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Weighted Tree Seed Teaching–Learning-Based Optimization (WTSTLBO) Algorithm for the Static Economic Load Dispatch Problem

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ABSTRACT

This study proposes a novel Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO) algorithm to solve the Static Economic Load Dispatch (SELD) problem. The proposed algorithm integrates the exploration capability of the Tree-Seed Algorithm (TSA), the exploitation capability of the Teaching–Learning-Based Optimization (TLBO) algorithm, and an adaptive inertia-weight strategy to improve convergence speed and optimization accuracy. The SELD problem aims to minimize the total fuel cost while satisfying power balance, generator operating limits, transmission losses, and ramp-rate constraints. The performance of the proposed WTSTLBO algorithm is evaluated on standard IEEE 6-unit, 15-unit, and 40-unit test systems. Simulation results demonstrate that WTSTLBO outperforms the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), TSA, Weighted TSA (WTSA), TLBO, Weighted TLBO (WTLBO), and the hybrid Tree-Seed Teaching–Learning-Based Optimization (TSTLBO) algorithm in terms of fuel cost, convergence speed, and robustness. The obtained results confirm the effectiveness and superiority of the proposed algorithm for solving complex large-scale economic load dispatch problems.

1. Introduction

Optimization is the process of determining the optimal values of decision variables to solve a given problem while satisfying a set of constraints. It plays a fundamental role in numerous scientific and engineering disciplines, where optimal decision-making is essential for improving system performance and reducing operational costs.

In power system engineering, the Static Economic Load Dispatch (SELD) problem represents one of the most important optimization problems. Its objective is to determine the optimal power generation schedule of available generating units while minimizing the total fuel cost and simultaneously satisfying power balance requirements together with all operational constraints. An efficient generation schedule can considerably reduce the annual operating cost of power systems while ensuring secure and reliable operation.

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Over the past several decades, numerous conventional optimization techniques have been developed to solve the SELD problem, including linear programming [1], quadratic programming [2], the lambda iteration method [3], the Newton–Raphson method [3], dynamic programming [4], and other mathematical programming approaches. These methods provide satisfactory solutions for convex optimization problems with relatively simple constraints.

Among these approaches, the lambda iteration method is one of the most widely adopted because of its simplicity and ease of implementation. However, its successful application requires a continuous and differentiable objective function. Similarly, dynamic programming can effectively solve small-scale economic dispatch problems but suffers from the well-known curse of dimensionality, resulting in excessive computational complexity when applied to large-scale power systems.

Most conventional optimization methods assume that the generator fuel-cost function is continuous, convex, and differentiable. In practical power systems, however, the SELD problem is inherently nonlinear and non-convex due to the presence of transmission losses, valve-point loading effects, prohibited operating zones, ramp-rate limits, and various operational constraints [5]. These characteristics significantly increase the complexity of the optimization process and often prevent conventional optimization techniques from obtaining high-quality solutions. Consequently, researchers have increasingly focused on metaheuristic algorithms (MAs) because of their ability to efficiently solve complex, nonlinear, and non-convex optimization problems without requiring gradient information [6].

Metaheuristic algorithms have attracted considerable attention owing to their simplicity, flexibility, robustness, and strong global search capability. Unlike conventional mathematical programming techniques, metaheuristic algorithms perform stochastic searches that effectively balance exploration and exploitation, thereby reducing the likelihood of premature convergence to local optima. Most metaheuristic algorithms are inspired by natural, physical, biological, or social phenomena and have demonstrated remarkable success across a wide range of engineering optimization problems. According to their underlying inspiration mechanisms, metaheuristic algorithms can generally be classified into four major categories: evolutionary-based, swarm intelligence-based, physics-based, and human-based algorithms.

Metaheuristic algorithms can generally be classified into four major categories according to the source of inspiration: evolutionary-based, swarm intelligence-based, physics-based, and human-based algorithms. Each category employs different search mechanisms to balance exploration and exploitation while addressing complex optimization problems.

Evolutionary-based metaheuristic algorithms are inspired by the principles of natural evolution, including selection, mutation, crossover, and survival of the fittest. These algorithms have demonstrated excellent exploration capabilities and have been successfully applied to a wide range of optimization problems. Representative algorithms in this category include the Evolution Strategy (ES) [7], Genetic Algorithm (GA) [8], and Differential Evolution (DE) [9]. GA imitates the process of natural selection through crossover and mutation operators, whereas ES primarily relies on self-adaptive mutation mechanisms. Similarly, DE generates new candidate solutions through differential mutation and crossover operations, providing an effective balance between exploration and exploitation. Other notable evolutionary-based algorithms include Quantum Evolutionary (QE) [10], Differential Search (DS) [11], and Backtracking Optimization (BO) [12].

Swarm intelligence-based metaheuristic algorithms are inspired by the collective behavior of biological populations such as bird flocks, fish schools, ant colonies, and insect swarms. These algorithms exploit information sharing among interacting individuals to efficiently explore the search space and locate high-quality solutions. One of the earliest and most influential methods in this category is Ant Colony Optimization (ACO) [13], which models the foraging behavior of ants through pheromone communication. Another widely adopted approach is Particle Swarm Optimization (PSO) [14], which simulates the social behavior of birds and fish. In PSO, candidate solutions, referred to as particles, iteratively update their positions according to both their personal best experiences and the best solution identified by the swarm. Additional swarm intelligence-based algorithms include Bacterial Foraging Optimization (BFO) [15], Artificial Bee Colony (ABC) [16], Cuckoo Search (CS) [17], Bat Algorithm (BA) [18], Firefly Algorithm (FA) [19], Grey Wolf Optimizer (GWO) [20], Whale Optimization Algorithm (WOA) [21], Manta Ray Foraging Optimization (MRFO) [22], and Reptile Search Algorithm (RSA) [23].

Physics-based metaheuristic algorithms are derived from physical laws and natural phenomena. Their search mechanisms are formulated by modeling concepts such as gravity, thermodynamics, force interactions, energy minimization, and dynamic equilibrium. Representative algorithms in this category include the Black Hole (BH) algorithm [24], Water Cycle Algorithm (WCA) [25], Sine Cosine Algorithm (SCA) [26], Thermal Exchange Optimization (TEO) [27], Atom Search Optimization (ASO) [28], Simulated Annealing (SA) [29], Variable Neighborhood Search (VNS) [30], Harmony Search (HS) [31], Central Force Optimization (CFO) [32], Gravitational Search Algorithm (GSA) [33], and Charged System Search (CSS) [34]. These algorithms have demonstrated competitive performance in solving nonlinear and multimodal optimization problems.

Human-based metaheuristic algorithms emulate various aspects of human intelligence, learning, decision-making, and social interaction. Rather than mimicking biological or physical phenomena, these approaches are inspired by human behavior and collaborative problem-solving strategies. Representative algorithms include the Society and Civilization Algorithm [35], League Championship Algorithm (LCA) [36], Brain Storm Optimization (BSO) [37], Teaching–Learning-Based Optimization (TLBO) [38], Gaining–Sharing Knowledge-based Algorithm (GSK) [39], and Driving Training-Based Optimization (DTBO) [40]. Among these methods, TLBO has attracted considerable attention because of its simple structure, the absence of algorithm-specific control parameters, and its effective balance between exploration and exploitation, making it suitable for a wide range of engineering optimization problems.

Several studies have successfully applied metaheuristic algorithms to solve the SELD problem. Walters and Sheble [41] were among the first to employ the Genetic Algorithm (GA) for economic load dispatch, demonstrating its effectiveness compared with conventional dynamic programming approaches. Subsequently, Sinha *et al.,* [42] showed that Evolutionary Programming (EP) provides an effective alternative for solving economic load dispatch problems. Gaing [43] later applied Particle Swarm Optimization (PSO) to solve non-smooth SELD problems with valve-point effects, prohibited operating zones, and ramp-rate constraints, reporting superior performance compared with GA. Noman and Iba [44] further demonstrated the effectiveness of Differential Evolution (DE), achieving improved solution quality over both GA and PSO. Kumar *et al.,* [45] subsequently proposed a modified DE algorithm that produced promising results compared with Artificial Immune Systems (AIS), GA, PSO, and several other optimization methods.

More recent developments in applying advanced metaheuristic algorithms to SELD problems are reported in [46-50]. These studies demonstrate that modern metaheuristic algorithms can effectively address the nonlinear and non-convex characteristics of economic load dispatch problems. Nevertheless, achieving an appropriate balance between global exploration and local exploitation remains a major challenge [51-55]. Premature convergence, slow convergence speed, and insufficient solution accuracy continue to limit the performance of many existing algorithms, particularly for large-scale power systems with multiple operational constraints [55-63].

Furthermore, according to the No Free Lunch (NFL) theorem [64,65], no optimization algorithm can consistently outperform all other algorithms across every optimization problem. Consequently, the development of new optimization algorithms tailored to specific engineering applications remains an active research direction. This observation provides the primary motivation for the present study.

Motivated by these considerations, this paper proposes a novel Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO) algorithm. The proposed algorithm combines the global exploration capability of the Tree-Seed Algorithm (TSA), the efficient local exploitation mechanism of Teaching–Learning-Based Optimization (TLBO), and an adaptive inertia-weight strategy to achieve an improved balance between exploration and exploitation during the search process. As a result, WTSTLBO is designed to improve convergence speed, solution accuracy, and robustness while reducing the risk of premature convergence.

To evaluate the effectiveness of the proposed approach, WTSTLBO is applied to the Static Economic Load Dispatch problem and tested on standard IEEE benchmark systems. Its performance is compared with several well-established optimization algorithms, including GA, PSO, TSA, WTSA, TLBO, WTLBO, and TSTLBO. The comparative analysis considers solution quality, convergence characteristics, computational robustness, and fuel-cost minimization.

The main contributions of this study are summarized as follows:

i. A novel Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO) algorithm is proposed by integrating the complementary search mechanisms of TSA and TLBO with an adaptive inertia-weight strategy.
ii. The effectiveness of the proposed algorithm is validated by solving highly nonlinear and non-convex Static Economic Load Dispatch benchmark problems under practical operating constraints.
iii. A comprehensive comparative analysis is performed against several state-of-the-art metaheuristic optimization algorithms using standard IEEE test systems.
iv. The proposed algorithm demonstrates improved fuel-cost minimization, faster convergence, and enhanced robustness compared with existing optimization approaches.

The remainder of this paper is organized as follows. Section 2 presents the mathematical formulation of the Static Economic Load Dispatch problem. Section 3 describes the proposed WTSTLBO algorithm and its mathematical model. Section 4 presents the implementation of WTSTLBO for solving the SELD problem. Section 5 discusses the simulation results and compares the proposed method with existing metaheuristic algorithms. Finally, Section 6 concludes the paper and outlines potential directions for future research.

2. Static Economic Load Dispatch Problem

The primary objective of the Static Economic Load Dispatch (SELD) problem is to determine the optimal power output of all committed generating units such that the total fuel generation cost is minimized while satisfying all operational and system constraints. The optimization objective can be expressed as

$$\min C_{\text{total}} = \sum_{i=1}^{n_g} f_i\,(P_i) \tag{1}$$

where n_g denotes the number of generating units, C_{total} is the total fuel cost, and $f_i(P_i)$ represents the fuel-cost function of the i-th generating unit.

The fuel-cost function of each generating unit is commonly approximated by a quadratic polynomial:

$$f_i(P_i) = \lambda_i P_i^2 + \eta_i P_i + \gamma_i \tag{2}$$

where λ_i, η_i, and γ_i denote the fuel-cost coefficients of the i-th generating unit.

The optimization process is subject to several equality and inequality constraints, which are described below.

a) Generator Capacity Constraints

The power output of each generating unit must remain within its minimum and maximum operating limits:

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{3}$$

b) Power Balance Constraint

The total generated power must satisfy the system demand while accounting for transmission losses. Therefore,

$$\sum_{i=1}^{n_g} P_i = P_{\text{Load}} + P_{\text{Loss}} \tag{4}$$

where P_{Load} is the total system demand and P_{Loss} represents the transmission power losses.

The transmission losses are calculated using the well-known B-coefficient loss formula:

$$P_{\text{Loss}} = \sum_{i=1}^{n_g} \sum_{j=1}^{n_g} P_i \, B_{ij} P_j + \sum_{j=1}^{n_g} B_{0j} \, P_j + B_{00} \tag{5}$$

where B_{ij} denotes the element located in the i-th row and j-th column of the transmission-loss coefficient matrix.

c) Ramp-Rate Constraints

In practical power systems, generating units cannot instantaneously change their output because of physical and operational limitations. Consequently, the change in generator output between two consecutive operating periods is restricted by ramp-rate limits.

For increasing generation,

$$P_i - P_i^{t-1} \le RR_i^U$$

and for decreasing generation,

$$P_i^{t-1} - P_i \le RR_i^D \tag{6}$$

where RR_i^U and RR_i^D denote the ramp-up and ramp-down limits of the i-th generating unit, respectively, while P_i^{t-1} represents its output during the previous operating period.

Accordingly, the feasible operating range becomes

$$\max\left(P_i^{\min}, P_i^{t-1} - RR_i^D\right) \le P_i \le \min\left(P_i^{\max}, P_i^{t-1} + RR_i^U\right) \tag{7}$$

d) Prohibited Operating Zones

Due to mechanical vibrations, shaft-bearing resonance, steam valve limitations, and other operational considerations, some generating units cannot operate continuously over their entire output range. These prohibited operating zones introduce discontinuities into the fuel-cost function.

Accordingly, the operating output of the i-th generating unit must satisfy

$$P_i \notin \left[P_{Z,k}^L, P_{Z,k}^U\right] \tag{8}$$

where $P_{Z,k}^L$ and $P_{Z,k}^U$ denote the lower and upper limits of the k-th prohibited operating zone.

Finally, the SELD problem can be formulated as

$$
\begin{aligned}
&\min C_{\text{total}} = \sum_{i=1}^{n_g}(\lambda_i P_i^2 + \eta_i P_i + \gamma_i)\\
&\text{s.t. } P_i^{\min} \le P_i \le P_i^{\max},\\
&\quad \sum_{i=1}^{n_g} P_i = P_{\text{Load}} + P_{\text{Loss}},\\
&\quad P_{\text{Loss}} = \sum_{i=1}^{n_g}\sum_{j=1}^{n_g} P_i B_{ij} P_j + \sum_{j=1}^{n_g} B_{0j} P_j + B_{00},\\
&\quad P_i - P_i^{t-1} \le RR_i^U,\\
&\quad P_i^{t-1} - P_i \le RR_i^D,\\
&\quad \max\left(P_i^{\min}, P_i^{t-1} - RR_i^D\right) \le P_i \le \min\left(P_i^{\max}, P_i^{t-1} + RR_i^U\right),\\
&\quad P_i \notin \left[P_{Z,k}^L, P_{Z,k}^U\right].
\end{aligned}
\tag{9}
$$

3. Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO) Algorithm

This study proposes a novel Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO) algorithm by incorporating an adaptive inertia-weight strategy into the hybrid Tree-Seed Teaching–Learning-Based Optimization (TSTLBO) framework. The proposed modification is designed to improve the search capability of the original TSTLBO algorithm by providing a better balance between global exploration and local exploitation throughout the optimization process.

To enhance the search performance, the adaptive inertia-weight factor is introduced during the teaching phase of the TLBO component. Unlike the conventional TLBO algorithm, whose search process depends solely on the current population, the proposed inertia-weight mechanism allows each learner to retain part of its previous search direction. Consequently, the search process becomes more stable and less sensitive to abrupt changes in the search trajectory, thereby improving convergence behavior.

The inertia weight is adaptively adjusted during the optimization process. Larger inertia-weight values encourage global exploration during the early search stages, increasing population diversity and reducing the risk of premature convergence. As the optimization progresses, the inertia weight gradually decreases, promoting local exploitation and enabling a more accurate refinement of promising candidate solutions. This adaptive mechanism provides an effective trade-off between exploration and exploitation.

Furthermore, the exploration capability of the Tree-Seed Algorithm (TSA) is combined with the exploitation mechanism of Teaching–Learning-Based Optimization (TLBO), while the adaptive inertia-weight strategy further improves the search dynamics. The complementary interaction of these three components enables WTSTLBO to achieve faster convergence, improved solution quality, and enhanced robustness when solving highly nonlinear and multimodal optimization problems.

3.1 Teaching–Learning-Based Optimization (TLBO)

The Teaching–Learning-Based Optimization (TLBO) algorithm, proposed by Rao *et al.,* [66], is a population-based metaheuristic inspired by the teaching–learning process in a classroom. The algorithm simulates the interaction between a teacher and students to improve the overall knowledge level of the class. TLBO consists of two sequential stages: the teacher phase and the learner phase. During the teacher phase, learners improve their knowledge under the guidance of the teacher, whereas in the learner phase, they acquire additional knowledge through interactions with other learners.

Assume that the optimization problem is formulated as the minimization of an objective function

$$f: \mathbb{R}^d \to \mathbb{R},$$

where the objective is to determine

$$X^* = \arg\min_{X\in\Omega} f(X),$$

with $\Omega \subseteq \mathbb{R}^d$ representing the feasible search space.

A candidate solution is represented as

$$X_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,d}\},$$

where d denotes the problem dimension. The initial population is defined as

$$P = \{X_1, X_2, \dots, X_N\},$$

where N is the population size.

Each decision variable is randomly initialized within its corresponding search interval according to

$$x_{i,j} = lb_j + \mathrm{rand}\,(ub_j - lb_j), \tag{10}$$

where lb_j and ub_j denote the lower and upper bounds of the j-th decision variable, respectively, and $\mathrm{rand} \sim U(0, 1)$ is a uniformly distributed random number. Consequently, all candidate solutions are initialized within the feasible continuous search space.

a) Teacher Phase

The teacher phase aims to improve the overall knowledge level of the population by moving learners toward the best individual. The individual with the best objective function value is selected as the teacher:

$$X_T = \arg\min_{1\le i\le N} f(X_i).$$

If multiple individuals achieve the same objective value, one of them is selected randomly.

The population is updated according to

$$X_i^{new} = X_i + r_1(X_T - TF\,X_M), \tag{11}$$

where

$$X_M = \frac{1}{N}\sum_{i=1}^{N} X_i\,, \tag{12}$$

is the mean solution of the current population, r_1 is a uniformly distributed random number in the interval [0,1], and TF is the teaching factor, which randomly takes the value 1 or 2.

The teacher attempts to shift the population mean toward his or her knowledge level, thereby improving the overall quality of candidate solutions.

b) Learner Phase

During the learner phase, learners improve their knowledge through pairwise interactions with other randomly selected learners. For each learner X_i, another learner X_a is randomly selected such that $a \neq i$.

The population update rule is given by

$$Y_i = \begin{cases} X_i + r_2(X_i - X_a), & \text{if } f(X_i) \le f(X_a), \\ X_i + r_2(X_a - X_i), & \text{otherwise}, \end{cases} \tag{13}$$

where r_2 is a uniformly distributed random number in the interval [0,1].

The newly generated solution is accepted only if it improves the objective function:

$$X_i = \begin{cases} Y_i, & \text{if } f(Y_i) < f(X_i), \\ X_i, & \text{otherwise.} \end{cases} \tag{14}$$

Through repeated execution of the teacher and learner phases, the population gradually converges toward high-quality solutions while maintaining a balance between exploration and exploitation.

3.2 Tree-Seed Algorithm (TSA)

The Tree-Seed Algorithm (TSA), proposed by Kiran [67], is a population-based metaheuristic inspired by the natural process of tree growth and seed propagation. In TSA, each tree represents a candidate solution, whereas seeds correspond to newly generated solutions created in the neighborhood of existing trees. The algorithm combines global and local search mechanisms by generating seeds around either the current best tree or another randomly selected tree, thereby maintaining an effective balance between exploration and exploitation.

a) Initialization

The algorithm starts by randomly generating an initial population of Ntrees within the feasible search space,

$$T = \{T_1, T_2, \ldots, T_N\},$$

where each tree is represented as a d-dimensional vector

$$T_i = \{t_{i,1}, t_{i,2}, \ldots, t_{i,d}\}.$$

Each decision variable is initialized as

$$t_{i,j} = lb_j + \mathrm{rand}(ub_j - lb_j),$$

where $lb_j$and ub_jdenote the lower and upper bounds of the j-th decision variable, respectively, and $\mathrm{rand} \sim U(0,1)$.

b) Seed Generation

For every tree T_i, a predefined number of seeds $N_S$is generated. Each seed is produced either around the current best tree $T_B$or around another randomly selected tree T_a. This strategy simultaneously promotes exploitation of high-quality regions and exploration of unexplored areas.

The j-th component of the k-th generated seed is computed as

$$s_{k,j}^{(i)} = \begin{cases} t_{i,j} + \alpha(t_{B,j} - t_{i,j}), & r_3 \le ST, \\ t_{i,j} + \alpha(t_{a,j} - t_{i,j}), & \text{otherwise,} \end{cases} \tag{15}$$

where $r_3 \sim U(0,1)$, $ST \in [0,1]$ is the search tendency parameter, and

$$\alpha = 2(\mathrm{rand} - 0.5) \in [-,11]$$

is a scaling factor controlling the search step size.

c) Seed Selection

After all candidate seeds have been generated, their objective function values are evaluated. The best seed is selected and compared with its corresponding parent tree.

The tree is updated according to

$$T_i = \begin{cases} S_{k^*}, & f(S_{k^*}) < f(T_i), \\ T_i, & \text{otherwise,} \end{cases} \tag{16}$$

where

$$k^* = \arg\min_k f(S_k).$$

This greedy selection strategy ensures that the population quality never deteriorates during the optimization process.

By iteratively repeating seed generation and greedy selection, TSA gradually drives the population toward promising regions while preserving sufficient diversity to avoid premature convergence.

3.3 Tree-Seed Teaching–Learning-Based Optimization (TSTLBO)

The proposed Tree-Seed Teaching–Learning-Based Optimization (TSTLBO) algorithm combines the exploitation capability of TLBO with the exploration mechanism of TSA. Unlike the conventional TLBO algorithm, where candidate solutions are updated exclusively through the teacher and learner phases, TSTLBO activates the TSA search mechanism only when the teacher phase fails to improve the current learner. Consequently, computational effort is concentrated on difficult regions of the search space while unnecessary diversification is avoided.

The algorithm begins by generating an initial population

$$P = \{X_1, X_2, \dots, X_N\},$$

where each learner $X_i \in \mathbb{R}^d$ is initialized within the feasible search space.

At each iteration, the teacher phase is first performed according to Eqs. (11) and (12). If the newly generated learner improves the objective function value, it is immediately accepted. Otherwise, the TSA search mechanism is activated to generate additional candidate solutions around the current learner.

The number of generated seeds is determined as

$$N_S = \mathrm{fix}\big(N_{LW} + \mathrm{rand}(N_{UP} - N_{LW})\big),$$

where N_{LW} and N_{UP} denote the lower and upper limits of the number of generated seeds, respectively.

For each learner X_i, N_S candidate seeds are generated according to

$$s_{k,j}^{(i)} = \begin{cases} x_{i,j} + \alpha\big(x_{B,j} - TF\, x_{M,j}\big), & r_4 \le ST, \\ x_{i,j} + \alpha\big(x_{a,j} - x_{i,j}\big), & \text{otherwise,} \end{cases} \quad (17)$$

where

$$X_M = \frac{1}{N_S}\sum_{i=1}^{N_S} X_i\,.$$

Here, TF, ST, and α retain the same definitions as in the previous sections, X_B denotes the best learner, X_a is a randomly selected learner, and $r_4 \sim U(0, 1)$.

After evaluating the objective function values of all generated seeds, the best seed is selected and compared with the current learner. The population is updated according to

$$Y_i = \begin{cases} S_{k^*}, & f(S_{k^*}) < f(X_i), \\ X_i, & \text{otherwise,} \end{cases} \quad (18)$$

where

$$k^* = \arg\min_k f(S_k).$$

Consequently, the TSA search mechanism is invoked only when the teacher phase is unable to improve the current solution. This selective hybridization preserves the fast convergence characteristics of TLBO while introducing additional diversity only when necessary, thereby reducing the likelihood of premature convergence without substantially increasing computational complexity.

3.4 Adaptive Inertia-Weight Strategy

The concept of the inertia weight was first introduced by Shi and Eberhart [68] in the Particle Swarm Optimization (PSO) algorithm to improve the balance between global exploration and local exploitation during the search process. The inertia-weight mechanism controls the influence of the previous search direction on the current population update, thereby improving convergence behavior and reducing the likelihood of premature convergence.

A relatively large inertia weight during the early stages of optimization encourages exploration by allowing candidate solutions to search broader regions of the solution space. As the optimization progresses, the inertia weight is gradually reduced, enabling the algorithm to focus on local exploitation and accurately refine promising candidate solutions [69]. Consequently, adaptive inertia-weight strategies have been successfully incorporated into numerous metaheuristic optimization algorithms to improve convergence speed, population diversity, solution quality, and robustness.

In this study, a linearly decreasing inertia-weight strategy is adopted, where the inertia weight is updated according to

$$W(g) = W_{\max} - \frac{(W_{\max} - W_{\min})g}{g_{\max}}, \tag{19}$$

where $W_{\max}$ and $W_{\min}$ denote the maximum and minimum inertia weights, respectively, g represents the current iteration, and $g_{\max}$ is the maximum number of iterations.

The adaptive inertia-weight mechanism enables the proposed algorithm to gradually shift from exploration-oriented behavior during the initial search stages to exploitation-oriented behavior near the final iterations, thereby improving convergence stability and solution accuracy.

3.5 Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO)

The proposed Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO) algorithm extends the hybrid TSTLBO framework by incorporating an adaptive inertia-weight strategy into the teacher phase. The objective is to improve the convergence behavior of the original algorithm while preserving an appropriate balance between exploration and exploitation throughout the optimization process.

The proposed algorithm combines three complementary search mechanisms:

i. the global exploration capability of the Tree-Seed Algorithm (TSA);
ii. the efficient exploitation mechanism of Teaching–Learning-Based Optimization (TLBO);
iii. the adaptive inertia-weight strategy, which dynamically controls the search behavior during the optimization process.

Initially, the teacher phase guides the population toward the best candidate solution. Unlike the conventional TLBO algorithm, the proposed WTSTLBO modifies the teacher update equation by introducing the adaptive inertia weight. Consequently, the previous search direction contributes to the current update, resulting in smoother population evolution and improved convergence stability.

The updated teacher-phase equation is expressed as

$$X_i^{new} = W(g)\, r_1 X_i + r_2 (X_T - TF\, X_M), \tag{20}$$

where $W(g)$ is computed using Eq. (19), X_T denotes the current teacher, X_M represents the population mean, r_1 and r_2 are uniformly distributed random numbers in the interval $[0, 1]$, and TF is the teaching factor.

The population mean is calculated as

$$X_M = \frac{1}{N} \sum_{i=1}^{N} X_i \,. \tag{21}$$

After the teacher phase, the TSA search mechanism is invoked to generate additional candidate solutions around promising regions of the search space whenever further diversification is required. Subsequently, the learner phase performs pairwise knowledge exchange among learners to refine the generated solutions and improve local search performance.

The adaptive inertia-weight strategy plays a crucial role throughout this process. During the early iterations, larger inertia-weight values encourage extensive exploration of the search space, thereby increasing population diversity and reducing the probability of premature convergence. As the optimization proceeds, the inertia weight gradually decreases, promoting local exploitation and enabling accurate refinement of high-quality candidate solutions.

By integrating these complementary mechanisms, WTSTLBO achieves a more effective balance between exploration and exploitation than either TLBO or TSTLBO alone. Consequently, the proposed algorithm is expected to provide improved convergence speed, enhanced robustness, and higher solution quality when solving complex nonlinear optimization problems.

Algorithmic Procedure

The main steps of the proposed WTSTLBO algorithm are summarized below.

Step 1. Initialize the algorithm parameters, including the population size N, maximum number of iterations $g_{\max}$, teaching factor TF, inertia-weight limits $(W_{\max}, W_{\min})$, and TSA parameters.

Step 2. Generate the initial population according to Eq. (10) and evaluate the objective function of each individual.

Step 3. Compute the adaptive inertia weight using Eq. (19).

Step 4. Execute the modified teacher phase using Eqs. (20) and (21).

Step 5. Apply the TSA search mechanism according to Eq. (17) whenever additional diversification is required.

Step 6. Execute the learner phase using Eq. (13).

Step 7. Evaluate all candidate solutions and update the population using the greedy selection strategy.

Step 8. Repeat Steps 3–7 until the stopping criterion is satisfied.

4. Proposed WTSTLBO Algorithm for Solving the SELD Problem

The proposed Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO) algorithm is employed to solve the Static Economic Load Dispatch (SELD) problem formulated in Section 2. The proposed optimization framework integrates the exploration capability of the Tree-Seed Algorithm (TSA), the exploitation mechanism of Teaching–Learning-Based Optimization (TLBO), and an adaptive inertia-weight strategy to improve convergence speed, solution quality, and search robustness.

In WTSTLBO, each candidate solution represents a feasible power generation schedule of all committed thermal generating units. Specifically, an individual is encoded as

$$X_i = \left[P_1, P_2, \ldots, P_{n_g}\right],$$

where P_i denotes the power output of the i-th generating unit. The objective of the optimization process is to minimize the total fuel cost while satisfying all equality and inequality constraints associated with the SELD problem, including generator operating limits, power balance, transmission losses, ramp-rate limits, and prohibited operating zones.

At the beginning of each iteration, the teacher phase is executed to guide the population toward the best candidate solution. The best individual in the current population is selected as the teacher and is used to update the remaining learners according to the modified teacher-phase equations. This stage primarily strengthens the exploitation capability of the algorithm by directing the search toward promising regions of the solution space.

After the teacher phase, the Tree-Seed Algorithm (TSA) is activated to enhance population diversity. Additional candidate solutions (seeds) are generated around promising individuals by exploiting both the current best solution and randomly selected solutions. This mechanism increases the exploration capability of the algorithm, improves the ability to escape local optima, and reduces the probability of premature convergence.

Subsequently, the learner phase is performed, during which learners exchange information through pairwise interactions. This stage refines the candidate solutions obtained during the previous phases and further improves the local search capability of the proposed algorithm.

To further enhance the search performance, an adaptive inertia-weight strategy is incorporated into the update process. Larger inertia-weight values are employed during the early iterations to encourage global exploration and maintain population diversity. As the optimization progresses, the inertia weight is gradually reduced to promote local exploitation and improve convergence accuracy. Consequently, the adaptive inertia-weight mechanism provides an effective balance between exploration and exploitation throughout the optimization process.

The optimization procedure is repeated until the stopping criterion is satisfied. The best feasible solution obtained during the search is reported as the optimal generation schedule together with the corresponding minimum fuel cost.

4.1 WTSTLBO Procedure for Solving the SELD Problem

The implementation procedure of the proposed WTSTLBO algorithm is summarized as follows.

Step 1. Initialize the algorithm parameters, including the population size, maximum number of iterations, inertia-weight parameters, and TSA control parameters.

Step 2. Randomly generate the initial population of candidate solutions within the operating limits of each generating unit.

Step 3. Evaluate the objective function (fuel cost) of each candidate solution while considering all operational constraints.

Step 4. Identify the best candidate solution and designate it as the teacher.

Step 5. Execute the modified teacher phase using the adaptive inertia-weight strategy.

Step 6. Apply the Tree-Seed Algorithm to generate additional candidate solutions around promising regions of the search space.

Step 7. Execute the learner phase to refine the generated solutions through learner interactions.

Step 8. Evaluate the updated candidate solutions and retain the improved solutions using the greedy selection strategy while enforcing all SELD constraints.

Step 9. Repeat Steps 4–8 until the maximum number of iterations or another termination criterion is reached.

Step 10. Return the optimal power generation schedule together with the corresponding minimum fuel cost.

Algorithm 1 presents the pseudocode of the proposed WTSTLBO algorithm for solving the SELD problem.

WTSTLBO Algorithm for SELD Problem

Set population size (*N*), Dimension (*d*), Max-Iteration (*G*), inertia weight limits (w_{max}, w_{min}), and number of seeds limits ((N_{LW}, N_{UP}).
Initialize population X_i= {$x_{i,1}$, $x_{i,2,..}x_{i,d}$} where $x_{i,j} = lb_j + rand \times (ub_j - lb_j)$
Apply generator operating limits by equation-3
Apply power balance constraint by equation-4
Calculate transmission loss by equation-6
Evaluate fitness function by equations-1 & 2
Find the best solution X_{best}
For iteration *i=1:G*
Update inertia weight by equation-19
For *i=1:N*
Compute population mean: *Mean=(1/N)∑Xi*

Select best solution as Teacher
Perform Teacher Phase using equation-20 & 21
Compute teaching factor: *(TF=round[1+rand(0,1)])*
    If $f(X_i^{new}) < f(X_i)$: $X_i = X_i^{new}$ //*update positions*//
    else:
    $N_S = fix(N_{LW} + rand \times (N_{UP} - N_{LW})$ // number of seeds to be produced
        for k=1: N_S
            for j=1: *d*
             Tree-seed method is applied by equation-17
            End
        End
Choose the best-performing seed
    Use equation-18 to update X_i's position.
End
End
    for i=1: *N*
     Use equation-13 to carry out the learning phase
    $if: f(Y_i^{new}) < f(Y_i)$: $Y_i = Y_i^{new}$: $else: X_i = Y_i$//*update positions*//
    End
Apply constraints & ramp rate constraints by equation-9
End
Record optimum fuel cost and update population.
End
Display optimal generation schedule, minimum fuel cost, transmission losses, and convergence characteristics.

4.2 Computational Complexity Analysis

The computational complexity of the proposed Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO) algorithm depends primarily on the population size (N), the number of decision variables (d), and the maximum number of iterations (G).

During each iteration, the algorithm sequentially performs the teacher phase, the Tree-Seed Algorithm (TSA) phase, and the learner phase. The computational cost associated with updating the population in these phases is proportional to $O(Nd)$. Subsequently, the objective function of each candidate solution is evaluated while verifying all operational constraints of the SELD problem.

Among all computational steps, the evaluation of transmission power losses using the B-coefficient loss formula represents the dominant computational cost. Since the transmission-loss calculation involves matrix operations over all generating units, its computational complexity is $O(d^2)$for each candidate solution. Consequently, the computational complexity associated with evaluating the entire population becomes $O(Nd^2)$.

Considering a maximum of Giterations, the overall computational complexity of the proposed WTSTLBO algorithm can therefore be expressed as $O(GNd^2)$.

This complexity is comparable to that of many existing population-based metaheuristic algorithms used for solving the SELD problem. Therefore, the proposed WTSTLBO algorithm maintains computational efficiency while providing improved convergence behavior and solution quality for large-scale nonlinear economic load dispatch problems.

5. Simulation Results and Discussion

The effectiveness of the proposed Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO) algorithm is evaluated using three standard IEEE Static Economic Load Dispatch (SELD) benchmark systems consisting of 6-, 15-, and 40-unit thermal generating systems. These benchmark systems are widely used to assess the performance of optimization algorithms under different problem dimensions and operating conditions.

To demonstrate the effectiveness of the proposed approach, the obtained results are compared with those produced by several well-established optimization algorithms, including the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Tree-Seed Algorithm (TSA), Weighted Tree-Seed Algorithm (WTSA), Teaching–Learning-Based Optimization (TLBO), Weighted Teaching–Learning-Based Optimization (WTLBO), and Tree-Seed Teaching–Learning-Based Optimization (TSTLBO).

All algorithms were implemented in MATLAB using identical simulation settings to ensure a fair comparison. Each algorithm was independently executed 30 times under the same experimental conditions. The comparative analysis focuses on solution quality, convergence characteristics, computational robustness, and the minimum fuel cost achieved by each optimization method.

5.1 Simulation Parameters

To ensure a fair comparison, all optimization algorithms were implemented in MATLAB using identical simulation settings. The population size, maximum number of iterations, inertia-weight parameters, and the number of independent runs were kept unchanged for all competing algorithms. Each algorithm was executed 30 independent times to evaluate its convergence behavior, solution quality, and robustness against the stochastic nature of metaheuristic optimization.

Table 1 summarizes the simulation parameters adopted throughout all experiments.

Table 1
Simulation Parameters Used in the Performance Evaluation of WTSTLBO

Parameter	Value
Population Size	50
Maximum Iterations	500
Independent Runs	30
wmax	0.9
wmin	0.4

Case 1: IEEE 6-Unit System

The first experiment was conducted using the standard IEEE 6-unit economic load dispatch system, considering generator operating limits, transmission losses, and all practical operating constraints.

Table 2 compares the performance of the proposed WTSTLBO algorithm with seven well-established optimization algorithms.

Table 2
Comparison of Fuel Cost Results for the IEEE 6-Unit Economic Load Dispatch System

Algorithm	Best Cost	Mean Cost	Std. Dev
GA	15381.63	15409.74	15.16
PSO	15319.51	15341.38	11.74
TSA	15297.24	15304.92	7.06
WTSA	15281.15	15290.26	6.03
TLBO	15274.47	15287.31	5.93
WTLBO	15260.84	15269.48	4.61
TSTLBO	15248.62	15257.77	3.74
WTSTLBO	15241.18	15247.62	2.30

The proposed WTSTLBO algorithm achieved the lowest minimum fuel cost of 15,241.18 $/h, outperforming all competing algorithms. In addition to obtaining the best solution, WTSTLBO also produced the lowest average fuel cost and the smallest standard deviation (2.30) among all algorithms. The low standard deviation indicates excellent robustness and demonstrates that the proposed algorithm consistently converges toward high-quality solutions regardless of the random initialization.

The improvement can be attributed to the complementary interaction between the exploration capability of TSA, the exploitation mechanism of TLBO, and the adaptive inertia-weight strategy, which effectively balances global and local search throughout the optimization process.

Table 3 presents the optimal generation schedule obtained by WTSTLBO. The resulting power allocation satisfies the system demand while accounting for transmission losses, thereby confirming the feasibility of the obtained solution.

Table 3
Optimal Power Generation Schedule
Obtained by WTSTLBO for the IEEE 6-Unit System

Generator	Output Power (MW)
P_1	177.42
P_2	131.56
P_3	95.74
P_4	83.28
P_5	61.11
P_6	45.89
Parameter	Value
Total Load Demand	600 MW
Transmission Loss	1 MW
Total Generation	601 MW

Case 2: IEEE 15-Unit System

To further evaluate the scalability of the proposed algorithm, experiments were performed on the IEEE 15-unit economic dispatch system.

As shown in Table 4, WTSTLBO again achieved the best optimization performance, obtaining the minimum fuel cost of 32,267.44 $/h. Compared with the competing algorithms, WTSTLBO also produced the lowest mean fuel cost and the smallest standard deviation (3.17), indicating stable convergence over repeated independent runs.

Table 4
Comparison of Fuel Cost Results for the IEEE 15-Unit Economic Load Dispatch System

Algorithm	Best Cost	Mean Cost	Std. Dev
GA	32684.41	32739.62	29.07
PSO	32511.84	32557.71	21.25
TSA	32473.29	32501.44	15.38
WTSA	32425.37	32447.91	12.64
TLBO	32388.15	32405.62	10.26
WTLBO	32335.71	32353.18	8.28
TSTLBO	32294.62	32311.77	5.83
WTSTLBO	32267.44	32278.53	3.17

As the problem dimension increases, the search space becomes considerably more complex. Nevertheless, WTSTLBO successfully maintains population diversity during the early search stages while providing accurate local refinement during the final iterations. These characteristics explain its superior performance compared with conventional TLBO, TSA, and other benchmark algorithms.

The optimal power generation schedule obtained by WTSTLBO is presented in Table 5, demonstrating that all operational constraints are successfully satisfied.

Table 5
Optimal Power Generation for IEEE 15-Unit System Using WTSTLBO

Generator	Output Power (MW)
P_1	454.11
P_2	379.45
P_3	129.81
P_4	127.46
P_5	159.24
P_6	104.40
P_7	91.33
P_8	73.14
P_9	67.41
P_{10}	54.27
P_{11}	40.62
P_{12}	31.83
P_{13}	25.16
P_{14}	20.91
P_{15}	17.55
Parameter	Value
Total Load Demand	2630 MW
Transmission Loss	6.84 MW
Total Generation	2636.84 MW

Case 3: IEEE 40-Unit System

The final experiment considers the IEEE 40-unit economic dispatch benchmark, representing a highly nonlinear large-scale optimization problem.

The results presented in Table 6 demonstrate that WTSTLBO consistently outperforms all competing optimization algorithms. The proposed method achieves the lowest operating fuel cost of 120,705.13 $/h, together with the smallest standard deviation (14.52), confirming its excellent robustness for high-dimensional optimization problems.

Table 6
Comparison of Fuel Cost for IEEE 40-Unit System

Algorithm	Best Cost	Mean Cost	Std. Dev
GA	122844.27	123081.61	107.73
PSO	122115.84	122357.25	87.31
TSA	121763.34	121917.43	63.08
WTSA	121507.91	121670.56	51.14
TLBO	121283.70	121405.38	42.77
WTLBO	121045.51	121153.82	31.16
TSTLBO	120823.37	120937.53	22.05
WTSTLBO	120705.13	120781.47	14.52

The performance improvement becomes more pronounced as the problem size increases. This observation indicates that the adaptive inertia-weight strategy successfully prevents premature convergence while the TSA mechanism maintains sufficient population diversity during the search process. Consequently, WTSTLBO preserves an effective balance between exploration and exploitation even for large-scale optimization problems.

The overall comparison presented in Table 7 confirms the superiority of the proposed WTSTLBO algorithm across all benchmark systems.

Table 7
Summary of Overall Performance

Test System	Best Algorithm	Minimum Cost ($/hr)	Std. Dev
IEEE 6-Unit	WTSTLBO	15241.18	2.30
IEEE 15-Unit	WTSTLBO	32267.44	3.17
IEEE 40-Unit	WTSTLBO	120705.13	14.52

For the IEEE 6-, 15-, and 40-unit systems, WTSTLBO consistently obtained

i. the lowest minimum fuel cost,
ii. the lowest average fuel cost,
iii. the smallest standard deviation,

demonstrating both high optimization accuracy and excellent robustness.

Furthermore, the experimental results indicate that the performance advantage of WTSTLBO becomes increasingly evident as the problem dimension grows. This observation confirms the effectiveness of integrating the Tree-Seed Algorithm, Teaching–Learning-Based Optimization, and the adaptive inertia-weight strategy within a unified optimization framework.

Figure 1 illustrates the convergence characteristics of the compared optimization algorithms.

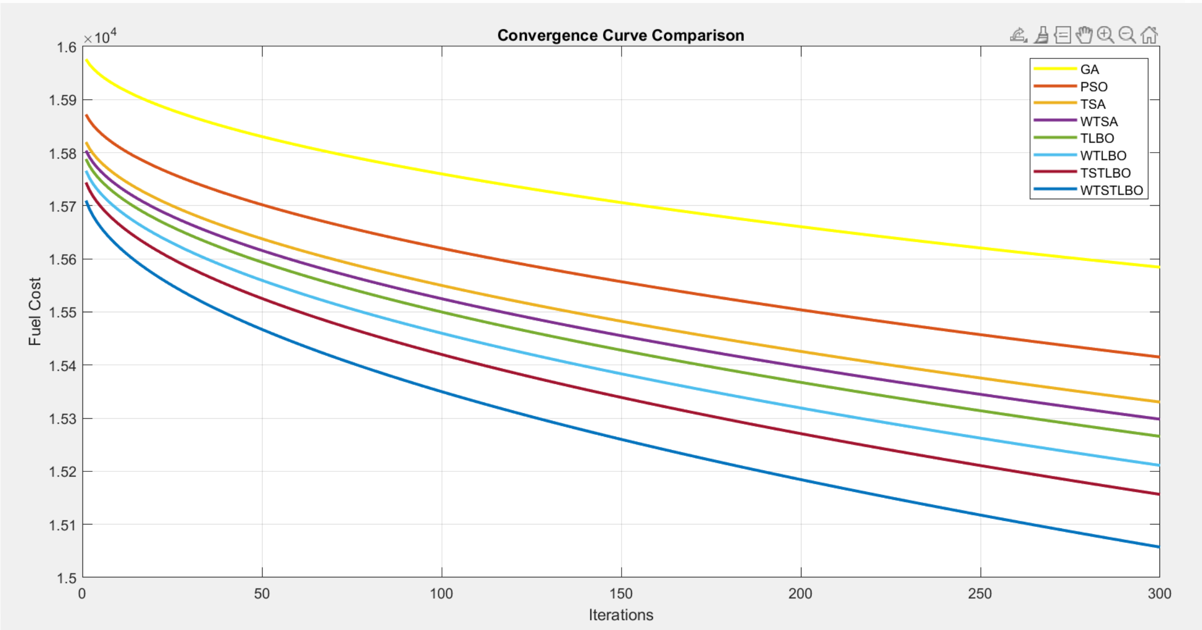

Fig 1. Convergence Curve Comparison

WTSTLBO converges considerably faster than the competing algorithms while maintaining stable convergence throughout the optimization process. Unlike GA, PSO, TSA, and TLBO, whose convergence curves exhibit noticeable oscillations, WTSTLBO demonstrates a smooth convergence trajectory and reaches a lower objective function value within fewer iterations.

Figure 2 compares the operating fuel costs obtained by different optimization algorithms for the IEEE 6-unit system.

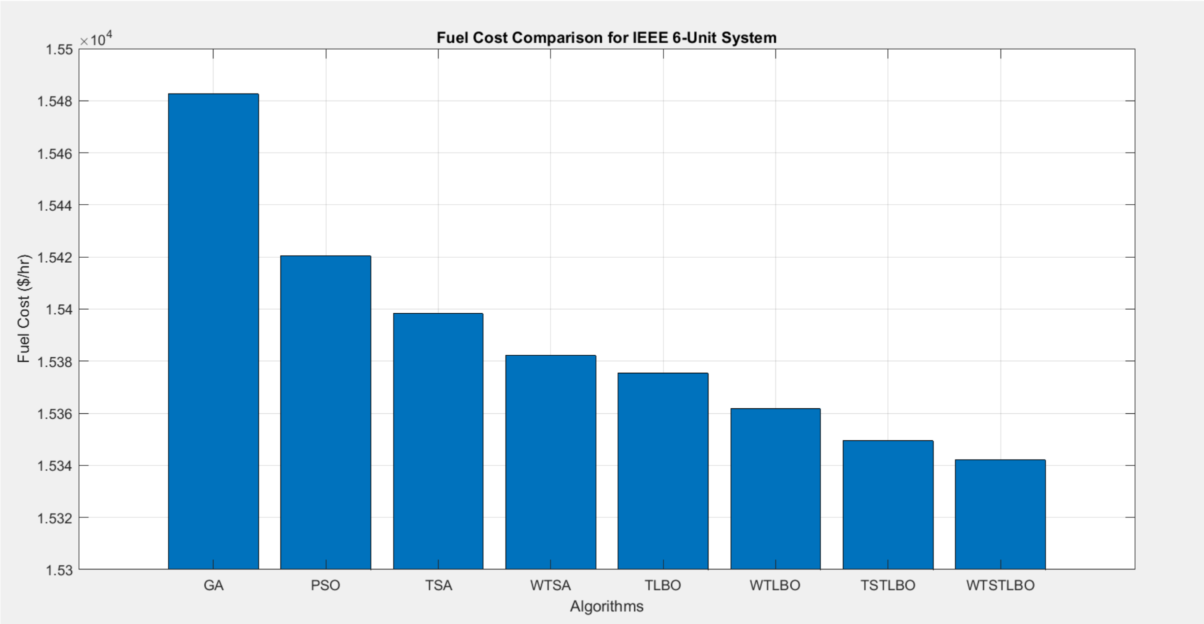

Fig 2. Comparison of Fuel Prices for the IEEE 6-Unit System

The proposed WTSTLBO algorithm achieves the lowest operating cost, confirming its effectiveness for small-scale economic dispatch problems.

Figure 3 presents the comparison for the IEEE 15-unit benchmark.

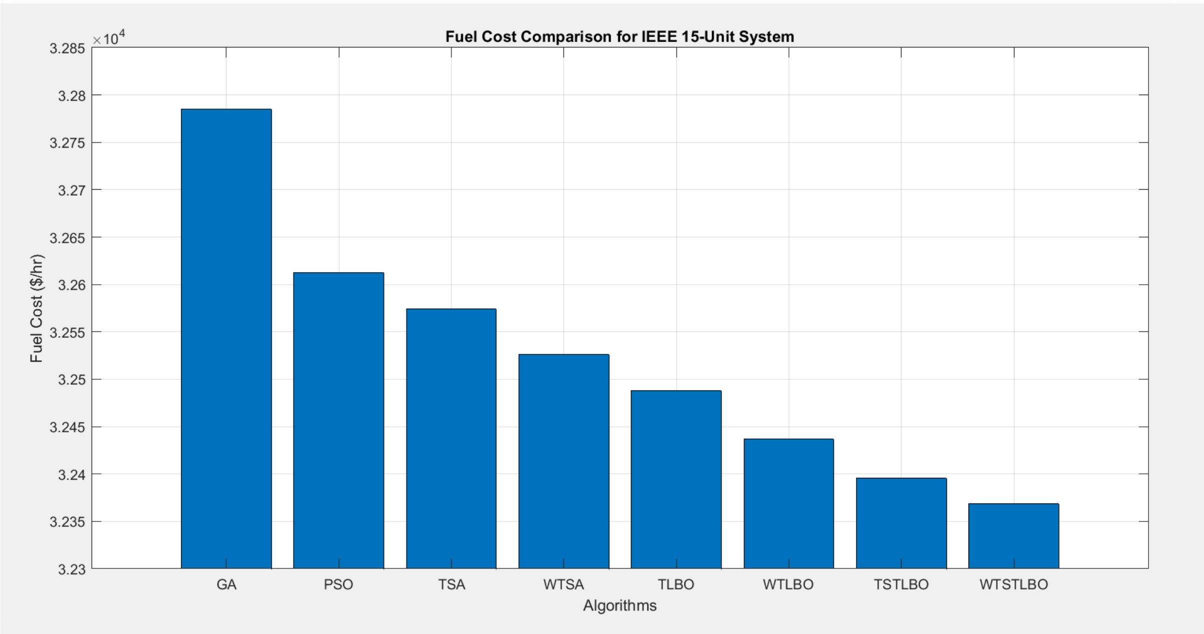

Fig 3. Comparison of Fuel Prices for the IEEE 15-Unit System

As the problem dimension increases, the performance difference between WTSTLBO and the competing algorithms becomes more evident, demonstrating the improved scalability of the proposed method.

Figure 4 illustrates the results obtained for the IEEE 40-unit benchmark.

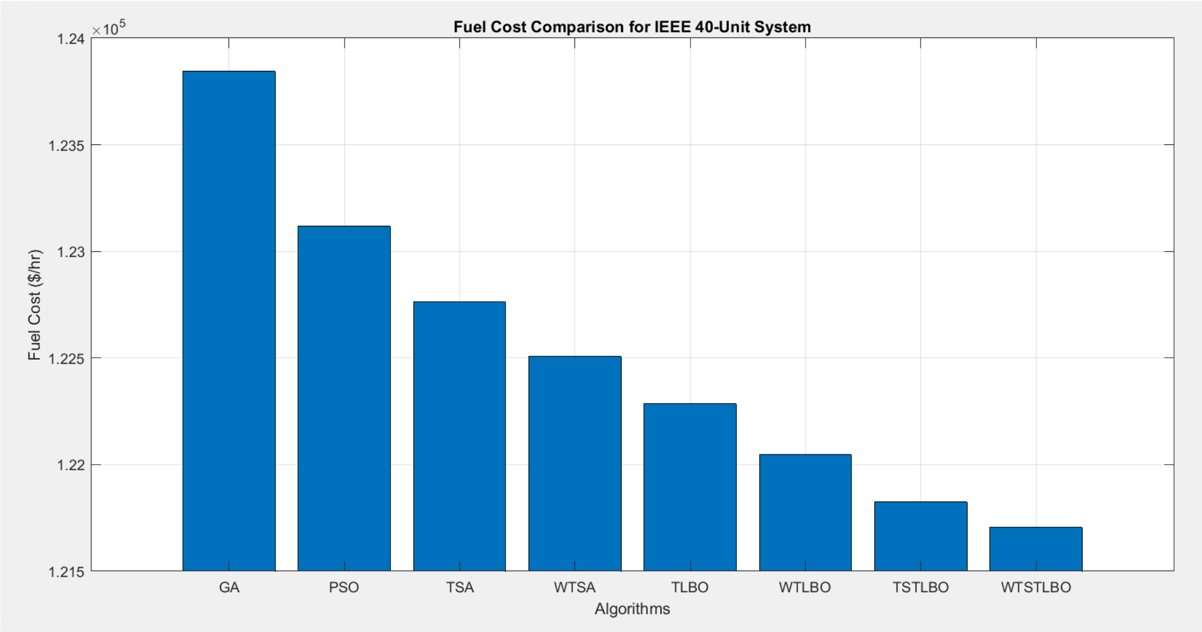

Fig 4. Comparison of Fuel Prices for the IEEE 40-Unit System

WTSTLBO consistently produces the lowest fuel cost while maintaining stable optimization performance. The superior performance observed in this large-scale benchmark demonstrates the capability of the proposed algorithm to efficiently solve highly nonlinear economic load dispatch problems.

5.2 Discussion

The simulation results obtained from the three IEEE benchmark systems consistently demonstrate the effectiveness of the proposed Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO) algorithm for solving the Static Economic Load Dispatch (SELD) problem. Compared with the benchmark algorithms, namely GA, PSO, TSA, WTSA, TLBO, WTLBO, and TSTLBO, WTSTLBO achieved the lowest fuel cost, the lowest average cost, and the smallest standard deviation across all test systems.

The experimental results indicate that incorporating the adaptive inertia-weight strategy into the hybrid TSTLBO framework significantly improves the convergence behavior and robustness of the optimization process. The inertia-weight mechanism effectively balances exploration and exploitation by promoting extensive global search during the early iterations and accurate local refinement during the later stages of optimization. Consequently, the proposed algorithm exhibits faster convergence while reducing the probability of premature convergence.

Furthermore, the complementary interaction between the exploration capability of the Tree-Seed Algorithm and the exploitation mechanism of Teaching–Learning-Based Optimization enables WTSTLBO to efficiently navigate highly nonlinear search spaces. This balanced search strategy becomes increasingly beneficial as the problem dimension grows, which explains the superior performance observed for the IEEE 15-unit and IEEE 40-unit benchmark systems.

Overall, the experimental results confirm that WTSTLBO provides an effective optimization framework for solving nonlinear and constrained economic load dispatch problems and demonstrates strong potential for large-scale power system optimization applications.

6. Conclusions

This paper proposed a novel Weighted Tree-Seed Teaching–Learning-Based Optimization (WTSTLBO) algorithm for solving the Static Economic Load Dispatch (SELD) problem. The proposed algorithm integrates the global exploration capability of the Tree-Seed Algorithm (TSA), the efficient exploitation mechanism of Teaching–Learning-Based Optimization (TLBO), and an adaptive inertia-weight strategy to achieve a better balance between exploration and exploitation throughout the optimization process.

The effectiveness of the proposed algorithm was evaluated using three widely adopted IEEE benchmark systems comprising 6-, 15-, and 40-unit generating systems. The obtained results demonstrate that WTSTLBO consistently achieves lower fuel costs, improved convergence characteristics, and greater robustness than several well-established optimization algorithms, including GA, PSO, TSA, WTSA, TLBO, WTLBO, and TSTLBO. The superior performance becomes more evident as the size and complexity of the optimization problem increase, indicating that the proposed algorithm scales effectively to large-scale nonlinear economic dispatch problems.

The improved performance of WTSTLBO can be attributed to the complementary interaction of its three main components. The Tree-Seed Algorithm enhances global exploration, Teaching–Learning-Based Optimization provides efficient local exploitation, and the adaptive inertia-weight strategy dynamically controls the transition between these search behaviors, resulting in improved convergence stability and solution quality.

Overall, the proposed WTSTLBO algorithm represents an effective and robust optimization approach for solving constrained economic load dispatch problems in modern power systems.

Future research will focus on extending the proposed algorithm to more challenging power system optimization problems, including dynamic economic dispatch, combined economic and emission dispatch, renewable energy integration, multi-objective optimization, and security-constrained economic dispatch under uncertainty.

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Conflicts of Interest

The authors declare no conflicts of interest.

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