Teaching Learning Based Optimization Applied to Mechanical Constrained Design Problems

Dhearendra Garg[1], Dr. Ashutosh Dwivedi[2]
[1,2]*Vindhya Institute of Technology and Science, Satna (M.P.)*

***Abstract*— A new efficient optimization method for mechanical design optimization is developed in this paper, TLBO (Teaching–Learning–Based Optimization). Focuses on how a teacher's influence on pupils. The TLBO algorithm follows in the footsteps of other algorithms inspired by nature and based on populations of solutions to arrive at a global solution. The population refers to all the pupils in a certain class. As part of the TLBO technique, there are two phases: one for the teacher and one for the learner. The "Teacher Phase" and "Learner Phase" are two separate stages of learning. All the TLBO method's basic ideas are laid out in detail. The approach's efficacy is investigated using five separate limited benchmark test functions, four distinct benchmark mechanical design difficulties, and six real-world optimization issues. Efficiencies such as best solution, average solution, convergence rate and computational effort are all considered when comparing it to other population-based optimization techniques. It is presented in this paper that TLBO was more effective than other optimization methods in tackling the mechanical design optimization difficulties under investigation. Engineers may be able to use this new method of optimization to solve additional optimization problems. For the optimization problem, MATLAB code is utilized to provide an optimized strategy for teaching and learning based on an evolutionary algorithm that simulates the teaching– learning phenomena that occur in classrooms. The mechanically constrained design (TLBO) method is investigated in this work, which studies analysis methods.**

***Index Terms*— Optimization, TLBO (Teaching–Learning–Based Optimization), MATLAB, mechanically constrained**

I. INTRODUCTION

TLBO, or Teaching–Learning–Based Optimization, is presented in this study as an innovative and efficient approach for mechanical design optimization. Inspired by the influence of a teacher on students, TLBO is a nature-inspired algorithm employing a population of solutions. The algorithm comprises two phases: the 'Teacher Phase' and the 'Learner Phase,' both contributing to the overall TLBO procedure. The study delves into the fundamental principles of TLBO and evaluates its performance using various benchmark test functions, mechanical design challenges, and real-world optimization problems. The comparison with other population-based optimization methods considers efficiency metrics like the best solution, average solution, convergence rate, and computing effort. The results demonstrate TLBO's superiority in addressing mechanical design optimization challenges, suggesting its adaptability to other engineering design optimization problems.

Teaching-learning-based optimization (TLBO) is a metaheuristic search algorithm rooted in the teaching and learning process. Over the years, TLBO has found applications in diverse scientific and technical domains. Acknowledging the variation in individual learning styles and outcomes, the research introduces a modified TLBO model, Leb TLBO, incorporating the concept of learning enthusiasm. Leb TLBO considers students' varying levels of learning enthusiasm, with high enthusiasm leading to increased probability of learning from others. Furthermore, a tutoring program is proposed for low-enthusiasm students, aiming to elevate their academic performance. Evaluation on CEC2014 benchmark functions illustrates the superiority of Leb TLBO over previous TLBO and non-TLBO methods, showcasing its potential for real-world problem-solving, particularly in chemical engineering optimum control scenarios.

The diversity in optimization algorithms, categorizing them as population-based, iterative-based, stochastic, deterministic, etc. Evolutionary algorithms (EA) and swarm intelligence algorithms (SI) are emphasized as significant population-based heuristics. Examples of evolutionary algorithms, such as genetic algorithms

(GA), differential evolution (DE), evolutionary strategy (ES), artificial immune algorithm (AIA), are provided, each mimicking different aspects of natural processes. Swarm intelligence algorithms like particle swarm optimization (PSO), ant colony optimization (ACO), and shuffled frog leaping (SFL) are discussed, drawing inspiration from collective behaviors of animals. Additionally, other algorithms based on natural phenomena, such as harmony search (HS), gravitational search algorithm (GSA), biogeography-based optimization (BBO), and League Championship algorithm (LCA), are introduced.

This emphasizing the need for careful parameter tuning in each algorithm for optimal performance. The challenges in identifying and adjusting specific parameters for algorithms like GA, PSO, ABC, and HS are highlighted. The discussion suggests that creating an optimization algorithm without algorithm-specific parameters requires further research and development. Classic analytical optimization techniques are deemed insufficient for handling complex real-world problems, leading to the development of metaheuristic search algorithms with superior performance on nonconvex and nondifferentiable situations. The paragraph emphasizes the importance of continued research to create unique and efficient algorithms for diverse optimization problems. The role of TLBO, with its simplicity, lack of specific parameters, and quick convergence, is reiterated in addressing a range of optimization challenges across various scientific and technical domains. The introduction of Leb TLBO further explores the integration of learning enthusiasm into the TLBO framework, showcasing its potential for enhancing optimization outcomes.

Engineering draws inspiration from nature to innovate engines, structures, and robots. Optimization is vital for achieving efficient and competitive designs. While implicit optimization based on judgment and experience may fall short in complexity, computer-based optimization utilizes vast processing capabilities for swift assessment of design possibilities. Engineers use quantitative models and design variables to form a design space, with criteria including objectives and constraints. Iterative adjustments by computer algorithms navigate this space, exploring trade-offs and relationships. Learning, evolving throughout life, is facilitated by various methods, including e-learning, providing flexible access to instructional materials. Cloud computing enhances this accessibility, overcoming traditional classroom boundaries.

The TLBO method, prone to local optima in complex optimization problems, has seen enhancements through various TLBO variants. These variants fall into three categories. First, modifications to teaching tactics or learner strategies aim to boost performance. For instance, Rao and Patel introduced a modified TLBO with additional instructors and an adjustable teaching factor. Second, hybrid TLBO approaches, combining TLBO with other search methods, aim to balance local and global searching, like TLBO-GC with a global crossover operator. Third, TLBO variants like TLCS incorporate additional search processes, such as cuckoo search, to optimize specific problems like structural design and machining parameters.

Design Optimization of Mechanical Components Using an Enhanced Teaching

The study explores the Teaching-Learning-Based Optimization (TLBO) method with a differential operator for optimizing mechanical components. Analysing a belt-pulley drive, a closed coil helical spring, and a hollow shaft, the study demonstrates the effectiveness of TLBO in finding improved solutions. The approach surpasses previous methods in obtaining optimal solutions for mechanical components. Optimization in mechanical design is crucial for efficiency, cost reduction, and enhanced component service. While classical optimization approaches have limitations, natural heuristic methods, like TLBO, show superiority. The study introduces a hybrid technique combining TLBO with a differential mechanism, addressing complex optimization challenges and utilizing Sequential Quadratic Programming (SQP) for fine-tuning the solutions.

Optimization Procedure

Teaching-Learning-Based Optimization (TLBO) is an evolutionary algorithm based on the teaching-learning process. It utilizes a population of students to represent possible solutions in an optimization problem, with an objective function determining each student's expertise level. The instructor represents the solution with the highest fitness. Orthogonal Teaching Learning-Based Optimization (OTLBO) is an enhanced variant incorporating orthogonal design to improve TLBO's speed and robustness. OTLBO demonstrates superior performance in terms of solution quality, speed, and stability when compared to other evolutionary algorithms. The orthogonal design technique divides the class of learners into partial vectors, finding optimal scales and ensuring fair comparisons of factors' impact. OTLBO is tested on benchmark functions, outperforming other evolutionary algorithms with a large number of parameters. The study aims to enhance the convergence time of TLBO without compromising solution quality, making it suitable for real-time applications. This work provides an overview of TLBO, describes the orthogonal design, presents OTLBO, details experimental findings, and concludes with future research prospects.

II. LITERATURE REVIEW

In the realm of optimization research, various studies have highlighted the efficacy of the Teaching Learning Based Optimization (TLBO) algorithm across diverse applications. Elkholy and Fathy (2016) utilized TLBO for optimizing a solar-powered water pumping system, showcasing its ability to adjust inverter parameters and maximize electricity generation from photovoltaic panels. Togan (2012) introduced TLBO for discrete optimization of planar steel frames, illustrating its efficiency compared to other algorithms. Yildiz (2013) proposed a hybrid TLBO approach for multi-pass turning operations, outperforming particle swarm and genetic algorithms. Crepinsek and Liu (2012) critically analyzed TLBO, emphasizing its strengths in confined benchmark functions but highlighting potential reporting errors. Abhishek and Kumar (2015) applied TLBO for CFRP composite machining optimization, demonstrating its superiority over genetic algorithms. Sahu and Pati (2015) utilized TLBO for designing a fuzzy-PID controller in power systems, showcasing its resilience and effectiveness. Barisal (2015) evaluated TLBO for load frequency management in multi-source power systems, highlighting its stability and robustness. Chatterjee and Naithani (2016) applied TLBO-optimized controllers for wind turbine stability, exhibiting superior dynamic performance. Ji, Wang, and Ge (2016) optimized LS-SVM forecasting with TLBO, surpassing other optimization methods. Kankal and Uzlu (2016) modeled Turkey's energy consumption with ANN-TLBO, outperforming alternative algorithms and providing valuable insights for future energy research. These studies collectively underscore TLBO's versatility and effectiveness in solving complex optimization challenges across diverse domains. The review encompasses diverse applications of the Teaching Learning Based Optimization (TLBO) algorithm, showcasing its versatility and effectiveness in solving complex optimization challenges. Lei and Gao (2017) focused on Hybrid Flow Shop Scheduling, utilizing TLBO for energy-efficient solutions and demonstrating competitive computational results. Bouche kara and Abido (2014) harnessed TLBO for optimal power flow in power systems, highlighting its effectiveness in comparison to other methods. Pickard and Carretero (2016) conducted a comprehensive analysis of TLBO's convergence and origin biases, emphasizing its performance implications and the need for user awareness. Rajinikanth and Satapathy (2017) applied TLBO to improve tumor segmentation in brain MRI, showcasing its therapeutic significance. Rao and Savsani (2012) proposed TLBO for continuous non-linear large-scale optimization problems, demonstrating its effectiveness through benchmark evaluations. Additionally, recent studies by Rao et al. (2020), Abderazek et al. (2021), and Sun et al. (2021) underscored the impact of TLBO in mechanical system design optimization, highlighting its competitive performance and effectiveness in handling complicated mechanical component design challenges. Moreover, Yildiz et al. (2020) explored the efficiency of various metaheuristic algorithms in solving real-world mechanical issues, positioning TLBO as a promising solution. The collective findings reinforce TLBO's standing as a robust optimization algorithm across diverse domains, providing efficient solutions to complex problems. This comprehensive review encompasses diverse applications and enhancements of optimization algorithms, focusing on mechanical design, constrained optimization, reliability-based design, and dynamic optimization challenges. De-la-Cruz-Martínez and Mezura-Montes (2020) experimentally evaluate nine boundary constraint-handling approaches for mechanical design optimization, with the Projection technique emerging as a superior performer. Fatemeh et al. (2019) introduce SP-QPSO, a hybrid technique for mechanically limited design optimization, outperforming traditional PSO and other methods.

Wang et al. (2019) explore the reliability-based design optimization of an explosive-actuated device using the polynomial chaos expansion approach, showcasing the correctness and effectiveness of the proposed notion. Khan and Gunpinar (2018) present Sample-TLBO (S-TLBO), an extension of TLBO for constrained and unconstrained CAD model sampling, demonstrating superiority in generating space-filling designs. Sarzaeim, Bozorg-Haddad, and Chu (2018) provide an overview of TLBO and its pseudocode, emphasizing its innovative metaheuristic optimization strategy based on teaching and learning concepts.

Chen et al. (2018) tackle dynamic optimization challenges in chemical process design using the TLBO algorithm. They propose a modified version, QITLBO, which combines diversity-improved teaching techniques and quadratic interpolation operators, outperforming eleven established metaheuristic algorithms. Wang, Li, and Feng (2018) enhance TLBO for restricted optimization by introducing effective teacher and learner phases based on subpopulations and ranking differential vectors. The proposed Improved TLBO (ITLBO) demonstrates superior performance in comparison to previous TLBO versions and various confined optimization evolutionary algorithms across benchmark functions.

The collective findings underscore the versatility and effectiveness of TLBO and its variants in addressing complex optimization challenges, showcasing their superiority over traditional methods in terms of efficiency, accuracy, and reliability. These studies contribute valuable insights to the field of optimization, providing innovative approaches for diverse applications, from mechanical design to constrained and dynamic optimization problems.

The review encompasses several studies investigating the effectiveness of the Teaching–Learning-Based Optimization (TLBO) algorithm and its variations in solving global optimization problems. Cheng and Prayogo (2018) introduce a novel variant called Fuzzy Adaptive Teaching–Learning-Based Optimization (FATLBO) by incorporating an operational status monitor, fuzzy adaptive teaching–learning algorithms, and a remedial operator. Through evaluations on complex benchmark functions, FATLBO exhibits superior worldwide optimization excellence and competitive performance compared to other optimization techniques.

Rao et al. (2011) initially introduced TLBO, emphasizing its basis on the teaching-learning process philosophy. TLBO demonstrated efficacy in solving benchmark issues with various features, surpassing other nature-inspired optimization approaches. Rao and Savsani (2011a, b) applied TLBO to optimize the design of a robot gripper, showcasing comparable results to previous studies. Rao et al. (2012a) further tested TLBO against various benchmark problems, highlighting its superiority in solving large-scale problems with high dimensionality compared to genetic algorithms (GA), artificial bee colony (ABC), particle swarm optimization (PSO), and harmony search (HS).

Rao et al. (2012b) extended TLBO to real-parameter optimization problems, both unconstrained and restricted. The study compared TLBO's performance against other optimization methods, emphasizing TLBO's efficiency in requiring fewer function evaluations to achieve optimal results. Rao and Patel (2012) introduced elitism to TLBO and examined its impact on the algorithm's performance in restricted optimization scenarios. The study explored the influence of population size, elite size, and the number of generations on TLBO's performance across 35 well-defined restricted optimization problems. TLBO with elitism consideration outperformed the strategy without elitism, showcasing its robust performance. The TLBO algorithm consistently demonstrated competitive results when compared to other optimization methods, including particle swarm optimization (PSO), differential evolution (DE), artificial bee colony (ABC), and evolutionary programming (EP), across various optimization tasks. The collective findings across these studies affirm the efficacy, versatility, and competitive performance of TLBO and its variants in addressing a wide range of optimization challenges.

III. METHODOLOGY

Optimization Algorithm

An Optimization Algorithm is a step-by-step process for determining the optimal value (maximum or lowest) of an objective function. There are several methods to choose from depending on the nature of our issue, ranging from the Genetic Algorithm to the Particle Swarm Optimization (PSO).

TLBO algorithm

When it comes to learning, the influence of teachers may have an enormous impact on the outcomes of students in a classroom. The instructor devotes his time and effort to the education of the students in his class. After that, students engage in self-reflection and self-improvement activities to increase their understanding.

As a general rule, when we need to optimize an issue, we tend to use a random optimization method that has certain parameters that can be fine-tuned in order to assist us discover the global optimal value as quickly and efficiently as feasible. The PSO method, for example, requires the inertial weight (W) and acceleration coefficients (c1 and c2) as parameters. When t he inertial weight (W) is 0.4–0.9, the Global Optimum is more easily achieved; on the other hand, the Local Optimum is more easily achieved when W is less than or equal to 0.4–0.9.

Never fear. In addition, I want to write an essay on the PSO algorithm.

However, unlike the W, c1, and c2 parameters in the PSO method, the TLBO algorithm does not call for any algorithm-specific parameters.

Theory

There are a number of learners in the population P and the decision variables in the optimization problem that they will use to learn from their instructor in this method. Learning may be done in two ways: As a result of the instructor (Teacher Phase) contact with other students is the best way to learn (Learner Phase). A student's test score (Fitness) is the most important thing to us, and we only maintain the top scores from each exam, whether they were earned by the student or the instructor.

Working

An optimization algorithm's efficiency may be assessed by implementing certain Test Functions and performing the global optimum. Let's use the Sphere Function as our Test Function to see if we can figure out how this approach works. In order to reduce this optimization issue, we'll use a test function.

Test Function — Sphere Function

Range of decision variables:- xi between -100 and 100 We take 5 learners and 2 subjects.

So, Learners = 5 and Decision Variables = 2.

According to our decision variables, objective function or test function becomes $x1^2 + x2^2$.

Teacher Phase

Initial population	x_1	x_2	$f(x)$	
	–55	36	4321	
	0	41	1681	
	96	–86	16612	
	–64	31	5057	
	–18	–27	1053	Teacher
Mean	–8.2	–1		

Table.1 Teacher Phase Initial Population

As we can see in the image above, we started with a sample of 5 students and 2 topics, or, to put it another way, 5 rows and 2 columns, each containing a different value from the set of choice factors we discussed before (xi between -100 and 100). We used the values of x_1 and x_2 in our goal function to obtain the fitness values. Next, we tallied the data in a separate column f. (x). In order to reduce our function's size, we will look at the table and choose 1053 as our best match, which we will then use as our teacher. There are -8.2 and 1 in each column, thus we compute the mean of each column.

We now use the following formula to get the difference between the means of each of the subjects:

Difference Mean of $x_1 = r_1 * Tf * (x_1$ from Teacher — Mean of $x_1)$ Difference Mean of $x_2 = r_2 * Tf * (x_2$ from Teacher — Mean of $x_2)$

Here, r_1 and r_2 are random numbers generated between 0 and 1. Tf is the teaching factor that maybe 1 or 2. We have taken $r_1 = 0.58$, $r_2 = 0.49$ and $T_f = 1$. Therefore,

$$\text{difference\_Mean}(x_1) = 0.58 * (-18 - (-8.2)) = -5.684$$

$$\text{difference\_Mean}(x_2) = 0.49 * (-27 - (-1)) = -12.74$$

We now multiply each value in the x1 column by the DM of x_1, and each value in the x_2 column by the DM of x_2. This completes the calculation. After that, we're presented with the following:

Table. 2 Difference Mean

x_1	x_2	$f(x)$
–60.684	23.26	4223.575
–5.684	28.26	830.9355
90.316	–98.74	17906.57
–69.684	18.26	5189.287
–23.684	–39.74	2140.199

By checking each value in x_1 and x_2 columns against the list of choice variables, we can then sum the difference means. In the event that a value breaches the lower or upper constraint, we alter that value to the opposite of what it was originally. We don't evaluate this Bounding Strategy since there is no violation shown in the preceding table. We then compute fitnesses and store them in a separate column, as seen in the table above, after any values have been constrained.

The next step is to compare each learner's new fitness values to their previous fitness values. After comparison, we maintain the x_1 and x_2 values of the learner with the lowest fitness value. We end up with a table that looks like this:-

Table. 3 Fitness value is minimum after comparison.

x_1	x_2	$f(x)$
–60.684	23.26	4223.575
–5.684	28.26	830.9355
96	–86	16612
–64	31	5057
–18	–27	1053

After completing the Teacher step of this algorithm, we are now at the end of our journey.

Learner Phase

During the learning phase, students will engage with each other. There are two ways to go about it, and each has its own set of pros and cons. In this essay, we'll cover both of these ways.

First Method

Every student has the opportunity to engage with a random learner in this approach. So, let's assume Student A interacts with Student B, and then we'll see which of the two is more physically fit. The most fit person will be the one to pass along the information. Learner 2's fitness level is superior to that of learner 1. In this case, the information is being transferred from student 2 to learner 1.

To get the new values of x1 and x2 for student 1, we use the formula for calculating the new values:

New x1 for L1 = Current x1 of L1 + r1 * (x1 of L2 — x1 of L1) New x2 for L1 = Current x2 of L1 + r2 * (x2 of L2 — x2 of L1)

Here, r1 and r2 are random numbers generated between 0 and 1. r1 is taken as 0.81 and r2 is taken as 0.92.

Next, we do interactions between L2 and L4, L3 and L5, L4 and L1, L5 and L3. In each case, we calculate the new values of x1 and x2. We arrange all the values in the table below: -

Table.4 Learner phase

x_1	x_2	$f(x)$	Interaction
–16.134	27.86	1036.486	1 and 2
41.552	25.7392	2389.075	2 and 4
3.66	–31.72	1019.554	3 and 5
–61.314	23.879	4329.613	4 and 1
–100(–110.34[a])	27.28	10744.2	5 and 3

[a]This value has crossed the given range of the variable and hence it is assigned the bound value

We use the Bounding method whenever we acquire new values for x1 and x2 in the Teacher phase or this Learner phase. If a value breaches a bound, we transfer it to that bound. L5's new x1 for L5 is -110.34, which breaks the lower constraint of -100.34 when we execute the interaction between L5 and L3. It is thus necessary to alter that number to -100 in order to keep it inside our decision- making ranges. We next estimated the fitness values based on the results of the bounds.

x1 and x2 are calculated by comparing the fitness values of this learner phase with those of the instructor phase. The best fitness values are only kept.

Table .5 compare the fitness of this learner phase

x_1	x_2	$f(x)$
–16.134	27.86	1036.486
–5.684	**28.26**	**830.9355**
3.66	–31.72	1019.554
–61.314	23.879	4329.613
–18	–27	1053

In other words, the TLBO Algorithm is now finished with its first iteration. We use this data as our starting population table in the following iteration. Then, it goes through the teacher and learner phases, respectively. As a result, the iterations are carried out until we discover the lowest number, which is 0.(Theoretically).

Second Method

During the learner phase, all learners engage with each other. There are a number of ways that one language might connect with another. Similarly, L2 has an effect on L1, L3, L4, and L5, as do the other members of the L family. And so on and so on. Afterward, we need to choose the best interaction tables and store them in a separate database. When the algorithm has completed one loop, then we may declare that it is complete. This is what you'll see as output tables:

x_1	x_2	$f(x)$	
−60.684	23.26	4223.575	
−16.134	27.86	1036.486	best
−100(−187.598[a])	100(123.779[a])	20000	
−57.998	16.1392	3624.242	
−26.11	-22.9792	1209.776	

[a]These values have crossed the given ranges of the variables and hence they are assigned the bound values

Table.6 First Learner interacting with each other Learner (Learner Phase)

x_1	x_2	$f(x)$	
38.866	32.86	2590.346	
−5.684	28.26	830.9355	best
−88.048	100(133.379[a])	17752.45	
41.552	25.7392	2389.075	
4.292	79.0992	6275.105	

[a]This value has crossed the given range of the variable and hence it is assigned the bound value

Table.7 Second Learner interacting with each other Learner (Learner Phase)

x_1	x_2	$f(x)$	
−30.914	14.5192	1166.483	
13.636	19.119	551.4767	best
96	−86	16612	
−33.6	21.64	1597.25	
3.66	−31.72	1019.554	

Table.8 Third Learner interacting with each other Learner (Learner Phase)

x_1	x_2	$f(x)$	
−61.314	23.879	4329.613	
−16.764	28.4792	1092.097	best
−100(−193.6[a])	100(138.64[a])	20000	
−64	31	5057	
−26.74	−22.36	1214.997	

[a]These values have crossed the given ranges of the variables and hence they are assigned the bound values

Table.9 Fourth Learner interacting with each other Learner (Learner Phase)

x_1	x_2	$f(x)$	
16.574	−73.239	5638.649	
−8.024	23.8392	632.692	best
−100(−110.34[a])	27.28	10744.2	
19.26	−80.36	6828.677	
−18	−27	1053	

[a]This value has crossed the given range of the variable and hence it is assigned the bound value

Table.10 Fifth Learner interacting with each other Learner (Learner Phase)

x_1	x_2	$f(x)$
−16.134	27.86	1036.486
−5.684	28.26	830.9355
13.636	**19.119**	**551.4767**
−16.764	28.4792	1092.097
−8.024	23.8392	632.692

Table 3.11 Update values of the variable and the objective function based on the best fitness values obtained (Leaner Phase)

IV. RESULT AND DISCUSSIONS

Optimization approach for teaching and learning is based on evolutionary algorithm that replicates the teaching learning phenomena of classrooms for the truss optimization issue, MATLAB code is used. Mechanically constrained design (TLBO) is studied in this thesis, which investigates truss analysis. The three main objectives of this thesis are as follows:

1. Cooperative design of truss structures with size and form limitations utilizing a collaborative optimization approach.
2. Optimization of truss design with frequency limitations using multi-class teaching and learning.
3. Modified teaching learning optimization for the design of trusses in space

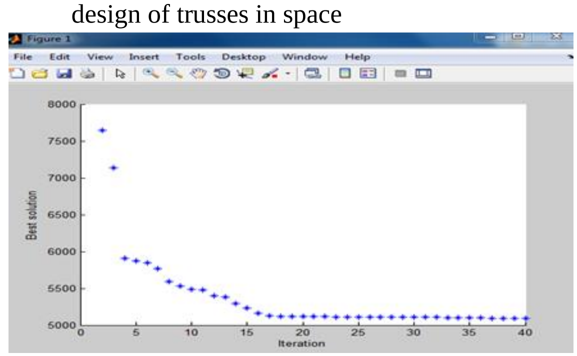

Figure 4.1 Modified Teaching Learning-Based Optimization

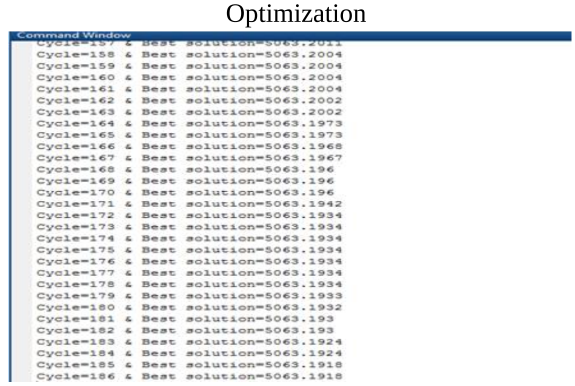

Figure 4.2 Best Solution and Iteration-1

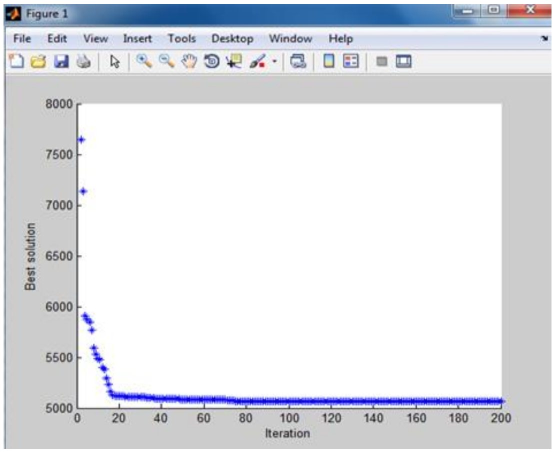

Figure 4.3 Cycle and Best Solution

```
function D=Data10
% Design parameters for the benchmark 10-bar truss problem
Coord=360*[2 1 0;2 0 0;1 1 0;1 0 0;0 1 0;0 0 0];
Con=[5 3;1 3;6 4;4 2;3 4;1 2;6 3;5 4;4 1;3 2];
Re=[0 0 1;0 0 1;0 0 1;0 0 1;1 1 1;1 1 1];
Load=zeros(size(Coord));Load(2,:)=[0 -1e5 0];Load(4,:)=[0 -1e5 0];
E=ones(1,size(Con,1))*1e7;
A=ones(1,10);
% Available sections
AV=[1.62, 1.8, 1.99, 2.13, 2.38, 2.62, 2.88, 2.93, 3.09, 3.13, 3.38, 3.47, 3.55, 3.63, 3.84,...
    3.87, 3.88, 4.18, 4.22, 4.49, 4.59, 4.80, 4.97, 5.12, 5.94, 7.22, 7.97, 11.5, 13.50,...
    13.90, 14.2, 15.5, 16.0, 16.9, 18.8, 19.9, 22.0, 22.9, 28.5, 30.0, 33.5];%in^2
%Allowable Stress
TM=25000;%psi
%Allowable Displacement
DM=2;%inch
%Density
RO=.1;%lb/in^3
LB=ones(1,10)*0.1;
UB=ones(1,10)*33.5;
D=struct('Coord',Coord','Con',Con','Re',Re','Load',Load','E',E','A',A','AV',AV','TM',TM','DM',DM','RO',RO','LB',LB,'UB',UB);
```

Figure 4.4 Best Solution and Iteration-2

As the above result presented in the graph shows design problem of truss data which is being optimized in 200 integration count and the best value at just above the 5000. We have the best solution for truss data as we have input in MATLAB.

V. CONCLUSIONS

It is proposed in this research work that TLBO (Teaching–Learning–Based Optimization) be used as an innovative and efficient optimization technique for the optimization of mechanical design. This method focuses on the effect of a teacher's influence on pupils and the implications of that influence. The algorithms that are inspired by nature and that use populations of solutions to arrive at a global answer, the TLBO algorithm is a good choice. The population refers to the whole group of pupils in a class. The first and second portions of the TLBO technique are divided into two parts: the 'Teacher Phase' and the 'Learner Phase.' The "Teacher Phase" and the "Learner Phase" are two separate periods of learning that are distinguished from one another. The core ideas of the TLBO approach are discussed in detail. In order to determine if the technique is successful, five separate limited benchmark test functions, four different benchmark mechanical design challenges, and six real-world optimization issues are used to evaluate its effectiveness. This approach is compared to other population-based optimization methods in terms of its efficiency, taking into consideration the best solution, the average solution, the convergence rate, and the amount of computation time required. The optimization strategy for teaching and learning is based on an evolutionary algorithm that simulates the teaching–learning phenomena seen in classrooms. MATLAB code is utilized to solve the truss optimization problem. This thesis examines mechanically constrained design (TLBO) via the lens of truss analysis. The results of the tests revealed that TLBO outperformed other optimization methodologies when it came to tackling the mechanical design optimization difficulties under investigation. Another advantage of this novel optimization technique is that it may easily be applied to other optimization difficulties in engineering design.

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