Optimization of Pressure Vessel using Teaching Learning Based Optimization (TLBO)

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Received 25.12.2025 **received in revised form** 02.05.2025**, accepted** 03.05.2025
DOI: 10.47904/IJSKIT.15.1.2025.86-89

Abstract- Pressure vessels are an essential component in industrial applications, where cost-effective design is critical. This paper presents the minimization of total cost of the pressure vessel with appropriate constraints using TLBO algorithm. The dimensions of the pressure vessel are considered as design variables. The optimized results achieved using the TLBO algorithm are evaluated against those derived from other optimization methods. The analysis concludes that TLBO demonstrates greater computational efficiency and ease of implementation.

Keywords: Pressure vessel, TLBO, Total cost, Constraint handling, Penalty.

1. INTRODUCTION

Pressure vessels are essential in sectors like chemicals, petroleum, nuclear energy, and aerospace. These structures are intended to contain liquids or gases under high pressure, and their design must guarantee safety, efficiency, and cost-effectiveness. The optimization of pressure vessel design requires balancing various objectives, including reducing material expenses, manufacturing costs, and weight while meeting safety regulations and operational needs. This represents a traditional engineering optimization challenge, frequently tackled with sophisticated computational methods.

In the 1980s and 1990s, Optimization methods as computational tools were applied. The pressure vessel design problems were solved using some traditional methods [1-8]. These techniques are intended to reduce material consumption or manufacturing expenses while maintaining adherence to safety regulations specified in standards such as the ASME Boiler and Pressure Vessel Code. Nevertheless, conventional optimization methods frequently encountered difficulties due to the nonlinear and multimodal characteristics of pressure vessel issues, resulting in either inadequate solutions or high computational costs.

Metaheuristic algorithms have transformed optimization in engineering, especially for intricate and constrained challenges. Some of the algorithms outlined in references [9-23] became widely used methods for addressing nonlinear design challenges. These algorithms utilize principles from biology and natural systems to navigate the solution space more efficiently than deterministic approaches. The performance of these optimization algorithms can be significantly influenced by the need for carefully tuned algorithmic parameters to ensure convergence. Selecting these parameters adds complexity to the optimization process and can vary depending on the specific problem at hand. Moreover, such algorithms are not always guaranteed to identify global optima within a predefined timeframe. Their convergence rates are often slow, resulting in increased computational costs, particularly for high-dimensional or nonlinear problems. This limitation has prompted a search for alternative methods, such as metaheuristics, which aim to reduce dependency on parameter tuning and improve convergence efficiency.

In this study, the design problem of pressure vessel is solved using TLBO algorithm, and s performance evaluated against other optimization methods.

This paper is organized in sections as described in details.

2. FORMULATION OF OPTIMIZATION PROBLEM

This section formulates the minimization problem as total cost of the pressure vessel with appropriate constraints and solved using TLBO algorithm. The dimensions of the pressure vessel as shown in Figure 1 are considered as design variables.

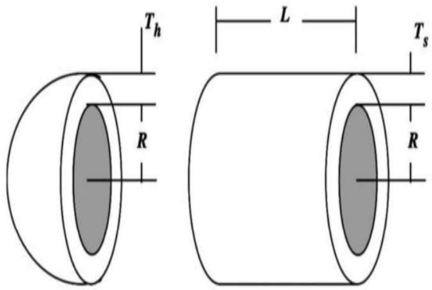

Figure 1: Pressure vessel

Vector form is written like

$$\boldsymbol{x} = [\,T_s, T_h, R\,, L]^T$$

The formulation is given [4] as

minimize $\quad Cost(\boldsymbol{x}) = 0.6224T_sRL + 1.7781T_hR^2 + 3.1661{T_s}^2L + 19.84{T_s}^2R$

Subjected to

$$\begin{aligned}
&C_1(\boldsymbol{x}) = 0.0193R - T_s \le 0\\
&C_2(\boldsymbol{x}) = 0.00954R - T_h \le 0\\
&C_3(\boldsymbol{x}) = 1296{,}000 - \pi R^2L - \tfrac{4}{3}\pi R^3 \le 0\\
&C_4(\boldsymbol{x}) = L - 240 \le 0\\
&10 \le R \le 200\\
&10 \le L \le 200\\
&T_s, T_h \in \begin{bmatrix} 0.0625, 0.1250, 0.1875, 0.2500, .. , \\ 6.00, 6.0625, 6.1250, 6.1875 \end{bmatrix}
\end{aligned} \tag{1}$$

To achieve an optimal solution, an unconstrained problem of equation (1) is written using a penalty function approach as outlined in reference [24]. In this method, the violation of constraints adds large penalty value to the objective function, effectively guiding the optimization process toward feasible regions of the solution space. This transformation guarantees the identification of the global optimum by ensuring that all constraints are satisfied through an appropriate optimization algorithm.

The reformulated unconstrained minimization problem is written as:

$$\mathrm{f(x)} = \mathrm{Cost(x)} + \sum_{\mathrm{B}=1}^{4} \mathrm{C_B}\,(\mathrm{CP})^{\mathrm{B}} \tag{2}$$

Where CP represents the higher value added to function if constraints are violated. Thus, function C_B is outlined like

$$C_B = \begin{cases} 1 & if\ g_B(x) \le 0 \\ 0 & otherwise \end{cases}$$

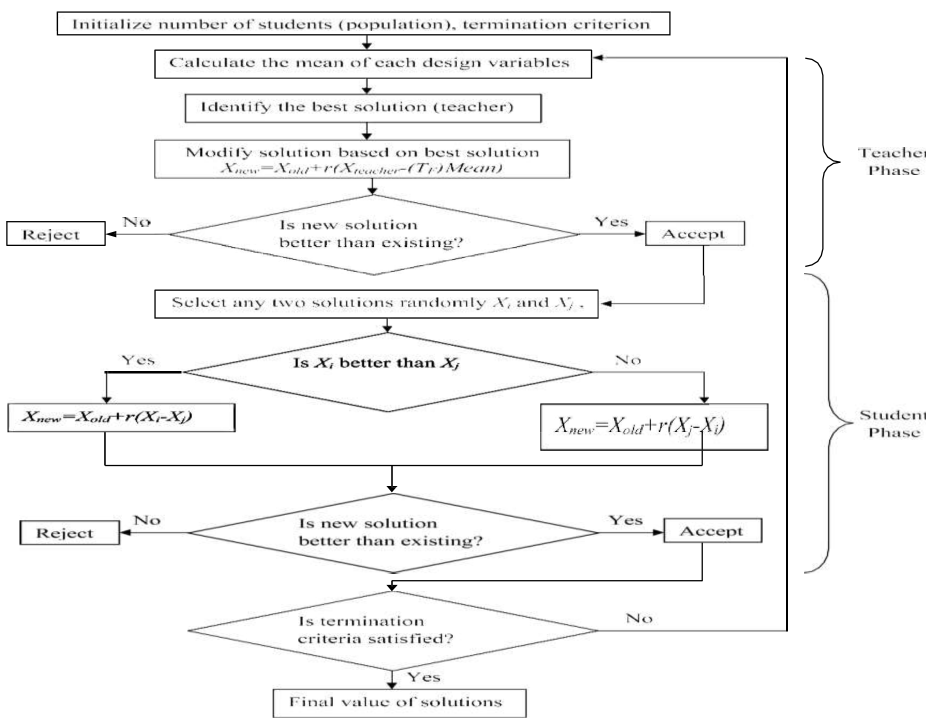

Figure 2: A flow chart of TLBO algorithm [25]

3. RESULTS AND DISCUSSIONS

This section describes the optimum results of the formulated optimization problem using the TLBO, which involves the teaching and learning (student) phases. These phases are mathematically modeled and implemented to guide the optimization process. TLBO obtains the optimal solution using population. The execution of TLBO is less complex than other metaheuristic algorithms. Also, no complex parameters are required [26,27]. In this approach, learners represent the population of potential solutions, and courses are analogous to the design variables in the optimization problem. The course marks of the learners correspond to the numerical values of these design variables, while their performance outcomes are comparable to the fitness function values in the optimization process. The iteration in the TLBO algorithm is done through phases until the desired solution is obtained. The TLBO algorithm is described by a flow chart in Figure 2.

The TLBO algorithm is applied to the design problem outlined in Equation (1) using a population size of 20 and running for 100 iterations. The best and average values of the function are achieved by performing 10 runs. The convergence rates for both function values are depicted in Fig. 3. The algorithm achieved the best and average function values of 6059.700 and 6059.740, respectively, within 2000 function evaluations. These outcomes, detailed in Table 1 demonstrate that the TLBO algorithm outperforms other optimization methods to achieve superior objective function values with fewer function evaluations.

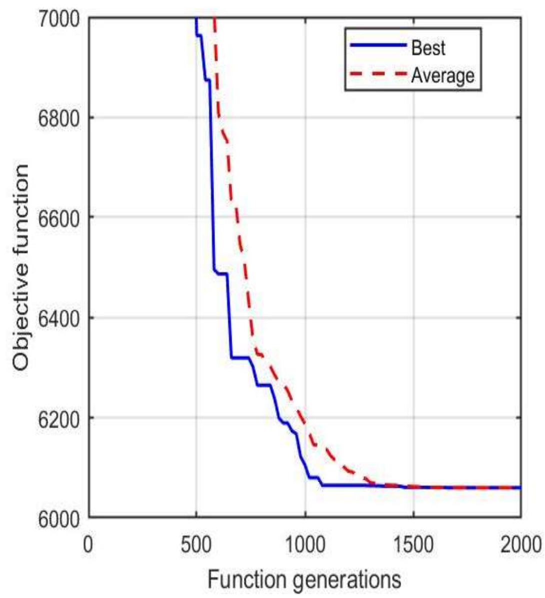

Figure 3: The convergence history for design problem

Table 1: Optimum results for given problem

Design variables $(\boldsymbol{x})$	EP [10]	EA [11]	GA [14]	PSO [17]	MPSO [19]	This Study
T_s	0.625	0.5	0.4375	0.4375	0.4375	**0.4375**
T_h	1	0.9345	0.8125	0.8125	0.8125	**0.8125**
R	90.7821	112.679	176.654	176.6366	176.636792	**176.636792**
L	51.1958	48.329	40.0974	42.09845	42.098446	**42.098446**
$Cost(x)$	7108.616	6410.381	6059.946	6059.714	6059.718932	**6059.700**
Function Evaluations	100000	42000	30000	30,000	4,00000	**2000**
Constraints violation	None	None	None	None	None	None

4. CONCLUSIONS

In this study, TLBO successfully minimized the cost of constructing the pressure vessel by optimizing key design variables such as shell thickness, head thickness, and overall dimensions, all while adhering to stringent safety and performance constraints. The results not only highlight the capability of TLBO to solve complex engineering problems but also emphasize its versatility in handling multi-variable, non-linear optimization tasks prevalent in the construction industry. Thus, TLBO gives the better optimized results compared to other optimization techniques.

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