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A Hybrid DE–TLBO Optimization Approach for Large-Scale Economic Load Dispatch

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Abstract: Economic Load Dispatch (ELD) is a critical optimisation problem in power system operation that aims to minimise total fuel cost while satisfying system demand and generator operating constraints. The presence of valve-point loading effects makes the ELD problem highly non-linear and non-convex, limiting the effectiveness of conventional optimisation methods. This paper proposes a hybrid optimisation approach that integrates Differential Evolution (DE) and Teaching–Learning-Based Optimization (TLBO) to enhance solution quality and convergence performance.

In the proposed DE–TLBO framework, DE is employed during the initial phase to perform global exploration of the search space, while TLBO is used in the later phase to intensify local exploitation and refine candidate solutions. A repair-based constraint handling strategy is incorporated to ensure strict satisfaction of generator limits and power balance constraints at every iteration. The effectiveness of the proposed approach is evaluated using the IEEE-40 generating unit test system under identical simulation conditions.

Simulation results demonstrate that the proposed DE–TLBO hybrid algorithm achieves lower fuel cost and improved convergence characteristics compared to standalone DE and TLBO algorithms. The findings confirm that hybrid metaheuristic optimisation provides a robust and efficient solution for large-scale, non-convex economic load dispatch problems.

Keywords: Economic Load Dispatch; Differential Evolution; Teaching–Learning-Based Optimization; Hybrid Metaheuristic Optimization; Valve-Point Loading Effect; IEEE-40 Generating Unit System

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I. INTRODUCTION

Economic Load Dispatch (ELD) is a fundamental optimisation problem in power system operation that aims to determine the optimal power output of generating units such that the total fuel cost is minimised while satisfying system demand and operational constraints [1], [2]. Efficient solution of the ELD problem is essential for achieving economical and reliable power system operation, particularly in large-scale thermal power systems.

In practical power systems, generator fuel cost characteristics are highly nonlinear due to valve-point loading effects, which arise from the sequential opening of steam admission valves in thermal units. These effects introduce ripples in the fuel cost curve, making the ELD problem non-convex and non-smooth [3], [4]. Under such conditions, conventional optimisation methods such as lambda-iteration, gradient-based techniques, and dynamic programming become inadequate, as they rely on convexity and differentiability assumptions and often converge to local optima [2], [5].

To address these challenges, a wide range of metaheuristic optimisation algorithms have been proposed, including Genetic Algorithms, Particle Swarm Optimization, Differential Evolution (DE), and Teaching–Learning-Based Optimization (TLBO) [6]–[9]. These algorithms are population-based and stochastic in nature, enabling effective exploration of complex search spaces without requiring gradient information. Among them, Differential Evolution has been widely applied to ELD problems due to its strong global search capability and simple control structure [10]. However, DE may exhibit slow convergence during later iterations because of limited local exploitation capability.

Teaching–Learning-Based Optimization is another effective metaheuristic inspired by the teaching–learning process in a classroom. TLBO is characterised by its parameter-light structure and efficient exploitation behaviour, which often results in faster convergence compared to other population-based algorithms [11], [12]. Nevertheless, when applied independently to large-scale ELD problems, TLBO may suffer from reduced exploration capability and premature convergence.

To overcome the limitations of standalone metaheuristic algorithms, hybrid optimisation approaches have been increasingly explored in recent studies. Hybrid methods aim to combine the complementary strengths of different algorithms to improve convergence behaviour, robustness, and solution quality for non-convex ELD problems [13], [14]. In this context, integrating the global exploration ability of DE with the local refinement efficiency of TLBO presents a promising strategy for large-scale economic load dispatch.

Motivated by these observations, this paper proposes a hybrid Differential Evolution and Teaching–Learning-Based Optimization (DE–TLBO) algorithm for solving large-scale, non-convex Economic Load Dispatch problems. The proposed approach employs DE in the initial phase to explore the search space effectively and switches to TLBO in the later phase to refine candidate solutions.

II.RELATED WORK .

The Economic Load Dispatch (ELD) problem has been extensively investigated over the past several decades, and a wide range of solution techniques have been proposed. Early research focused primarily on conventional optimisation methods, which were developed under simplified assumptions of convex and smooth generator fuel cost functions. Classical techniques such as lambda-iteration and gradient-based methods provided fast and reliable solutions for small-scale systems; however, their applicability was limited when realistic generator characteristics were considered [1], [2].

The inclusion of valve-point loading effects and other practical constraints transformed the ELD problem into a highly non-convex optimisation task. Under such conditions, conventional approaches were found to suffer from premature convergence and poor solution quality [3], [4]. This limitation motivated the adoption of metaheuristic optimisation algorithms, which are capable of handling nonlinear and non-smooth objective functions without relying on gradient information.

Genetic Algorithms (GA) were among the first metaheuristic techniques applied to ELD problems and demonstrated improved performance for non-convex formulations [5]. Subsequently, Particle Swarm Optimization (PSO) gained significant attention due to its simplicity and fast convergence characteristics. Several studies reported successful application of PSO to ELD problems with valve-point effects and practical constraints [6], [7]. However, PSO often requires careful parameter tuning and may converge prematurely in large-scale systems.

Differential Evolution (DE) has emerged as a powerful evolutionary optimisation technique for continuous problems. Its strong global exploration capability and simple control parameters make it suitable for solving large-scale ELD problems [8], [9]. Various DE-based approaches have been reported to achieve competitive fuel cost values for non-convex ELD formulations. Nevertheless, DE may exhibit slow convergence during later iterations due to limited exploitation capability [10].

Teaching–Learning-Based Optimization (TLBO) is a relatively recent metaheuristic algorithm that has attracted attention due to its parameter-light structure and ease of implementation. TLBO has been successfully applied to ELD and related power system optimisation problems, often achieving faster convergence compared to parameter-sensitive algorithms [11], [12]. Despite these advantages, standalone TLBO may experience reduced exploration capability when applied to high-dimensional ELD problems.

III.PROBLEM STATEMENT

The Economic Load Dispatch (ELD) problem is formulated as a constrained optimisation problem whose objective is to minimise the total fuel cost of thermal generating units while satisfying system demand and operational constraints [1], [2].

3.1 Objective Function

For a power system comprising N thermal generating units, the total fuel cost is expressed as:

$$\min F = \sum_{i=1}^{N} F_i(P_i)$$

where the fuel cost function of the i-th generator is modelled as a quadratic function with valve-point loading effect:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + |e_i \sin(f_i(P_{i,\min} - P_i))|$$

Here, P_i denotes the power output of the i-th generator (MW), a_i, b_i, and c_i are fuel cost coefficients, and e_i and f_i represent valve-point loading coefficients. The inclusion of the sinusoidal term introduces non-smoothness and non-convexity in the objective function, making the ELD problem more challenging to solve using classical optimisation methods [3], [4].

3.2 Equality Constraint

The total generated power must satisfy the system load demand. This requirement is expressed by the power balance constraint:

$$\sum_{i=1}^{N} P_i = P_D$$

where P_D is the total system load demand (MW). In this study, transmission losses are neglected to focus on algorithmic performance, which is a common assumption in benchmark ELD studies [6], [8].

3.3 Inequality Constraints

Each generating unit must operate within its specified minimum and maximum power limits:

$$P_{i,\min} \le P_i \le P_{i,\max}, i = 1,2,\ldots,N$$

These constraints ensure safe and reliable operation of the generating units.

IV PROPOSED DE -TLBO Hybrid Optimization Method

This section presents the proposed hybrid Differential Evolution and Teaching–Learning-Based Optimization (DE–TLBO) approach developed to solve the non-convex Economic Load Dispatch (ELD) problem. The hybrid framework is designed to combine the complementary strengths of Differential Evolution (DE) and Teaching–Learning-Based Optimization (TLBO) to improve convergence behaviour and solution quality for large-scale ELD problems.

4.1 Differential Evolution Overview

Differential Evolution is a population-based evolutionary optimisation algorithm that operates through mutation, crossover, and selection mechanisms. Owing to its strong global exploration capability and simple control parameters, DE has been widely applied to continuous optimisation problems, including non-convex ELD formulations [8], [9]. In DE, candidate solutions are iteratively evolved by perturbing existing solutions using scaled vector differences, enabling effective exploration of the search space. However, DE may experience slow convergence during later iterations due to limited local exploitation capability [10].

4.2 Teaching–Learning-Based Optimization Overview

Teaching–Learning-Based Optimization is a population-based metaheuristic inspired by the teaching–learning process in a classroom environment. TLBO operates through two sequential phases, namely the teacher phase and the learner phase, which aim to improve the mean performance of the population and promote knowledge sharing among individuals [11], [12]. TLBO is characterised by its parameter-light structure and efficient exploitation capability, often resulting in faster convergence. Nevertheless, when applied independently to large-scale problems, TLBO may suffer from reduced exploration and premature convergence.

4.3 Hybridization Strategy

To overcome the limitations of standalone DE and TLBO algorithms, a sequential hybridisation strategy is adopted in this work. In the proposed DE–TLBO framework, the optimisation process is divided into two distinct stages:

1. **Exploration Stage:**

Differential Evolution is employed during the initial phase of the optimisation process to explore the search space extensively and identify promising regions. The mutation and crossover operations help maintain population diversity and avoid premature convergence.

2. **Exploitation Stage:**

After a predefined switching iteration, the population is transferred to the TLBO framework. The teacher and learner phases are then used to intensify local search and refine candidate solutions around high-quality regions.

The transition from DE to TLBO ensures a balanced trade-off between exploration and exploitation, which is critical for solving large-scale non-convex ELD problems.

4.4 Constraint Handling Mechanism

A repair-based constraint handling strategy is integrated into both stages of the hybrid algorithm to ensure the feasibility of candidate solutions. After each update, generator operating limits are enforced by boundary correction, and power balance is satisfied through redistribution of generation among units. This approach avoids the need for penalty parameter tuning and ensures strict compliance with system constraints throughout the optimisation process [6], [14].

4.5 Advantages of the Proposed Hybrid Approach

The proposed DE–TLBO hybrid optimisation method offers several advantages:

- Improved convergence characteristics compared to standalone algorithms
- Enhanced balance between global exploration and local exploitation
- Robust performance for large-scale, non-convex ELD problems
- Reduced sensitivity to algorithm-specific parameter tuning

These advantages are validated through simulation studies conducted on the IEEE-40 generating unit test system, as discussed in the following section.

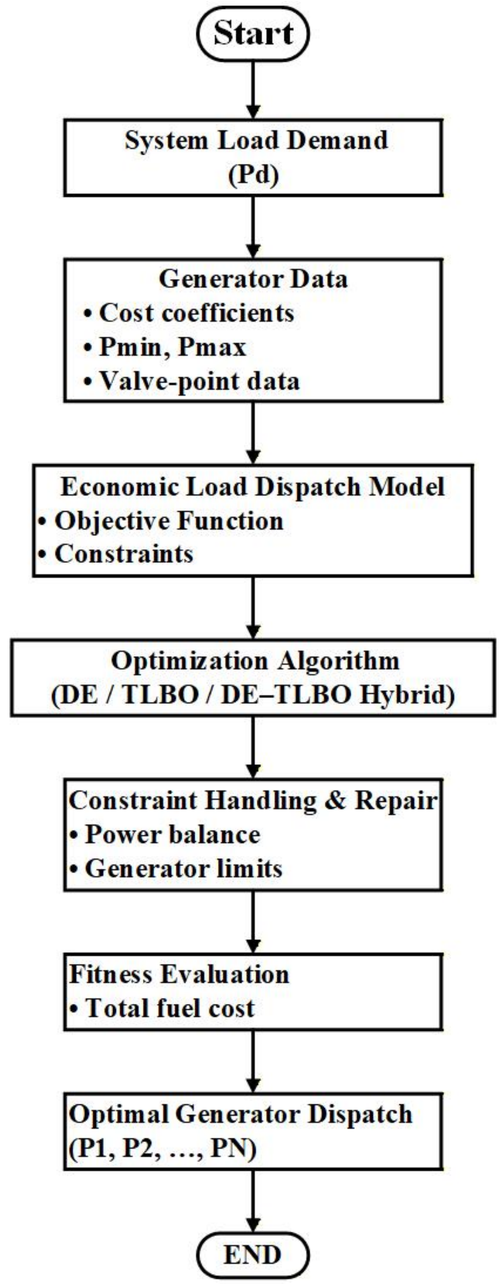

Figure 1 Flowchart of the proposed DE–TLBO hybrid optimization algorithm

V.SIMULATION SETUP AND RESULT

5.1 Simulation Setup

The performance of the proposed DE–TLBO hybrid optimisation algorithm is evaluated using the IEEE-40 generating unit test system, which is widely adopted in the literature for validating large-scale Economic Load Dispatch (ELD) solutions. The test system consists of 40 thermal generating units supplying a fixed load demand. Each generator is characterised by a quadratic fuel cost function with valve-point loading effects, making the optimisation problem non-convex and highly nonlinear.

All simulations were carried out using MATLAB under identical operating conditions for fair comparison. The same population size, maximum number of iterations, initial population generation method, and constraint handling strategy were applied to Differential Evolution (DE), Teaching–Learning-Based Optimization (TLBO), and the proposed DE–TLBO hybrid algorithm. Transmission losses were neglected to focus on the optimisation capability of the algorithms, which is a common assumption in benchmark ELD studies.

The primary performance metrics used for evaluation include total fuel cost, convergence characteristics, generator dispatch profile, constraint satisfaction, and computational time.

5.2 Results and Discussion

Table 1: Results of ELD for IEEE 40 generating units

Methods	Fuel Cost ($/Hr)
DE	77040.8668
TLDO	77223.7200
DE-TLDO hybrid	75464.2075

Table 1 compares the minimum fuel cost obtained for the IEEE-40 generating unit system using DE, TLDO, and the proposed DE–TLDO hybrid algorithm. The results indicate that both DE and TLDO achieve comparable fuel costs, reflecting similar optimisation performance when applied individually. In contrast, the proposed hybrid algorithm attains a lower fuel cost, demonstrating improved economic performance. This reduction confirms that combining the exploration capability of DE with the exploitation strength of TLDO enhances solution quality for large-scale economic load dispatch problems.

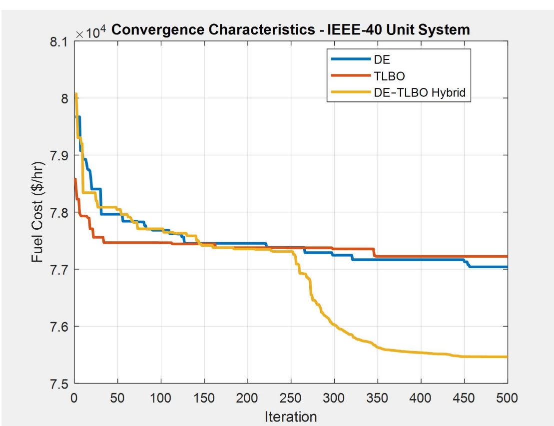

Figure 2 Convergence Characteristics of DE, TLBO, and DE–TLBO Hybrid for IEEE-40 Unit System

Figure 2 illustrates the convergence behaviour of Differential Evolution (DE), Teaching–Learning-Based Optimization (TLBO), and the proposed DE–TLBO hybrid algorithm for the IEEE-40 generating unit system. It can be observed that all algorithms converge towards feasible solutions; however, the convergence paths differ significantly. DE exhibits a steady but relatively slower convergence, while TLBO shows faster initial improvement followed by early stagnation. In contrast, the proposed DE–TLBO hybrid demonstrates both rapid early exploration and improved refinement in later iterations, resulting in a lower final fuel cost. This behaviour confirms the effectiveness of combining DE-based exploration with TLBO-based exploitation.

VI.CONCLUSION

This paper presented a hybrid Differential Evolution and Teaching–Learning-Based Optimization (DE–TLBO) approach for solving the non-convex Economic Load Dispatch (ELD) problem considering valve-point loading effects. The ELD problem was formulated as a constrained optimisation task, and a repair-based constraint handling mechanism was employed to ensure strict satisfaction of generator operating limits and power balance requirements.

The proposed hybrid framework integrates the strong global exploration capability of Differential Evolution with the efficient local exploitation behaviour of Teaching–Learning-Based Optimization. By adopting a sequential hybridisation strategy, the algorithm effectively balances exploration and exploitation during different phases of the optimisation process.

Simulation studies conducted on the IEEE-40 generating unit system demonstrate that the proposed DE–TLBO hybrid algorithm achieves improved convergence characteristics and lower total fuel cost compared to standalone DE and TLBO algorithms under identical operating conditions. The hybrid approach consistently produces feasible dispatch solutions with negligible power balance error and acceptable computational effort.

The results confirm that hybrid metaheuristic optimisation provides a robust and efficient solution for large-scale, non-convex economic load dispatch problems. The proposed DE–TLBO framework can serve as a reliable optimisation tool for practical power system operation and offers a strong foundation for further research in advanced economic dispatch applications.

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