Improved Elitist Teaching Learning Based Optimization to Enhance the Teacher Learning Performance

Trupti Ayachit[1] Amit Sariya[2]
[1]Student [2]Assistant Professor
[1,2]Department of Computer Science & Engineering
[1,2]Alpine Institute of Technology, Ujjain, India

Abstract— TLBO is a robust and effective search algorithm. The most salient advantage of this algorithm is that it does not require the tuning of any kind of controlling parameters. The principle idea behind TLBO is the simulation of teaching process in the traditional classroom. The performance of TLBO ends in two basic stages: (1) "teacher phase" or learning from the teacher, and (2) "learner phase" or trade off information between learners. MATLAB tool is used for the implementation of this model. In this work, another optimization construct approach with respect to TLBO is proposed. This methodology is utilized to enhance the outcomes. TLBO algorithm is adjusted and a versatile teaching factor is presented. Besides, more than one teacher is presented for the learners. The introduced adjustments improve the investigation and misuse limits of the fundamental TLBO algorithm. This work demonstrated different results that have been contrasted and past algorithms that came beforehand.

Key words: Data Mining, Optimization, MATLAB, Teaching–Learning-Based Optimization (TLBO), Elitist TLBO

I. INTRODUCTION

The wide-spread of dispersed data systems prompts the development of large data accumulations in business, science and on the Web. These data collections contain a wealth of data, which, however should be found. Data mining gives strategies that permit separating from expansive data collections obscure connections among the data items that are valuable for decision making. Hence data mining produces novel, unsuspected translations of data [1].

TLBO is an optimization algorithm taking into account instructing and learning process in a classroom. Teaching-learning is a critical procedure where each individual tries to take in something from different people to enhance themselves. TLBO [2] technique is based with respect to the impact of the impact of a teacher on the output of learners in a class. It is a populace based technique and like other populace based strategies it utilizes a populace of answers for continue to the global solution. A gathering of learners constitute the populace in TLBO.

The remainder of this paper is organized as follows. Section II discusses works relevant to our experiment. Section III presents the experiment design and definition. Section IV provides and discusses the test results of the experiment. Section V presents the experiment conclusions.

II. LITERATURE SURVEY

TLBO algorithm for shape and size optimization of truss structures with Dynamic recurrence requirements by A. Baghlani, et. al. has been proposed to take care of the optimization issue. The confused issue of truss shape and measure optimization with various frequency limitations is explored in this paper. Different benchmark issues are unraveled with this procedure and the outcomes are contrasted and those found by different techniques including metaheuristics, for example, PSO, HS and FA. In all experiments, the outcomes demonstrate that TLBO prompts exceptionally tasteful results i.e. lighter structures which fulfill all frequency limitations. The consequences of this study show incredible innate limit of the methodology in managing with confounded dynamic non-linear optimization problems [3].

TLBO Algorithm for Dealing with Real-Parameter Optimization Problems by Kailin Wang et. al. has worked concerning TLBO from the logarithmic and investigative perspectives. Subsequently, in this paper ideas and algorithms of TLBO then overview the running component of TLBO for managing the genuine parameter optimization problems, lastly gather its real-world applications with a sorting system taking into account the grouping, multi-objective optimization. Parameter optimization, and structure optimization, have been talked about. The principle point of interest of this work is to offer the users some assistance with employing TLBO without knowing subtle elements of this algorithm. a test correlation for showing the adequacy of TLBO on 5 benchmark assessment capacities have additionally been performed [4].

Elitist Teaching Learning Opposition based Algorithm (ETLOBA) for Global Optimization by Anguluri Rajasekhar et. al. has proposed another variation of TLBO, termed as ETLOBA has been proposed for numerical capacity optimization. The proposed strategy is engaged with two components to achieve the precise global optimum with less time unpredictability. One of them is elitism, which fortifies the ability of optimization technique by holding the best arrangement got in this way, then again Opposition strategy helps in improving the capacity of seeking. As ETLOBA had leverage of both Elitism and Opposition based learning, henceforth it tries to get ideal arrangements with guaranteed convergence. the outcomes got by ETLOBA are been contrasted and new state-of-art optimization strategies like ABC, HS and so forth., demonstrates the prevalence of the proposed approach in taking care of persistent optimization issues [5].

An enhanced TLBO algorithm for taking care of unconstrained optimization issues by R. Venkata Rao, Vivek Patel has proposed an enhanced TLBO algorithm. TLBO algorithms reenact the teaching–learning phenomenon of a classroom to tackle multi-dimensional, straight and nonlinear issues with considerable productivity. In this paper, the essential TLBO algorithm is enhanced to improve its investigation and misuse limits by presenting the idea of number of educators, versatile teaching factor, tutorial training and self-motivated learning. Execution of the

enhanced TLBO algorithm is evaluated by actualizing it on a scope of standard unconstrained benchmark capacities having diverse qualities. Two new search systems are presented in the proposed approach as tutorial training and self motivated learning. In addition, the showing element of the fundamental TLBO algorithm is changed and a versatile showing element is presented. Besides, more than one educator is presented for the learners. The displayed alterations improve the investigation and abuse limits of the essential TLBO algorithm. The consequences of optimization obtained utilize the enhanced TLBO algorithm are approved them with those got utilizing the essential TLBO and other optimization algorithms [6].

Weighted Teaching-Learning-Based Optimization for Global Function Optimization by Suresh Chandra Satapathy, Anima Naik, K. Parvathi have proposed an enhanced rendition of TLBO algorithm, called the WTLBO. This algorithm utilizes a parameter as a part of TLBO algorithm to build union rate. Execution correlations of the proposed strategy are pro- vided against the first TLBO and some other exceptionally prevalent and intense transformative algorithms. The weighted TLBO (WTLBO) algorithm on a few benchmark optimization issues demonstrates a stamped change in execution over the customary TLBO and different algorithms also. The proposed approach, known as Weighted-TLBO (WTLBO) depends on the characteristic wonders of human brain (a learner's brain) in forgetting the lessons learnt in last session. The paper recommended an incorporation of a parameter known as "weight" to address this phenomenon while utilizing the learning mathematical statement as a part of teaching and learning phases of fundamental TLBO algorithm. In spite of the fact that, incorporation of a parameter, for example, weight may appear to expand the unpredictability of the essential TLBO algorithm while tuning the parameter, the recommended approach in the work in setting up the weight parameter facilitates the undertaking and ready to give better results contrasted with fundamental TLBO and all other explored algorithms in this work for a few benchmark capacities. The proposed WTLBO is ready to discover global optima results as well as does in quicker calculation time [7].

A relative investigation of a TLBO algorithm with respect to multi-objective unconstrained and obliged capacities by R. Venkata Rao, G.G. Waghmare have examined TLBO on numerous elements. Multi- objective optimization is the procedure of at the same time upgrading two or additionally clashing goals subject to specific imperatives. Real-life engineering outlines regularly contain more than one clashing target capacity, which requires a multi- objective approach. In a single-objective optimization issue, the ideal arrangement is plainly characterized, while an arrangement of exchange offs that offers ascend to various arrangements exists in multi- objective optimization issues. Every arrangement represents to a specific execution exchange off between the goals and can be viewed as ideal. In this paper, the execution of an as of late created improvement TLBO algorithm is assessed against the other optimization algorithms over an arrangement of multi-objective unconstrained and obliged test capacities and the outcomes are thought about. The TLBO algorithm was seen to beat the other enhancement algorithms for the multi-objective unconstrained and obliged benchmark issues [8]

A TLBO based with respect to orthogonal configuration for tackling global optimization issues by Suresh Chandra Satapathy, Anima Naik and K Parvathi have proposed an algorithm. In hunting down ideal arrangements, TLBO. This paper introduces an, enhanced variant of TLBO algorithm taking into account orthogonal outline, and we call it OTLBO (Orthogonal Teaching Learning Based Optimization). OTLBO makes TLBO quicker and stronger. It utilizes orthogonal plan and produces an optimal offspring by a statistical optimal method. Another choice technique is connected to diminish the quantity of eras and make the algorithm unite quicker. We assess OTLBO to take care of some benchmark capacity optimization issues with local minima. Reenactments demonstrate that OTLBO can locate the close ideal arrangements in all cases. Contrasted with other best in class transformative calculations, OTLBO performs fundamentally better regarding the quality, speed, and stability of the last arrangements [9].

III. PROPOSED METHODOLOGY

A. Improved Elitist TLBO

1) Initialization

Taking after are the documentations utilized for portraying the TLBO

N: number of learners in class i.e. "class size"

D: number of courses offered to the learners

MAXIT: most extreme number of suitable cycles

The populace X is haphazardly introduced by a search space limited by matrix of N rows and D sections. The jth parameter of the ith learner is relegated values haphazardly utilizing the mathematical statement.

$$x^{0}_{(i,j)} = x^{min}_{j} + rand * (x^{max}_{j} - x^{min}_{j}) \quad (1.1)$$

where rand speaks to a consistently conveyed irregular variable inside of the range (0, 1), x^{min}_{j} *and* x^{max}_{j} the base and most extreme worth for jth parameter. The parameters of i[th] learner for the era g are given by

$$X^{g}_{(i)} = [x^{g}_{(i,1)}, x^{g}_{(i,2)} \dots, x^{g}_{(i,j)}, \dots, x^{g}_{(i,D)}] \quad (1.2)$$

2) Teacher phase

The mean parameter Mg of every subject of the learners in the class at era g is given as

$$M^{g} = [m^{g}_{1}, m^{g}_{2}, \dots, m^{g}_{j}, \dots, m^{g}_{D}] \quad (2.1)$$

The learner with the base target capacity worth is considered as the teacher XgTeacher for individual cycle. The Teacher phase makes the algorithm continue by moving the mean of the learners towards its teacher. To get another arrangement of enhanced learners an arbitrary weighted differential vector is framed from the present mean and the coveted mean parameters and added to the current populace of learners.

The signs of the students are computed and sorted in ascending order. At that point, the quantity of students is separated into two halves.

For first half:

$$X1new^{g}_{(i)} = X^{g}_{(i)} + rand * T_{F} \quad (2.2)$$

TF is figured taking into account number of students. For first half of the students, the teaching element is:

$$T_F = round\,[\max\_marks - \min\_marks] \quad (2.3)$$

where, TF is not a parameter of the TLBO algorithm.

The estimation of TF is not given as a input to the algorithm and its worth is chosen by the algorithm utilizing Eq. (2.3).

For second half:

$$X2new^{g}_{(i)} = X^{g}_{(i)} + rand * score_i \quad (2.4)$$

Score is computed in view of the students and their knowledge. For the first $\frac{n}{5}$ students, the score is designated 2, for next $\frac{n}{5}$ students, the score is distributed 4 and so on.

The score is given as a reason, the more equivalent educated person connect, the more their knowledge increments while, if slightest knowledgeable person collaborates with most knowledgeable person, then the knowledge of greatest knowledgeable person expands the minimum.

If $Xnew^{g}_{(i)}$ is observed to be predominant learner than $X^{g}_{(i)}$ in generation g, than it replaces inferior learner $X^{g}_{(i)}$ in the matrix.

3) Learner phase

In this phase the collaboration of learners with each other happens. The procedure of shared connection tends to build the knowledge of the learner. The random interaction among learners enhances his or her knowledge. For a given learner $X^{g}_{(i)}$,, another learner $X^{g}_{(r)}$ is randomly chosen (i ≠ r). The i[th] parameter of the matrix Xnew in the learner phase is given as

$$\begin{cases} X^{g}_{(i)} + rand * \left(abs(X^{g}_{(i)} - X^{g}_{(r)})\right) if\ f\left(X^{g}_{(i)}\right) < f\left(X^{g}_{(r)}\right) \\ X^{g}_{(i)} + rand * \left(abs(X^{g}_{(r)} - X^{g}_{(i)})\right) \quad otherwise \end{cases} \quad (3.1)$$

Where, rand (0,1) is a consistently conveyed arbitrary number inside of the range [0,1]. The mean estimation of the scale component is 0.75. This takes into consideration stochastic varieties in the accessible arrangements and in this manner holds learner assorted qualities as the search progresses.

Consequently the wellness of the best arrangement in a populace is substantially less prone to get stagnant until a genuinely global optimum is reached.

4) Algorithm termination

The algorithm is ended after MAXIT cycles are finished.

The flowchart of entire proposed algorithm is appeared beneath in figure 2.

B. Flow Chart of Proposed Method

The proposed algorithm deals with 10 iterations. The outcomes have been appeared for 10 emphases alongside the imprints. The outcomes demonstrate the updation of imprints in each iteration. The student of the student with least stamps is taken. It is demonstrated that the amount of least stamps are expanded. Taking after table gives the perspective of the working of the algorithm.

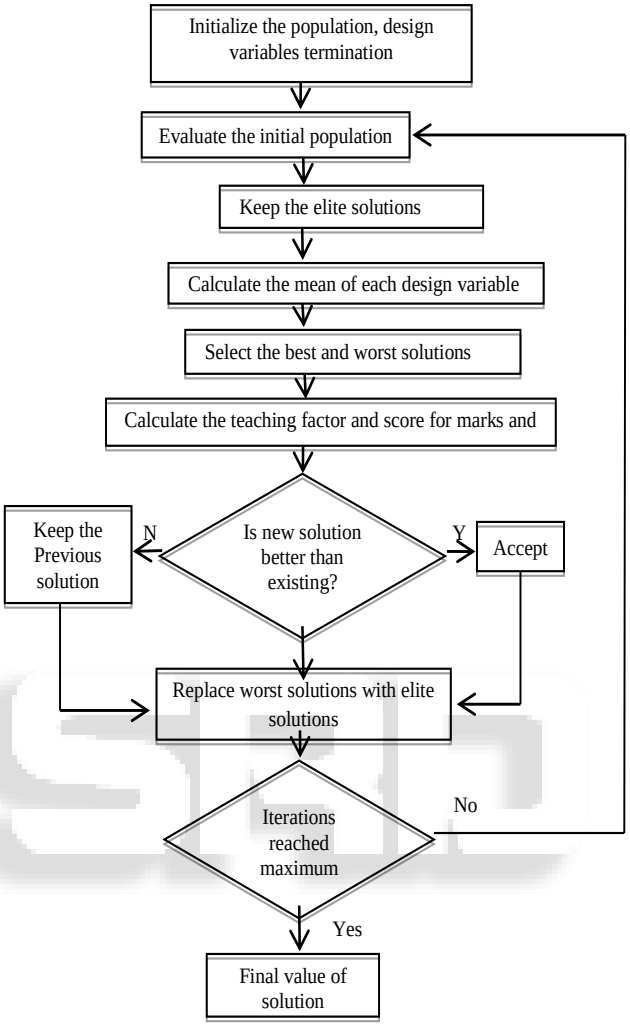

Fig. 1: Flowchart of Proposed TLBO Technique

IV. RESULT ANALYSIS

In the result analysis, the experiment of proposed work performed by using MATLAB.

The algorithm is applied to find out the better results from the improved elitism based TLBO algorithm. We have implemented and proposed a new algorithm for finding better and optimized results. Also the time taken by the proposed algorithm is less.

	Result	Score_Sub1	Score_Sub2	Score_Sub3	Score_Sub4	Score_Sub5
Iteration 1	8.075278729586098e+20	40.6824	61.9892	49.043	73.3665	35.7342
Iteration 2	6.459777493610062e+20	56.1734	43.9373	39.0713	40.5446	52.5762
Iteration 3	6.566487397518491e+20	50.205	33.548	40.1881	45.5166	55.6732
Iteration 4	5.156746965802197e+20	48.5904	51.692	38.8988	39.8246	53.2533
Iteration 5	2.604871398523393e+19	33.6137	55.0874	35.7962	73.3291	35.8666
Iteration 6	-30073.6559	36.2125	63.7712	35.02	55.4768	34.8942
Iteration 7	-26856.0986	44.5212	57.8164	34.7632	49.982	37.4978
Iteration 8	2.547368796469216e+20	34.9603	77.0827	36.7267	41.9843	43.4183

Iteration 9	2.409514375318742e+21	44.508	55.0781	49.1663	50.6386	50.6975
Iteration 10	2.008037194269066e+21	41.5819	86.8574	42.8137	71.7555	39.8884

Table 1: Results of Base Algorithm

So, the final result generated after the iterations are:-
Result of the student with minimum marks after the updation = 2.008037e+21

A. Marks of the Student:

Marks 41.5818836823
Marks 86.8573537830
Marks 42.8137239653
Marks 71.7555352930
Marks 39.8884127204

	Result	Score_Sub1	Score_Sub2	Score_Sub3	Score_Sub4	Score_Sub5
Iteration 1	5.542158025800744e+21	41.5054	50.863	95	86.7727	91.6241
Iteration 2	5.542158025800744e+21	41.6357	51.3824	95	95	91.8279
Iteration 3	1.389932523790003e+23	47.9506	95	60.7644	71.0493	83.517
Iteration 4	2.955122332820502e+23	55.8937	95	94.1011	81.4174	91.2706
Iteration 5	3.935033475537026e+23	79.7606	95	95	94.3284	95
Iteration 6	4.148761056760018e+23	69.886	86.0273	88.5295	81.0342	95
Iteration 7	5.991362943113742e+2	84.0927	95	95	94.3859	95
Iteration 8	7.509382473146596e+23	87.5665	95	95	94.8974	95
Iteration 9	8.234480791905256e+23	91.9935	95	91.6064	95	94.8555
Iteration 10	8.473830411174461e+23	73.5608	95	94.083	95	95

Table 2: Results of Proposed Algorithm

B. Marks of the Student:

89.8321741585
91.5382856758
95.0000000000
94.1219505707
94.5370300974

Comparison graph of the signs of the student with minimum imprints initially are appeared with the help of the graph below:-

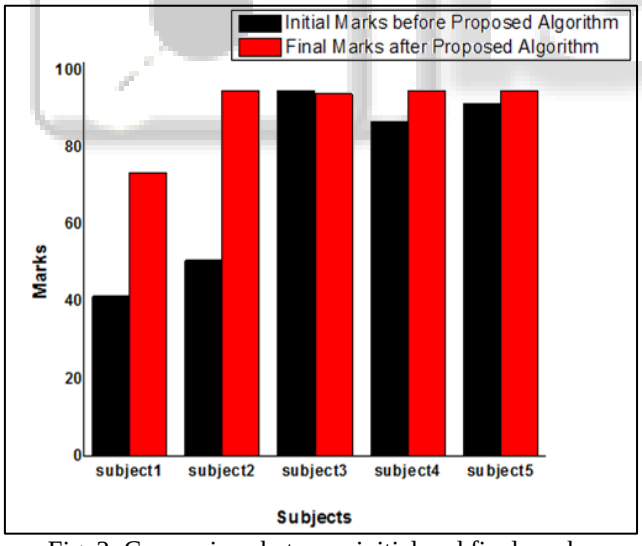

Fig. 2: Comparison between initial and final marks

V. CONCLUSION

In this work, we talked about the new and rising field of optimization algorithms. Few of the known algorithms are GA, Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Ant Colony Optimization (ACO) and so on however this is an absolutely new field. It depends on the idea of classroom teaching. It is an imperative device now to take care of global optimization issues. TLBO is as of late being utilized as another, solid, exact and vigorous enhancement procedure plan for global optimization over ceaseless spaces.

In this work, another optimization construct approach with respect to TLBO is proposed. This methodology is utilized to enhance the outcomes. TLBO algorithm is adjusted and a versatile teaching factor is presented. Besides, more than one teacher is presented for the learners. The introduced adjustments improve the investigation and misuse limits of the fundamental TLBO algorithm. This work demonstrated different results that have been contrasted and past algorithms that came beforehand.

The algorithm proposed is executed on various factors like CPU time utilization, the score of the students updated after applying the proposed algorithm. Thus, the algorithm is better in various factors.

The future work related to this field can work upon: -

1) Improving the TLBO algorithm further using new optimization techniques like PSO, ACO, etc.
2) The database should be real and big. We have performed the experiments on synthetic data. Thus, a real-world scenario is needed so as to get the best results.

REFERENCES

[1] Dr. Sudhir B. Jagtap, " Census Data Mining and Data Analysis using WEKA", International Conference in "Emerging Trends in Science, Technology and Management-2013, Singapore.
[2] Rao, R.V. and Patel, V. ''An elitist teaching–learning-based optimizationalgorithm for solving complex constrained optimization problems'', Int. J.Ind. Eng. Comput., 3(4), 2012, pp. 535–560.
[3] A. Baghlani, et. al. , "Teaching-learning-based optimization algorithm for shape And size optimization of truss structures with Dynamic frequency constraints", IJST, Transactions of Civil Engineering, Vol. 37, No. C+, 2013, pp. 409-421.

[4] Kailin Wang et. al., "Teaching-Learning-Based Optimization Algorithm for Dealing with Real-Parameter Optimization Problems", Applied Mechanics and Materials Vols 380-384, 2013, pp 1342-13.
[5] Anguluri Rajasekhar et. al., "Elitist Teaching Learning Opposition based Algorithm for Global Optimization", 2012 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2012, pp. 1124-1129.
[6] [6] R.V. Rao, V. Patel, "An improved teaching-learning-based optimization algorithm for solving unconstrained optimization problems", Scientia Iranica, Transactions D: Computer Science & Engineering and Electrical Engineering 20, 2013, pp. 710–720.
[7] Chandra Satapathy, Anima Naik, K. Parvathi, "Weighted Teaching-Learning-Based Optimization for Global Function Optimization", Applied Mathematics, 2013, 4, 429-439.
[8] R. Venkata Rao , G.G. Waghmare, "A comparative study of a teaching–learning-based optimization algorithm on multi-objective unconstrained and constrained functions", Journal of King Saud University – Computer and Information Sciences, 2014.
[9] Suresh Chandra Satapathy, Anima Naik and K Parvathi," A teaching learning based optimization based on orthogonal design for solving global optimization problems", SpringerPlus, 2013, 2:130.

