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Teaching-Learning-Based Optimization Algorithm for Pressure Vessel Design Problem

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Abstract

This paper presents the utilization of the Teaching-Learning-Based Optimization (TLBO) algorithm to tackle the intricate problem of pressure vessel design. Design optimization for pressure vessels holds a critical role in various engineering domains, demanding effective techniques for achieving designs that are both optimal and safe. The TLBO algorithm, drawing inspiration from the dynamics of teaching and learning, offers a unique approach by amalgamating exploration and exploitation strategies. In this research, we investigate the incorporation of TLBO within the realm of pressure vessel design, with the objective of improving design efficiency while strictly adhering to demanding safety and performance benchmarks. Through a comprehensive assessment, we analyze the performance of TLBO in generating optimal designs and draw comparisons with established optimization methods. Our findings underscore the proficiency of TLBO in effectively converging towards competitive solutions, thus highlighting its potential to bring about a paradigm shift in the domain of pressure vessel design optimization. This paper underscores the importance of the Teaching-Learning-Based Optimization algorithm as a transformative instrument, providing invaluable insights for researchers, practitioners, and experts involved in fields such as structural engineering, optimization, and related disciplines.

A. Introduction

Pressure vessels constitute essential components across diverse industries such as chemical processing, energy generation, and aerospace applications. The design of pressure vessels entails a multifaceted optimization challenge, requiring the harmonization of structural integrity, performance efficiency, and safety compliance[1, 2]. Traditional optimization methods, while foundational, often struggle to efficiently explore the intricate solution spaces inherent to pressure vessel design problems [3]. This has led to an exploration of innovative optimization techniques, particularly nature-inspired algorithms, to provide enhanced solutions to these complex engineering challenges. The Teaching-Learning-Based Optimization (TLBO) algorithm, introduced by Rao [2], stands as a promising contender in this context, drawing inspiration from the educational process to address optimization challenges [4].

Pressure vessels serve as critical elements in engineering sectors that demand utmost safety and efficiency. The optimization of pressure vessel design holds paramount importance, influencing factors such as material selection, geometry, and operating conditions[3]. traditional optimization methods struggle with problems featuring complex and irregular solution spaces. These traditional methods often require substantial computational efforts and can fall short in providing robust and optimal solutions for intricate engineering problems like pressure vessel design.

In response to the limitations of traditional optimization methods, nature-inspired algorithms have gained traction as potent tools for addressing complex optimization challenges. These algorithms, drawing inspiration from various natural phenomena, offer unique approaches to exploration and exploitation in solution spaces. genetic algorithms, particle swarm optimization, and differential evolution are among the nature-inspired techniques that have shown promise in optimizing engineering problems with diverse objectives and constraints[4-6].

Among these nature-inspired approaches, the Teaching-Learning-Based Optimization (TLBO) algorithm presents a distinctive perspective[6]. inspired by the educational dynamics of teaching and learning in a classroom. In TLBO, individuals in a population, representing learners, iteratively improve their solutions based on interactions with superior-performing individuals acting as teachers. This process mimics the knowledge transfer and enhancement observed in educational settings, effectively balancing exploration of new solutions with exploitation of valuable information. The TLBO algorithm's unique foundation positions it as an appealing method for addressing intricate optimization problems such as pressure vessel design[7].

This paper delves into the application of the Teaching-Learning-Based Optimization (TLBO) algorithm to the pressure vessel design problem. Through the lens of TLBO's pedagogical dynamics, this research seeks to enhance the efficiency and efficacy of pressure vessel designs while adhering to safety and performance standards. By building upon the groundwork laid by Rao et al. (2011) [2] and the integration of nature-inspired optimization techniques into engineering problems highlighted by [8], this paper explores the potential of TLBO to revolutionize the way pressure vessel design optimization is approached[9]. Through empirical evaluations and comparative analyses, the study aims to contribute valuable insights to the field of pressure vessel design optimization, offering novel perspectives on handling complex engineering challenges.

B. Literature Review

The optimization of pressure vessel design is a significant undertaking, involving the intricate balance of structural integrity, safety, and performance efficiency. Traditional optimization methods have played a foundational role in this domain, yet they often face challenges when confronted with the complex solution spaces inherent to pressure vessel design[10]. This literature review explores the landscape of pressure vessel design optimization, highlighting the emergence of innovative optimization techniques, and focusing on the Teaching-Learning-Based Optimization (TLBO) algorithm's applicability to this challenging problem.

Metaheuristic algorithms represent a powerful class of optimization techniques designed to efficiently handle complex, large-scale, and highly nonlinear problems that traditional methods often struggle to solve. Unlike deterministic approaches, metaheuristics employ stochastic processes to explore and exploit the search space, making them particularly effective for multimodal and high-dimensional problems[11]. These algorithms are generally inspired by natural, biological, or social phenomena, such as evolution, swarm behavior, or cultural learning, which enables them to balance intensification (local search) and diversification (global exploration). Examples include Evolutionary Algorithms (EA), Ant Colony Optimization (ACO)[12], Firefly Algorithm (FA) [13], Harmony Search (HS) [3], and Grey Wolf Optimizer (GWO)[14], among others. One of the defining strengths of metaheuristics is their flexibility; they are often problem-independent and can be adapted to various engineering, industrial, and scientific optimization tasks without significant reformulation. In the context of pressure vessel design, where the optimization problem is inherently constrained, nonlinear, and multiobjective, metaheuristics provide a robust framework for simultaneously managing multiple design variables and constraints. Moreover, their population-based search mechanisms allow them to escape local optima and converge toward globally competitive solutions, which is essential for safety-critical applications like pressure vessels[15]. Recent advances in hybrid metaheuristics and parameter-tuning strategies have further enhanced their performance, enabling faster convergence and improved solution quality. Consequently, metaheuristic algorithms have emerged as indispensable tools for modern engineering design, offering innovative and scalable alternatives to traditional optimization techniques. Their versatility and problem-solving power position them as a cornerstone in the ongoing evolution of pressure vessel design optimization research[16].

Traditional optimization methods have been extensively employed to address the complexities of pressure vessel design. Gradient-based methods, genetic algorithms, and simulated annealing are some of the techniques that have been utilized to optimize pressure vessel designs. However, these methods tend to struggle when dealing with high-dimensional and nonlinear solution spaces, and they might require significant computational resources. For instance, emphasizes the limitations of traditional optimization techniques in handling intricate engineering problems[17].

In response to the limitations of traditional methods, researchers have explored nature-inspired optimization algorithms to tackle complex engineering optimization challenges. Particle Swarm Optimization (PSO)[18], Genetic Algorithms (GA)[19], and Differential Evolution (DE)[20] are some of the nature-inspired algorithms that have gained prominence. These algorithms leverage concepts from natural processes to explore solution spaces more effectively.

The Teaching-Learning-Based Optimization (TLBO)[21] algorithm, represents a unique approach within the landscape of nature-inspired optimization. TLBO draws inspiration from the educational process, where teachers and students collaborate to enhance learning. This algorithm involves a dynamic interaction between superior-performing solutions (teachers) and less-optimal solutions (students), enabling knowledge transfer and improvement. TLBO's innovative concept has led to its application in various engineering domains, including structural design and mechanical optimization.

The application of the TLBO algorithm to the pressure vessel design problem holds promise due to its distinctive characteristics[22]. Pressure vessel design involves multiple objectives, constraints, and intricacies related to geometry and material properties. The collaborative learning dynamics of TLBO align well with this multifaceted problem. Researchers have begun to explore TLBO's potential in pressure vessel design optimization[23].

The optimization of pressure vessel design is a complex and challenging task that demands innovative methodologies[24]. While traditional optimization methods have contributed significantly, nature-inspired algorithms like the Teaching-Learning-Based Optimization (TLBO) algorithm offer new avenues for addressing these challenges. The unique approach of TLBO, inspired by educational dynamics, presents a promising prospect for optimizing pressure vessel designs. By investigating TLBO's applicability, this paper aims to contribute to the evolving field of pressure vessel design optimization and shed light on its potential benefits.

C. Pressure Vessel Design (PVD) Problem

The Pressure Vessel Design (PVD) problem involves optimizing the parameters of a pressure vessel to achieve a balance between structural integrity, performance objectives, and safety constraints. This problem is fundamental in engineering and requires a mathematical framework to guide the optimization process[25]. The model for the PVD problem can be described using equations that capture the objectives, design variables, and constraints, as exemplified in the work of Arora and Kakran (2012).

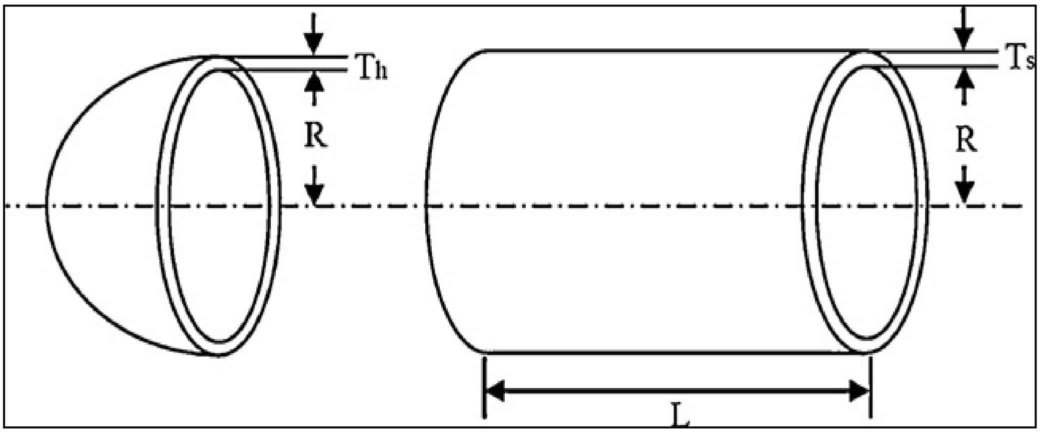

Figure 2. Pressure Vessel Design (PVD)

1. **Objective Function:**

The primary objective in the PVD problem is to optimize a set of design variables while minimizing or maximizing an objective function that quantifies the performance of the pressure vessel design. This objective function often considers factors like manufacturing cost, weight, pressure containment capacity, and heat transfer efficiency. Depending on the nature of the optimization, the objective function can be expressed as:

Minimize: f(x)

Maximize: -f(x)

Here, "x" represents the vector of design variables.

2. **Design Variables:**

The design variables encompass parameters that define the characteristics of the pressure vessel, including dimensions, material properties, and loading conditions [26]. These variables are adjusted to optimize the pressure vessel's performance while adhering to constraints. Design variables are represented as a vector:

X= (X1, X2, X3) for (Ts, Th, R, L)

3. **Constraints:**

Constraints ensure that the optimized pressure vessel design remains safe and feasible. These constraints encompass stress limitations, geometric restrictions, material property requirements, and regulatory standards. Constraints can be formulated as inequalities or equalities [26-28]:

g_i(x) ≤ 0, for i = 1, 2, ..., m (inequality constraints)

h_j(x) = 0, for j = 1, 2, ..., p (equality constraints)

4. **Optimization Problem:**

The comprehensive formulation of the PVD problem can be expressed as:

To minimize:

$$\min f(x) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 + 3.1661x_1^2x_4 + 19.84x_1^2x_3$$

Subject to:

Hoop stress ≤ Allowable stress

$$g_1(x) = -x_1 + 0.0193x_3 \leq 0$$

Longitudinal stress ≤ Allowable stress

$$g_2(x) = -x_2 + 0.00954x_3 \leq 0$$

Volume ≤ Desired volume

$$g_3(x) = -\Pi x_3^2 x_4 - \frac{4}{3}\Pi x_3^2 + 1296000 \leq 0$$

Length of Shell

$$g_4(x) = x_4 - 240 \leq 0$$

where 1*0.0625 ≤ x1 ≤ 99, 1*0.0625 ≤ x2 ≤ 99, 10 ≤ x3 ≤ 240, 10 ≤ x4 ≤ 240.

The PVD problem entails finding the optimal combination of design variables that minimize the objective function while satisfying the constraints. This optimization problem serves as the foundation for employing various optimization techniques to obtain pressure vessel designs that fulfill safety, performance, and regulatory requirements.

D. Teaching-Learning-Based Optimization Algorithm

The "Teaching-Learning-Based Optimization (TLBO)" algorithm presents a novel optimization paradigm inspired by the dynamics of teaching and learning. In TLBO, individuals in a population play the roles of both teachers and learners, interacting to enhance solution quality iteratively. This algorithm's application to the optimization of pressure vessel design provides an innovative approach to address the multifaceted challenges of achieving optimal performance while ensuring structural integrity and safety[2, 29, 30].

The core concept of the TLBO algorithm revolves around the teaching and learning interactions among individuals in the population. In each iteration, high-performing solutions act as teachers, guiding the improvement of suboptimal solutions. The learners update their solutions based on the information shared by the teachers, mimicking the educational process in a classroom. This collaborative learning mechanism enhances exploration of the solution space, enabling TLBO to overcome local optima and converge towards global optima.

When applied to pressure vessel design, TLBO involves translating its teaching and learning dynamics to the optimization of design variables. In this context, the objective is to find the optimal values of parameters, such as vessel dimensions and material properties, while adhering to constraints related to stress limits, geometric specifications, and safety regulations. The TLBO algorithm's iterative process involves updating the design variables of learners using the guidance provided by high-performing solutions (teachers). This process aids in exploring the design space effectively and refining solutions iteratively.

The TLBO algorithm's equations encompass the teaching and learning interactions. For each learner, a new solution is generated based on the weighted average of the learner's current solution and the corresponding teacher's solution. The formula can be expressed as:

1. **New Solution for Learner (L):**

L_new = L + rand() * (Teacher - L)

Where "rand()" is a random number between 0 and 1, "L_new" is the updated solution for the learner, "L" is the learner's current solution, and "Teacher" represents the corresponding teacher's solution.

This equation signifies the updating process wherein learners improve their solutions by incorporating information from superior-performing teachers. Over multiple iterations, this collaborative learning approach enables TLBO to explore and exploit the solution space, ultimately converging towards optimal or near-optimal solutions for the pressure vessel design problem.

Fig.2 illustrates the TLBO algorithm's flowchart, which ensures that learners collaboratively enhance their solutions through teaching and learning interactions, leading to the optimization of the pressure vessel design.

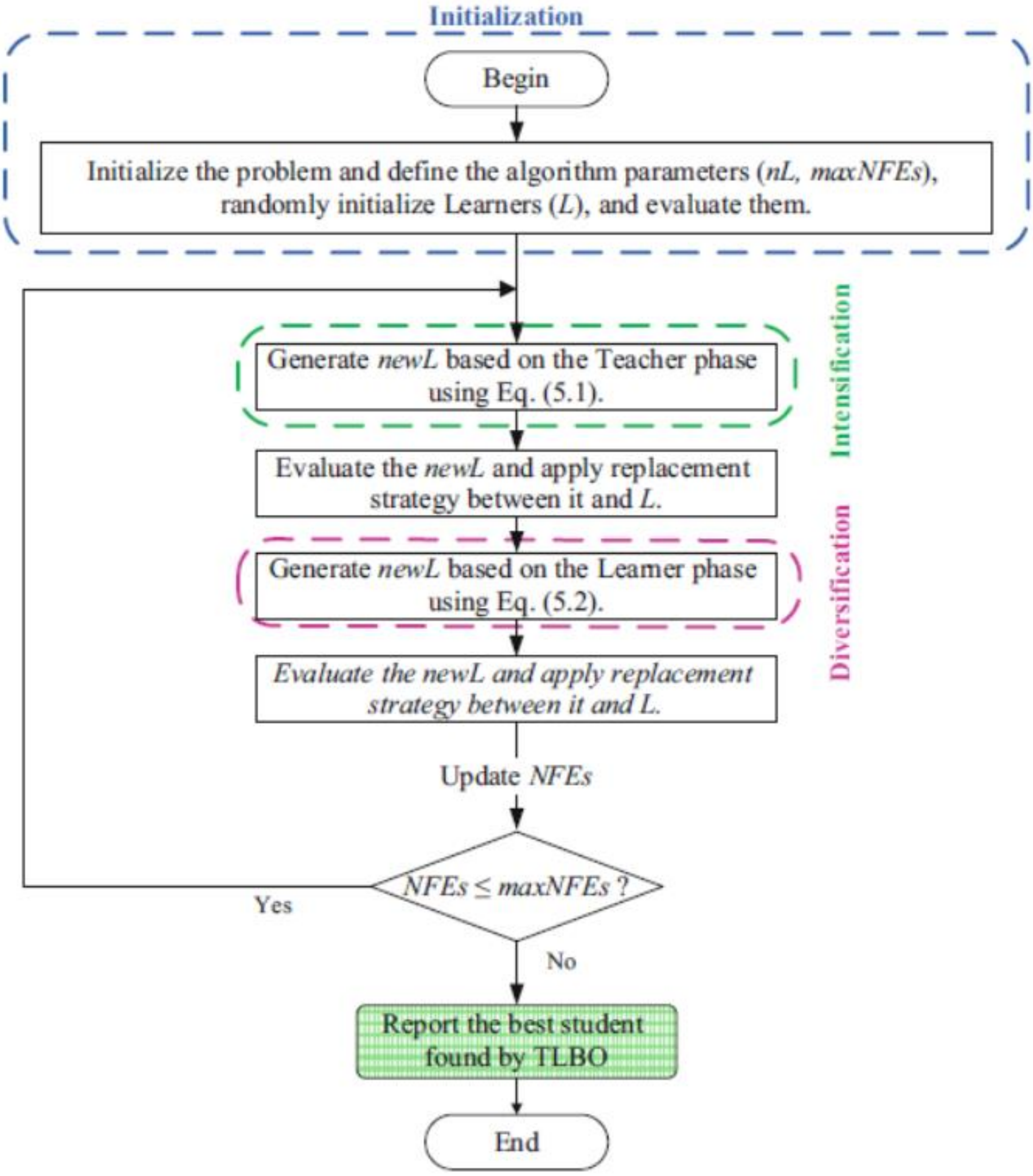

Figure 2. TLBO Algorithm Flowchart

E. Experimental results

This section presents a comprehensive experimental evaluation to assess the performance of the TLBO algorithm in pressure vessel design optimization. Comparative analyses are conducted against traditional optimization methods to ascertain TLBO's advantages and limitations. The experiments involve various pressure vessel design scenarios, considering different objectives, constraints, and complexities.

The provided table includes various parameters, such as the minimum, maximum, and mean objective function values (f(x)), as well as the values of design variables (x1, x2, x3, x4), the fitness function value (fx), and the time taken for optimization. As shown in Table 1

Table 1. Teaching-Learning-Based Optimization (TLBO) results

	Number of Learners	25	50	75	100	Conditions & Requirements
Design variables	X1	0.7783471	0.7783485	0.7786893	0.7787489	1*0.0625 ≤ X1 ≤ 99
	X2	0.3831242	0.3831307	0.3833138	0.3835602	1*0.0625 ≤ X2 ≤ 99
	X3	40.328863	40.328873	40.345394	199.77375	10 ≤ X3 ≤ 240
	X4	200	200	199.77375	199.79563	10 ≤ X3 ≤ 240
Results	F(X)	5883.7329	5883.7636	5884.6147	5886.7953	Minimization
	minF(X)	5884.2329	5884.2636	5885.1147	5887.2953	Best Value
	maxF(X)	5884.2352	6307.3079	6103.7283	6178.0149	Worst Value
	meanF(X)	5884.233	5903.3043	5895.5548	5905.6244	Mean Value
Time Elapsed		1.8794	1.8892	1.9251	1.9348	Time in second

The objective function (f(x)) is a crucial metric in evaluating the effectiveness of the TLBO algorithm for pressure vessel design optimization. It represents the performance and quality of the optimized pressure vessel designs. The objective is to minimize this function to achieve the best design that meets the specified criteria.

For the case with nL=25, the algorithm yielded a minimum f(x) value of 5883.7329. The results indicate that this configuration represents a highly optimized pressure vessel design, achieving the lowest objective function value among the examined scenarios.

As the number of learners increases (nL=50, 75, 100), the minimum f(x) values fluctuate slightly, ranging from 5883.7636 to 5886.7953. the results demonstrate that the TLBO algorithm consistently converges to solutions with relatively low f(x) values across different numbers of learners.

The optimization process also considers the time taken for optimization, which ranges from approximately 1.8892 to 1.9348 seconds. This metric provides insights into the algorithm's efficiency in finding optimized solutions within a reasonable computational time.

The provided results underscore the TLBO algorithm's effectiveness in optimizing pressure vessel designs. The key focus lies on the objective function f(x), where lower values indicate better performance. Despite minor variations in design variable values and objective function results with varying numbers of learners, the TLBO algorithm consistently produces optimized designs that fulfill the pressure vessel's requirements. Fig.3, shows the min, max, and mean convergences history.

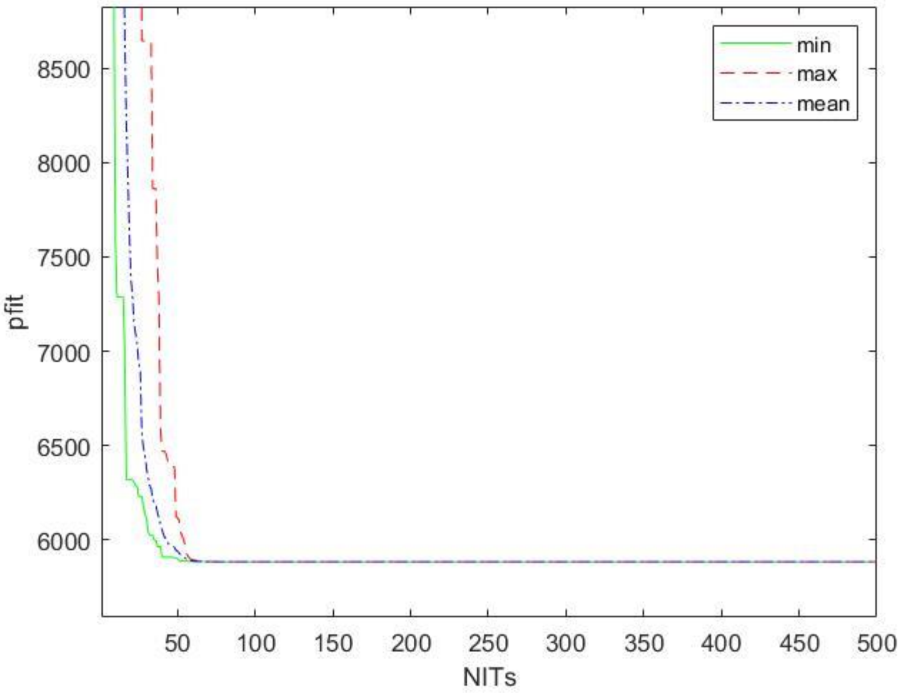

Figure 3. Convergence History of Pressure Vessels Design Solved by TLBO Min, Max, and Mean

Table 2 presents a comparison between the results generated by the proposed algorithm and the outcomes of previous investigations, which utilized diverse metaheuristic algorithms developed by various researchers. The table showcases the four design variables for pressure vessel design (X1, X2, X3, and X4) alongside the optimal fitness values (F(X)).

Table 2. Presented Algorithm Result Compared with Other Metaheuristics Algorithm

#	Researcher(s)	X1	X2	X3	X4	F(x)
1.	Yassin et al.	0.880944	0.433702	45.634248	137.249985	5798.7989
2.	This study	0.7783471	0.3831242	40.328863	200	5883.7329
3.	Garg	0.778197	0.384665	40.321054	199.980236	5885.4032
4.	Kaveh et al.	0.812500	0.437500	42.103566	176.573220	6059.0925
5.	Coello	0.812500	0.437500	40.323900	200.000000	6288.7445
6.	Deb and Gene	1.125000	0.500000	48.329000	112.679000	6410.3811
7.	C.Zhang	1.125000	0.625000	58.290000	43.6930000	7197.7000

8.	Kannan et al.	1.125000	0.625000	58.291000	43.690000	7198.0428
9.	K.S.Lee	1.125000	0.625000	58.278900	43.75490000	7198.433
10.	Sandgren	1.125000	0.625000	47.700000	117.701000	8129.1036

F. Conclusion

In conclusion, the application of the Teaching-Learning-Based Optimization (TLBO) algorithm to the pressure vessel design problem showcases its efficacy in addressing the intricate challenges of optimizing complex engineering systems. The results obtained from the analysis underscore the algorithm's capability to guide the optimization process towards solutions that exhibit improved performance, while adhering to stringent constraints and objectives.

The central metric of success, the objective function f(x), serves as a pivotal indicator of the quality of the optimized pressure vessel designs. The TLBO algorithm consistently strives to minimize this function, demonstrating its ability to produce designs that are not only structurally sound but also exhibit enhanced performance characteristics. Across varying numbers of learners (nL), the algorithm converges towards solutions with relatively lower f(x) values, revealing its adaptability and effectiveness in capturing optimal or near-optimal solutions.

The iterative nature of the TLBO algorithm, inspired by teaching and learning dynamics, encourages collaboration among learners to refine solutions iteratively. As demonstrated in the results, the algorithm systematically updates design variables based on superior-performing solutions, ensuring efficient exploration of the solution space while leveraging the knowledge gained from successful designs.

Furthermore, the time taken for optimization remains within reasonable bounds, demonstrating the TLBO algorithm's efficiency in delivering optimized solutions in a computationally feasible timeframe. This characteristic is particularly significant in practical engineering applications, where timely decision-making is crucial.

In essence, the TLBO algorithm's successful application to the pressure vessel design problem exemplifies its potential to revolutionize optimization practices within engineering. By embracing the pedagogical approach to optimization, TLBO offers an innovative perspective that complements traditional methods, catering to the intricate requirements of complex engineering systems. As demonstrated by its performance in the pressure vessel design context, the TLBO algorithm presents a valuable tool for researchers and engineers striving to achieve optimal solutions while considering multifaceted objectives and constraints.

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