Gi}^{2}+\xi_{i}\exp(\lambda_{i}P_{Gi})\right) \quad (53)$$

where F_{Ei} represent the emissions produced by the ith generator and the α_i, β_i, γ_i, ξ_i and λ_i, are the emission factors of the ith unit, γ_i (ton/(h MW^2)), α_i (ton/h), β_i (ton/(h MW)), have been associated with SOX, and λ_i (1/MW) and ξ_i (ton/h) are related to NOX respectively.

Table 12 displays the outcomes of ELBO in contrast to the original TLBO and many other algorithms examined in recent literature. The suggested ELBO achieves an optimum solution with a lower objective function value compared to the other approaches. The convergence properties of the Evidence Lower Bound (ELBO) were also shown in Fig. 10.

4. Minimizing the real power loss

One of the primary objectives of an electrical energy transmission network is to minimize power losses (P_{Loss}) during the transmission of electrical power. Therefore, in this section, we have considered it as a separate function and optimization has been performed on it. Here is a description of the objective function:

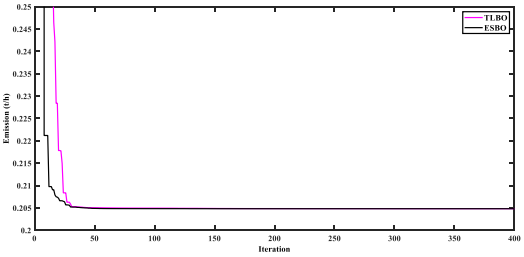


Figure 10. Convergence of TLBO and ELBO.

TABLE 12. Comparison of the best outcomes using algorithms.

Algorithm	Fuel cost ($/h)	Emission (t/h)	Power losses (MW)	V.D. (p.u.)
ELBO	944.3387	**0.20482**	3.2233	0.8938
TLBO	944.4459	0.20483	3.2571	0.8881
MSA [63]	944.5003	**0.20482**	3.2358	0.87393
MFO [63]	945.4553	0.20489	3.4295	0.70968
FPA [63]	948.949	0.20523	4.492	0.42761
MSFLA [182]	-	0.2056	-	-
DSA [44]	944.4086	0.2058255	3.2437	-
ABC [65]	944.4391	0.204826	3.2470	0.8463
ARCBBO [181]	945.1597	**0.20482**	3.2624	0.8647
GBICA [185]	944.6516	0.2049	-	-
MPSO-SFLA [88]	-	0.2052	-	-
AGSO [68]	953.629	0.2059	-	-

$$J(x,u) = P_{Loss} = \sum_{\substack{k=1 \\ k=(i,j)}}^{NTL} g_k \left(V_i^2 + V_j^2 - 2V_i V_j \cos\delta_{ij}\right) \tag{54}$$

Where g_k shows the conductance of branch *k, NTL* depict the number of network lines and *NPQ* depict the number of *PQ* buses. Table 13 displays the end findings, whereas Fig. 11 displays the algorithm's convergence characteristic. The suggested enhanced algorithm was able to identify the proper solution in the necessary number of iterations, according to the findings.

5. Minimizing the non-smooth fuel cost

In power system optimization problems, whose generators are usually operated with fossil fuels, opening and closing the valves of fuel supply tanks alter the fuel consumption. Hence in this paper, the valve-point effects are considered by modifying the objective function of this problem, as follows [182].

$$J = \sum_{i=1}^{NG} \alpha_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \sin\left(e_i \left(P_{Gi}^{\min} - P_{Gi}\right)\right)\right| \tag{55}$$

where d_i and e_i show cost factors of the *i*th generator with the valve-point effects.

The results obtained by ELBO algorithm in comparison with solutions reported in several previous papers have been shown in Table 14, which illustrate the effectiveness of ELBO. The convergence characteristics of this problem has been given in Fig. 12.

Table 13. Comparison of the best outcomes using algorithms.

Method	Fuel cost ($/h)	Emission (t/h)	Power losses (MW)	V.D. (p.u.)
ELBO	967.6376	0.2073	**3.0896**	0.8995
TLBO	967.6680	0.2073	3.1028	0.9018
MSA	967.6636	0.20727	3.1005	0.88868
MFO	967.6785	0.20727	3.1111	0.91558
FPA	967.1138	0.20756	3.5661	0.3893
GWO	968.38	-	3.41	-
ALC-PSO	967.7683	-	3.1700	-
ARCBBO	967.6605	0.2073	3.1009	0.8913
EGA	967.93	-	3.244	-

DSA	967.6493	0.20826	3.0945	-
EEA	952.3785	-	3.2823	-
ABC	967.6810	0.207268	3.1078	0.9008
Jaya	967.6827	-	3.1035	0.1272
EGA-DQLF	967.86	-	3.2008	0.12178

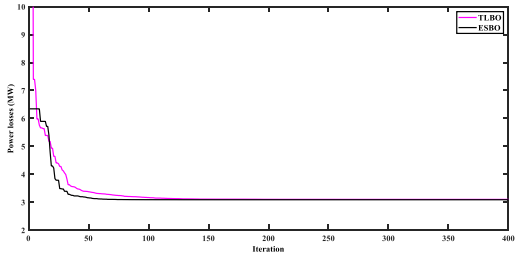


Figure 11. Convergence characteristics of TLBO and ELBO.

Table 14. Comparison of the best outcomes using algorithms.

Method	**Fuel cost ($/h)**	Emission (t/h)	Power losses (MW)	V.D. (p.u.)
ELBO	**832.1622**	0.4378	10.6849	0.8619
TLBO	832.3310	0.4385	10.7701	0.6044
PSO	832.6871	-	-	-
SP-DE	832.4813	0.43651	10.6762	0.75042

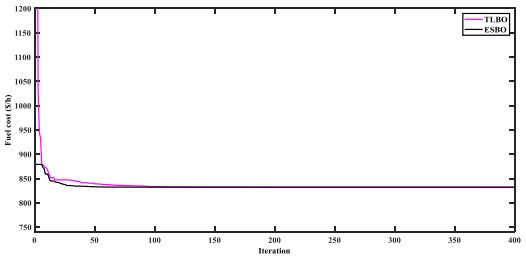


Figure 12. Convergence of TLBO and ELBO.

To assess the effectiveness of the proposed ELBO, we want to compare and evaluate its efficiency in three more problems, namely issues 6, 7, and 8. In these problems, many objective functions are optimized concurrently, which transforms our problem into a multi-objective OPF.

6. Minimizing the losses and fuel cost

In the first problem of multi-objective optimization, we consider network power losses plus a factor (λp) of the OPF function. The coefficient has been formulated as the previous articles. The total cost for this issue is as follows:

$$J = \sum_{i=1}^{NG} \alpha_i + b_i P_{Gi} + c_i P_{Gi}^2 + \lambda p * P_{Loss} \tag{56}$$

Where, λp has been chosen as 40 [192].

According to the data shown in Table 15, it can be concluded that the proposed ELBO yields adequate outcomes in comparison to the original algorithm, SF-DE [192] and MSA [63].

7. Minimizing the voltage deviation and fuel cost

By just focusing on the basic OPF objective function in this optimization issue, the produced solutions may not accurately reflect the network voltage profile. Therefore, the goal function may be divided into two components. The first component involves lowering the fuel cost function, while the second part aims to reduce voltage deviations from the reference value

of 1 p.u. in the load buses, in order to improve the network's voltage profile. In general, this OPF case have been written as follows [95]:

$$J = \sum_{i=1}^{NG}(\alpha_i + b_i P_{Gi} + c_i P_{Gi}^2) + \lambda v * \sum_{i=1}^{NPQ}|V_i - 1.0| \quad (57)$$

In Eq.(57), 100 has been chosen as the value of λv [192].

Table 16 summarizes the comparison of the minimal fuel cost ($/h) and V.D. (p.u.) of the TLBO and ELBO methods. The best solutions obtained from these analyses have been contrasted with those obtained from the current investigations. The optimal solutions given in the table illustrate well the power of ELBO, which succeeded in obtaining suitable solutions in this case.

Table 15. Comparison of the best outcomes using algorithms.

Method	**Fuel cost ($/h)**	Emission (t/h)	**Power losses (MW)**	V.D. (p.u.)
ELBO	**859.0628**	0.2289	4.5280	0.9351
TLBO	859.2003	0.2289	4.5332	0.9436
MSA	859.1915	0.2289	4.5404	0.92852
SF-DE	859.1458	0.2289	**4.5245**	0.92731

Table 16. Comparison of the best outcomes using algorithms.

Method	**Fuel cost ($/h)**	Emission (t/h)	Power losses (MW)	**V.D. (p.u.)**
ELBO	**803.7071**	0.3641	9.8599	**0.0948**
TLBO	803.7692	0.3652	9.8583	0.0993
MPSO	803.9787	0.3636	9.9242	0.1202
MFO	803.7911	0.36355	9.8685	0.10563
ECHT-DE	803.7198	0.36384	9.8414	0.09454
MOMICA [193]	804.9611	0.3552	9.8212	0.0952
MOICA [193]	805.0345	-	-	0.1004
MNSGA-II [193]	805.0076	-	-	0.0989
BB-MOPSO [193]	804.9639	-	-	0.1021
NKEA [193]	804.9612	-	-	0.099

8. Minimizing the fuel cost, losses, emission and voltage deviation

The 30-bus system's OPF issue from earlier, we considered all four objective functions, same as MOMICA [193] and MSA [63]; which can be said to be a comprehensive OPF's objective function.

$$J = \sum_{i=1}^{NG}(\alpha_i + b_i P_{Gi} + c_i P_{Gi}^2) + \lambda v * \sum_{i=1}^{NPQ}|V_i - 1.0| + \lambda p * P_{Loss} + \lambda e * \sum_{i=1}^{NG} F_{Ei}(P_{Gi}) \quad (58)$$

The $\lambda v = 21$, $\lambda p = 22$ and $\lambda e = 19$ have been chosen to maintain equilibrium among the various functions of OPF [192]. Considering the outcomes contrasted in Table 17, ELBO is an acceptable and reliable algorithm for the comprehensive OPF's objective function in electrical transmission networks.

Table 17. Comparison of the best outcomes using algorithms.

Method	**Fuel cost ($/h)**	**Emission (t/h)**	**Power losses (MW)**	**V.D. (p.u.)**
ELBO	**830.1750**	0.2531	**5.5802**	0.2989
TLBO	830.5085	0.2555	5.7412	0.3004
MSA	830.639	0.25258	5.6219	**0.29385**
MFO	830.9135	0.25231	5.5971	0.33164
MOMICA	830.1884	0.2523	5.5851	0.2978
MOICA	831.2251	0.267	6.0223	0.4046
MNSGA-II	834.5616	0.2527	5.6606	0.4308
BB-MOPSO	833.0345	**0.2479**	5.6504	0.3945
NKEA	834.6433	0.2491	5.8935	0.4448

B. The second system

For evaluating the efficiency of the proposed ELBO in larger scale electrical transmission networks, a IEEE 57-bus transmission network [194], Fig. 13, is considered. The system includes seven generating units, 80 branches, 15 tap

changing transformers, 3 shunt reactive compensators and total demand of 1250.8 MW. The data of this test system was extracted from [194].

1. Minimizing the fuel cost

In the 57-bus system initial OPF challenge, for demonstrating the efficiency of the ELBO, we examined the same simple original objective function, as follow:

$$J = \sum_{i=1}^{NG} F_i(P_{Gi}) = \sum_{i=1}^{NG} \left(\alpha_i + b_i P_{Gi} + c_i P_{Gi}^2 \right) \tag{59}$$

The obtained optimal solutions via ELBO with several solutions reported in the previous articles are given in the Supplementary Material's Table S.2. Table 18 also presents a comparative study between the obtained optimal value of this problem from ELBO and some other recent algorithms.

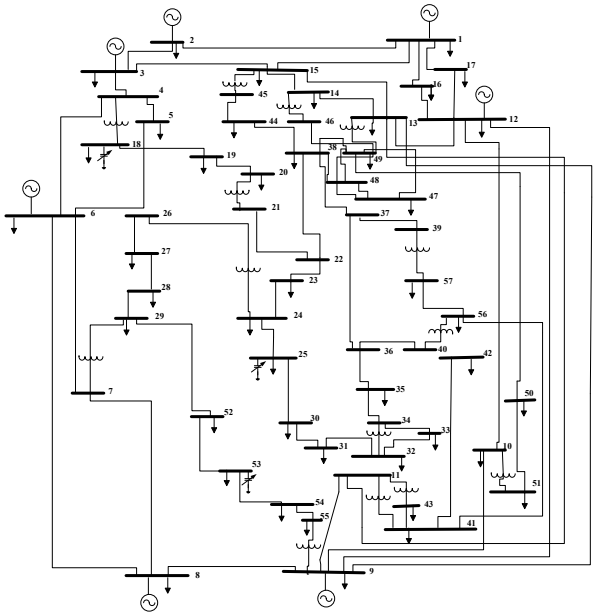


Figure 13. Single line diagram of IEEE 57-bus transmission network.

It must clearly say that the improved algorithm proposed in this study is able to achieve better solutions. Additionally, Fig. 14 provides the convergence characteristic of ELBO compared to the TLBO technique.

Table 18. Comparison of the best outcomes using algorithms.

Method	**Fuel cost ($/h)**	Emission (t/h)	Power losses (MW)	V.D. (p.u.)
ELBO	**41677.3441**	1.9018	15.0648	1.6812
TLBO	41703.5462	1.8907	16.7136	1.4394
MPSO	41678.6762	1.9443	15.1271	1.3397
MFO	41686.4119	2.0036	15.611	1.2938
EADDE	41713.62	-	16.09	1.0977
MICA	41683.048	-	15.2658	1.4487
ARCBBO	41686.0	-	15.3769	-
ICBO	41697.33	-	15.5470	1.3173
DSA	41686.82	-	-	1.0833
LTLBO	41679.5451	-	15.1589	-

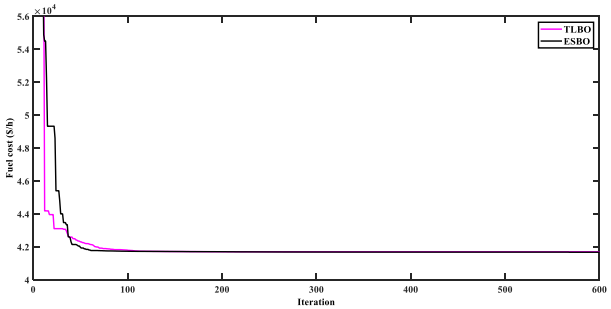


Figure 14. Convergence of TLBO and ELBO.

2. Minimizing the voltage deviation and fuel cost

One of the primary security and service metrics is bus voltage. In the OPF issue, focusing just on fuel expense would provide a viable optimum outcome that results in an incorrect voltage profile. Thus, the basic OPF problem should be considered as follows to account for voltage profile improvement.

$$J = \sum_{i=1}^{NG}(\alpha_i + b_i P_{Gi} + c_i P_{Gi}^2) + \lambda v * \sum_{i=1}^{NPQ}|V_i - 1.0| \tag{60}$$

Table 19 displays the ideal findings that were achieved. Based on this table, it can be concluded that the voltage profile of the 57-bus system in this situation is much better than it was in the previous example. Also, ELBO has been able to reach acceptable and appropriate solutions in comparison with the previously proposed methods. For better study, the optimal solutions obtained via various optimizers are given in Table S. 3 in the Supplementary Material.

Table 19. Comparison of optimal results via algorithms.

Method	**Fuel cost ($/h)**	Emission (t/h)	Power losses (MW)	V.D. (p.u.)
ELBO	**41692.4372**	1.9093	15.4500	0.9237
TLBO	41706.9438	1.9625	16.8427	0.9026
MPSO	41721.6098	2.0096	16.2453	0.67813
MFO	41718.87	2.0149	16.2189	0.6780
EADDE	42051.44	-	19.32	0.7882
MICA	41974.4346	-	20.303	0.5416
MSA	41714.98	1.9551	15.9214	0.6782
DSA	41699.40	-	-	0.7620
MICA-TLA	41959.18		19.909	**0.5390**

3. Minimizing the fuel cost, losses, emission and voltage deviation

In the last problem of power flow optimization, we considered all four objective functions, as in [63], [193]:

$$J = \sum_{i=1}^{NG}(\alpha_i + b_i P_{Gi} + c_i P_{Gi}^2) + \lambda v * \sum_{i=1}^{NPQ}|V_i - 1.0| + \lambda p * P_{Loss} + \lambda e * \sum_{i=1}^{NG} F_{Ei}(P_{Gi}) \tag{61}$$

To balance the various goals of the issue, the weight factors λv = 1000, λp = 100 and λe = 1000were chosen.

It can obvious from the results compared in Table 20 that, ELBO is an acceptable and reliable optimization method for OPF problem in electrical networks. The final solution for this case is also given in the Supplementary Material's Table S.4.

Table 20. Comparison of the best outcomes using algorithms.

Algorithm	**Fuel cost ($/h)**	**Emission (t/h)**	**Power losses (MW)**	**V.D. (p.u.)**
ELBO	**41929.1688**	**1.4328**	13.2513	0.9509
TLBO	42003.5234	1.4732	14.025	0.9601
MOMICA [193]	41983.0585	1.496	13.6969	**0.797**
MOICA [193]	41998.5661	1.7605	13.3353	0.8748
MNSGA-II [193]	42070.82476	1.4965	14.4557	0.8896
BB-MOPSO [193]	41994.0191	1.5336	**12.609**	1.0742
NKEA [193]	42065.9964	1.5174	13.9764	1.042

C. The third system

Using the IEEE 118-bus test network, a common benchmark in electrical engineering, we analyze the performance of

the proposed ELBO in controlling larger-scale power systems [195]. There are 186 branches, 9 transformers, 12 capacitors, 2 reactors, and 54 generators in this system. There are 129 control parameters in all, including 54 for the bus voltage levels and the active power outputs of the generator, 9 for the tap adjustments of the transformer, and 12 for the reactive power contributions from the shunt capacitors. There is a voltage range of 0.94 to 1.06 p.u. for all busses. Shunt capacitor reactive power may be tuned between 0 and 30 MVAR, and tap settings on transformers are studied between 0.90 and 1.10 p.u. [196].

The first case: traditional OPF

In the first case, we can write the following quadratic cost function for traditional OPF generators that don't use renewable energy sources like solar or wind. Results from other algorithms investigated in the domain of electrical engineering are compared to the suggested ELBO's performance in Table 21. Methods for addressing OPF issues on a grand scale are also covered in depth in literature reviews. These statistics demonstrate how ELBO outperforms alternative optimization approaches in obtaining optimum OPF solutions via comparison analysis. With ELBO reaching a minimum cost of $129,515.8195per hour, the simulation results show a significant decrease in cost, exceeding the outcomes provided by other algorithms.

Table 21. Comparison of the best outcomes using algorithms.

Method	Min	Mean	Max	Std.	Time (s)
ELBO	129,515.8195	129,520.7104	129,529.6390	5.18	457
TLBO	129,519.0082	129,527.9553	129,534.6114	8.06	460
CO [197]	130,114.8259	130,174.7329	130,286.1126	106.49	684
GBBLCO [197]	129,540.7925	129,549.8814	129,561.3545	4.26	658
INFO [198]	138,672.82	142,884.29	143,578.68	445.7	1378
AOA [198]	139,569.56	143,175.14	145,509.84	801.2	1134
COA [198]	138,685.15	142,950.74	144,007.34	699.4	730
MCOA [198]	129,537.37	129,549.25	129,555.14	6.37	726
Rao-3 [199]	131,793.1	-	-	-	806.7
MFO [63]	129,708.1	-	-	-	-
CS-GWO [195]	129,544.0	129,558.9	129,568.8	10.7	4252.5
EWOA [200]	140,175.8	-	-	-	-
IABC [201]	129,862.0	129,895.0	-	40.8	4157.8
FPA [63]	129,688.7	-	-	-	-
MCSA [202]	129,873.6	-	-	-	-
ICBO [70]	135,121.6	-	-	-	-
MRao-2 [199]	131,457.8	-	-	-	1160.3
FHSA [199]	132,138.3	132,138.3	132,138.3	0.0	-
Rao-2 [199]	131,490.7	-	-	-	804.6
PSOGSA [87]	129,733.6	-	-	-	-
Rao-1 [199]	131,817.9	-	-	-	808.0
ETFWO [203]	129,542.8215	129,550.8843	129,561.7019	7.13	723.76
GWO [84]	139,948.1	142,989.3	145,484.6	797.8	1766.2
MSA [63]	129,640.7	-	-	-	-
GBLCSBO [204]	129,517.8425	129,523.7694	129,530.0372	8.19	1516
CSBO [204]	129,621.7754	129,714.4929	129,985.1247	73.41	1502
MVO [204]	140,087.5320	142,951.1445	145,673.5718	5594.75	1485
GWO [204]	140,026.8167	143,118.7531	145,379.1020	2403.61	1664
SOA [204]	138,559.6359	142,711.5410	144,619.1239	1839.70	1630
SSO [199]	132,080.4	-	-	-	-

The second case: OPF containing a quadratic cost function for conventional generators, with the integration of solar and wind energy sources.

The second case is an OPF that integrates solar and wind power in addition to traditional generators with a quadratic cost function. It may be expressed as follows:

To solve the OPF problem, we need to account for the operating expenses of conventional generators and create a quadratic cost function for them. The issue becomes more complicated when renewable energy sources like solar and wind are included because of their intermittent nature and varying outputs. The main objective is to maximize the system's power flow while taking into account the specific features and financial consequences of renewable and conventional energy

sources [205-209]. Like the last case study, this one employs renewable energy sources on board a number of buses. Solar power plants are situated at 6, 15, and 34 buses, while wind turbines are situated at 18, 32, 36, 55, 104, and 110 buses.

Table 22 displays the ideal solution for this situation, as determined by the suggested ELBO algorithm, with a comparison of the TLBO method's findings with the solutions found in reference [196]. The findings show that ELBO is an excellent approach for large-scale, realistic power system optimization and load distribution.

Table 22. Comparison of the best outcomes using algorithms.

Method	Min	Mean	Max	Std.	Time (s)
ELBO	103,381.0925	103,395.3268	103,412.5024	8.25	580
TLBO	103,390.1163	103,408.7919	103,419.5405	15.64	575
INFO [198]	106,849.00	109,114.19	113,867.14	504.6	1405
AOA [198]	116,994.05	120,201.73	124,011.65	1095.3	1240
COA [198]	107,008.21	109,639.71	112,617.55	818.2	759
MCOA [198]	103,395.78	103,406.94	103,415.67	10.42	781
DEEPSO [196]	103,407.6296	103,889.1446	104,507.4884	292.8782	-
CO [197]	103,514.9208	103,724.1056	104,249.3264	546.73	668
GBBLCO [197]	103,382.2317	103,535.9940	103,816.4361	83.19	672
DS [196]	110,992.4249	112,680.2902	114,787.7786	953.6529	-
BSA [196]	117,149.9833	120,443.2982	123,385.1256	1638.0949	-
MSA [196]	107,695.0619	111,205.0554	116,303.6361	1857.2167	-

D. Discussions

Table 23 describes the final results after 30 runs for each of the single-objective optimization functions by each algorithm based on the characteristics of best, average, and worst result and also the average amount of simulation time. Specifically, the proposed ELBO algorithm has better efficiency and optimization strength than many optimization methods. Coati Optimization Algorithm,

Table 23. Comparison of optimal results via two TLBO and ELBO algorithms for single-objective functions.

Optimizers	Indexes	IEEE 30-bus network		
		Problem 1	Problem 2	Problem 3
TLBO	Best	800.4791	646.4612	0.20482
	Mean	800.7308	646.6947	0.20482
	Worst	801.2143	647.0035	0.20482
	Std.	1.36	0.75	0.0
	mean CPU time (sec)	20.5	21.3	21.1
ELBO	Best	800.515	648.8523	0.20483
	Mean	800.8085	649.4131	0.20495
	Worst	801.3376	650.5247	0.22065
	Std.	1.84	8.72	0.08
	mean CPU time (sec)	20.3	21.0	21.1

Table 23. Continued

Optimizers	Indexes	IEEE 30-bus network		IEEE 57-bus network
		Problem 4	Problem 5	Problem 9
TLBO	Best	3.0896	832.1622	41677.3441
	Mean	3.0937	832.2340	41683.9249
	Worst	3.0975	832.2718	41689.0845
	Std.	0.007	0.095	17.25
	mean CPU time (sec)	20.5	21.3	57.0
ELBO	Best	3.1028	832.3310	41703.5462
	Mean	3.1725	832.4005	41725.9243
	Worst	3.2406	832.4963	41748.4206
	Std.	0.48	0.73	64.25
	mean CPU time (sec)	20.5	21.4	56.8

The amalgamation of the instructional and learning phases of TLBO inside the ELBO algorithm yields both

empirical and theoretical effects. It theoretically optimizes the process by minimizing unnecessary processes and improving the synergy among exploitation and exploration methods. This method has been proven effective, exhibiting enhanced convergence characteristics and solution precision, as shown by tests via engineering optimization and CEC2014 benchmarks challenges.

The integration of these stages in ELBO enhances convergence by reducing premature convergence and fostering solution variety. Moreover, while the integrated phase somewhat elevates computing cost, the hybrid configuration substantially lowers the total iterations required, leading to a comprehensive enhancement in computational efficacy.

Given the intrinsic robustness of TLBO, attaining even marginal improvements in its framework is difficult. Nonetheless, the incorporation of evolutionary processes and a new combined phase in ELBO has produced significant progress, positioning it as a valuable and effective optimization method.

The trigonometric mutation phase was included to the novel search section of the proposed method to offer varied search orientations and improve the algorithm's exploration capabilities. This approach, derived from differential evolution, computes located in the middle point of a triangle created by three randomly chosen persons, using scaled deviations to enhance solution quality. Comprehensive studies and simulations confirmed the efficacy of this method in enhancing search variety and reducing premature convergence.

Trigonometric mutation was selected for its ability to enhance the teaching-learning process of TLBO; nonetheless, it is important to acknowledge that many other techniques have been suggested in the literature. These solutions, acknowledged for their efficacy, might function as alternative or extra elements in the ongoing enhancement of TLBO. This highlights the adaptability of ELBO in incorporating novel strategies to tackle the specific difficulties of optimization issues.

Although the suggested ELBO algorithm exhibits efficacy and resilience, it is crucial to recognize certain constraints. A major problem is the existence of control factors that need meticulous adjustment for optimum performance. This paper offers estimated ranges for these control factors derived from numerous tests, however their optimization is contingent upon the unique situation.

Furthermore, it is essential to recognize that no one optimization technique can be universally superior for all problem types, due to the extensive variety and complexity of optimization issues. The ELBO method, like to other meta-heuristics, may demonstrate differing degrees of efficiency based on the problem's structure and restrictions. Ongoing study and improvement are essential to improve its flexibility and performance in many fields.

5. Conclusions

This study, a novel efficient improved optimizer, namely evolutionary studying-based optimization (ELBO) algorithm, has used in both 30 and 57 bus electrical transmission networks to optimize OPF difficulties with various target functions. This problem includes optimally selecting control variables such as transformer pulses, reactive power sources and generator outputs, as well as generator voltages. When compared to all current investigations, the suggested ELBO approach yields trustworthy and effective outcomes. This research illustrates the efficacy of the suggested ELBO algorithm in addressing diverse optimization challenges. Although ELBO has shown encouraging outcomes, several opportunities for more study and enhancement exist:

Application to numerous optimization challenges: Future research may investigate the use of ELBO across several fields, including data science, transportation, biology, and finance, to evaluate its adaptability and resilience.

Exploration of chaotic and binary variants: Expanding the Evidence Lower Bound (ELBO) to include binary and chaotic optimization contexts may provide new avenues for addressing intricate and discrete challenges in engineering and computer sciences.

Creation of multi-objective variants: Formulating a multi-objective version of ELBO may enable the algorithm to address real-world issues with conflicting aims, hence improving its relevance to actual difficulties.

Hybridization with the modern optimizers: Merging ELBO with other robust optimization techniques may mitigate its limitations by using the advantages of complementing approaches. These hybrid algorithms may improve the equilibrium between exploration and exploitation while mitigating the danger of early convergence.

Data Availability:

All data generated or analysed during the current study are included in this published article and its results tables. No additional datasets were generated or used.

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Taybeh Salehnia: Formal analysis, Writing , Software implementation, Simulation setup, and Performance evaluation, Conceptualization, Methodology design, and Final manuscript review.
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Maytham N Meqdad: Formal analysis, Experimental design, Data curation, Supervision, Validation, Methodology design, Writing .

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