A New Variant of Teaching Learning Based Optimization Algorithm for Global Optimization Problems

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This paper presents a new variant of teaching learning based optimization (TLBO) algorithm for solving global optimization problems. The performance of the TLBO algorithm depends on coordination of teacher phase and learner phase. It is noticed that sometimes performance of TLBO algorithm is affected due to lack of diversity in teacher and learner phases. In this work, a new variant of TLBO algorithm is proposed based on genetic crossover and mutation strategies. These strategies are inculcated in TLBO algorithm for improving its search mechanism and convergence rate. Genetic mutation strategy is applied in teacher phase of TLBO algorithm for improving the mean knowledge of leaners. While, Crossover strategy is applied in learner phase of TLBO algorithm to find the good learner. The effectiveness of the proposed algorithm is tested on several bench mark test functions of CEC'14. From simulation results, it is stated that the proposed algorithm provides more optimized results in comparison to same class of algorithms.

Povzetek: V prispevku je opisan nov globalni optimizacijski algoritem na osnovi učenja optimizacije (TLBO).

1 Introduction

Optimization is an active area of research and it provides robust and viable solutions for complex real-world problems. A lot of efforts are needed to find optimal solution for these problems due to increase dimensionality, differentiability, multi-modality and rotation characteristics. Hence, a lot of research has been carried out in this direction to design a real-time numerical optimizer. This optimizer can provide more accurate, fast and computationally efficient optimization algorithms. Large numbers of algorithms have been developed by research community for solving many numerical optimization techniques. These algorithms can solve optimization problems efficiently and effectively. But, according to no free lunch theorem, there is no universal algorithm that can solve all optimization problems accurately. Over the past few decades, population based meta-heuristic algorithms have attained more popularity among research community. These algorithms have ability to turn itself according to problem domain and provide successful results for many complex problems. It is noticed that large numbers of optimization problems exist in the fields of engineering and science. These problems can be categorized as unimodal and multimodal optimization problems. Further, it can be characterized as unimodal separable and inseparable, and multimodal separable and inseparable. In literature, it is found that numbers of algorithms have been reported for solving these problems either maximizing or minimizing the objective function. Moreover, these algorithms are also adopted for solving real-life problems such as clustering, classification, scheduling, path planning, resource allocation, and many other problems. These algorithms are divided into two categories i.e. exact and approximation algorithms [1]. Exact algorithms find the optimal solution within bounded time, but having exponential computational time. The approximate algorithms provide better results in terms of time and solution using heuristics. Further, the meta-heuristic algorithms are also applied for solving the wide range of optimization problems. These algorithms are sub branch of approximate algorithms. In past decade, many meta-heuristic algorithms are developed for finding exact solution of optimization problems. Most of these are inspired through natural phenomena's such as swarm behavior, insect's characteristics, physics law and process etc. Some of are Simulated Annealing (SA) algorithm [2], Genetic Algorithm (GA) [3], Particle Swarm Optimization (PSO)

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[4], Ant Colony Optimization (ACO) [5], Harmony Search (HS) [6], Artificial Bee Colony (ABC) [7, 33], Firefly Algorithm (FA) [8], League Championship Algorithm (LCA) [9], Water Cycle Algorithm (WCA) [10], CSS [11, 12], MCSS[13, 14, 15], TLBO [16, 17,], CSO[47,48] and Mine Blast Algorithm (MBA) [18].

Recently, Rao et al., have developed teaching learning based optimization (TLBO) algorithm to solve the constrained and unconstrained optimization problems. This algorithm is inspired from class room based teaching methodology [19]. In short span of time, this algorithm become more popular among researchers and has been applied to solve variety of problems. A lot of optimization problems have been solved by using TLBO algorithm and provides better results in comparison to existing algorithms [20-24]. Still, there are several shortcomings that can affect the performance of TLBO algorithm such as quality of solution, stuck in local optima when solving global optimization problems, premature convergence, tradeoff between searching capability and local search ability. Hence, the aim of this work is to design an effective and efficient algorithm for addressing the convergence and quality of solution issues of TLBO algorithm. In order to overcome the aforementioned issues, this work investigates the capability of genetic crossover and mutation operators for improving the performance of TLBO algorithm. It is observed that proposed algorithm provides better results than traditional TLBO and other existing optimization algorithms.The rest of paper is organized as follows: the section 2 describes the related work on improvements in TLBO algorithm and its applicability in diverse fields. Section 3 introduces basic TLBO algorithm. The proposed genetic TLBO algorithm is illustrated in section 4. Section 5 illustrates the simulation results of proposed TLBO algorithm using benchmark functions. The entire work is concluded into section 6 and future work reported in section 7.

2 Related works

This section describes the recent work reported on TLBO algorithm. Several studies have been published on the modifications of TLBO algorithm. Some of these are highlighted in this section. To make the effective tradeoff between exploration and exploitation capabilities, Rao et al. have developed an improved TLBO algorithm, called I-TLBO [25]. In this work, authors have introduced the concept of multiple teachers, adaptive teaching factor, self-motivated learning and tutorial training. The self learning and tutorial training methods can be acted as search methods. Further, to explore the local optimum solution in the hope of global optimum solution. The concept of multiple teachers is incorporated in TLBO algorithm to avoid premature convergence. Moreover, adaptive teaching factor is inculcated for fine tuning between exploration and exploitation capabilities. From results, it is seen that I-TLBO effectively overcome the aforementioned problems. Satapathy et al., have presented a new version of TLBO algorithm, called mTLBO for improving the convergence rate [26]. The proposed mTLBO algorithm is applied on global optimization problems for obtaining optimal solution. The proposed algorithm includes the concept of tutorial classes in learner phase to improve the outcomes of learners. The performance of mTLBO is compared with other state of art algorithm like PSO, DE, ABC and GA and it is observed that addition of tutorial class concept improves the results of TLBO algorithm. To enhance local search ability and quality of solutions, Haung et al., have incorporated levy flight based teaching learning process for TLBO algorithm [27]. The proposed algorithm is adopted to solve several engineering optimization problems especially industrial optimization problems. It is seen that the proposed algorithm outperforms than traditional TLBO algorithm. For improving the global performance of traditional TLBO algorithm, Zou et al., have developed an improved variant of TLBO algorithm based on learning experience [28]. Further, a copy operator is also integrated in TLBO algorithm and called it LETLBO. It is noticed that the learning experiences of learners are evaluated using two random possibilities. The performance of algorithm is tested on eighteen standard benchmark functions and compared with state of art algorithms. It is stated that above mentioned improvements significantly improve the global performance of TLBO algorithm. Ouyanget et al. have presented a new variant of TLBO algorithm to address global search and local optima issues, called GC-TLBO [29]. In GC-TLBO, a global crossover operator is introduced for addressing global search issue. Whereas, the local optima issue is controlled using perturbed mechanism. The experimental results reveal that the proposed improvements make the TLBO algorithm more effective and significant one. Ghasemi et al. have developed gaussian bare bones teaching learning optimization algorithm, called GBTLBO for improving the quality of solutions [30]. The results stated that GBTLBO algorithm provides better performance than other algorithms being compared. To avoid the premature convergence and preserve the population diversity, Zou et al. have developed an improved TLBO algorithm based on dynamic group strategy [31]. Moreover, quantum behaved learning scheme is also inculcated into learner phase of TLBO algorithm to maintain population diversity. The feasibility of proposed algorithm is evaluated on eighteen benchmark functions. Simulation results stated that the proposed algorithm is one of effective and efficient algorithm for solving global optimization problems. Lim and Isa have presented a new algorithm by combining PSO and TLBO algorithms for solving global optimization algorithm, called TPLPSO [32]. The performance of TPLPSO is investigated on twenty benchmark functions and it is found that the TPLPSO exhibits better performance than other algorithm being compared. To identify the most relevant gene in the development of the breast cancer, Sahbeig et al. proposed a combination of TLBO and fuzzy adaptive PSO algorithm, called TLBO-PSO [36]. The performance of the proposed algorithm is evaluated using accuracy, sensitivity and specificity parameters. It is revealed that the proposed algorithm obtains higher accuracy rate i.e. 91.88 as compared to other algorithms. Kumar et al. have applied a hybrid TLBO-TS algorithm to deal with problem of simultaneous selection and scheduling of projects [37]. The proposed approach is tested on several datasets and compared with TLBO and TS algorithms. It is seen that combination of TLBO-TS algorithm provides faster convergence than TLBO and TS algorithms. Patel et al. have applied teaching-learning based optimization (TLBO) to design ultra-low reflective coating over a broad wavelength-band using multilayer thin-film structures for optoelectronic devices [38]. The results of TLBO algorithm are compared with GA using Wilcoxon singed ranked test. It is observed that TLBO algorithm gives more effective results than GA. To enhance the performance of original TLBO algorithm and make the balance between local and global searches, Ji et al. developed an improved version of TLBO algorithm, called I-TLBO [39]. In proposed algorithm, a self feedback phase is incorporated to enhance the performance of original TLBO algorithm. The effectiveness of proposed algorithm is tested on several combinatorial optimization problems. It is stated that the proposed improvements have significant impact on the performance of TLBO algorithm. To solve numerical structural analysis problems, Cheng and Prayogo presented fuzzy adaptive teaching learning based optimization algorithm, called FATLBO [40]. In proposed algorithm, three search strategies are included for improving searching capabilities. The performance of proposed algorithm is examined over five well known engineering structural problems. The results show that the proposed algorithm gives excellent and competitive performance. To analyze and predict the time series data, Das and Padhy desgined a hybrid model based on support vector machine (SVM) and TLBO [41]. The proposed model avoids user defined control parameters. The validity and efficacy of proposed model is evaluated on COMDEX commodity futures index. The results stated that proposed model is more effective and performs better than PSO-SVM and SVM models. Kankal and Uzlu adopted neural network with TLBO approach for modeling and forecasting long term electric energy demand in turkey [42]. In proposed approach, TLBO algorithm is used to optimize the parameters of neural network. The simulation results of ANN-TLBO approach is compared with ANN-BP and ANN-ABC models. It is revealed that ANN-TLBO approach provides efficient results than others. Kiziloz et al. applied multi-objective TLBO algorithm for feature subset selection in binary classifications problems [43]. The performance of the proposed algorithm is evaluated on well known benchmark problems and compared with large number of meta-heuristic algorithms such as GA, PSO, NSGA, TS and SS. It is seen that TLBO is one of the competitive algorithms for feature subset selection problem. Prakash et al. presented quasi-oppositional self-learning teacher-learner-based-optimization (QOSL-TLBO) for solving non-convex economic load dispatch (ELD) problem [44]. In this algorithm, self learning mechanism is incorporated in teacher and learner phases. The robustness of the proposed algorithm is evaluated on standard IEEE generator system. Further, the results are compared with well known algorithms. It is seen that the proposed algorithm achieves minimum total cost for all generations. Zheng et al. adopted TLBO to solve multi-skill resource constrained project scheduling problem (MS-RCPSP) with make-span minimization criterion [45]. To make effective balance between exploration and exploitation processes, the concept of reinforcement learning is introduced in TLBO algorithm. From simulation results, it is stated that the computational cost of proposed algorithm is far better than compared algorithms. Birashk et al. designed a cellular TLBO algorithm for dynamic multi objective optimization (DMOO) problems [46]. The performance of cellular TLBO algorithm is evaluated and compared with state of art algorithms using well known DMOO problems. It is observed that cellular TLBO algorithm gives superior results than other algorithms.

3 Teaching learning based optimization (TLBO) algorithm

TLBO is a population based meta-heuristic algorithm. Like other population based algorithms, the global solution is represented using population [19]. TLBO algorithm works on the concept of classroom learning paradigm. The teachers are available to teach and enhance the knowledge of learners. The aim of teacher is to improve the learning capability of learners. Further, a learner can also enhance its skills by acquiring the knowledge from other learners. TLBO algorithm consists of two phases: Teacher phase and Learner phase. The detailed discussions on these phases are outlined as given below.

Teacher Phase: The aim of this phase is to improve the learning skills of students such that results of class improve significantly and this can lead the mean result of class. In general, teacher can improve the result up to certain level. In practice, several constraints are responsible for results such teaching method, teachers capability, learners grasping ability, interaction of learners to others and knowledge of learners. In teacher phase, M denotes the learner’s knowledge mean and T describes any teacher in iteration. The main task of teacher is to enhance present knowledge of learners. To achieve the same, the present mean knowledge of learners i.e. M to move towards the teacher knowledge i.e. T and it can be described using equation 1.

$$X_{i,new} = X_{i,old} + r * (X_{Teacher} - T_f \times X_{mean}) \qquad 1\ )$$

In equation 1, $X_{Teacher}$ and X_{mean} represent the teacher and the mean of the knowledge of learner in i^{th} iteration, T_f denotes the teaching factor, and r is a random number in the range of 0 and 1. The teaching factor is computed using equation 2.

$$T_f = \text{round}\big(1 + \text{rand}(0,1)\big) \qquad (2)$$

Learner Phase: The aim of the learner phase is to enhance the knowledge of learner from others. Hence, to improve learning ability, a learner can interact with other learners randomly. In learner phase of TLBO algorithm, learners learn knowledge from others. This learning capability of learners can be expressed as follows.

If i^{th} learner wants to interact with the k^{th} learner and the fitness of k^{th} learner is higher than i^{th} learner, then the position of i^{th} learner will be updated otherwise k^{th} learner. This can be summarized in equations 3-4.

$$X_{i,new} = X_{i,old} + r_i \times (X_k - X_i) \quad (3)$$

Else

$$X_{i,new} = X_{i,old} + r_i \times (X_i - X_k) \quad (4)$$

If the fitness of i^{th} learner is better than old position, then new position take over the old one otherwise not.

4 Proposed TLBO algorithm

This section describes the working of proposed TLBO algorithm for solving global optimization problems. In this work, two amendments are made in TLBO algorithm for improving search mechanism and convergence rate. Hence, to achieve the same, genetic crossover and mutation operators are incorporated into TLBO algorithm. The genetic mutation operator is adopted in teacher phase. Further, genetic crossover operator is used to enhance learning capability of a learner through different learners. These improvements are illustrated in Algorithm 1 and Algorithm 2.

Algorithm 1: Teacher Phase of TLBO algorithm

For d=1 to N
For j =1 to D
$\quad \text{DifferenceMean} = r(T_{mean} - T_f \times M_i)$
$\quad T_f = \text{round}(1 + \text{rand}(0,1))$
IF (DifferenceMean $< rand()$)
Apply genetic mutation operator on T_{mean} and M_i
Compute Difference Mean and generate the new mean of knowledge ($X_{i,new}$) using equation 3.
Else
$\quad X_{i,new} = X_{i,old} + \text{DifferenceMean}_i$
End
End
Accept $X_{i,new}$ if $f(X_{i,new})$ is better than $f(X_{i,old})$
End

The aim of these operators is to maintain population diversity during teacher and learner phases, and further, overcome the chance of trapping in local optima. In learner phase, the knowledge of learner is not enhanced gradually, the fitness of leaner is compared with random function. If, it is less than random number, the crossover operator is applied to find other learner to enhance its skills and knowledge.

Algorithm 2: Learner Phase of TLBO algorithm

For i =1 to N
Randomly pick two learners X_i and X_k such that $i \neq j$
IF ($F(X_i) < F(X_k)$)
IF ($F(X_i) < \text{rand}()$)
Apply genetic crossover operator on X_i and X_k and generate the new position of learner X_k
End IF
$\quad X_{i,new} = X_{i,old} + r_i \times (X_k - X_i)$
Else
$\quad X_{i,new} = X_{i,old} + r_i \times (X_i - X_k)$
End
Accept $X_{i,new}$ if $f(X_{i,new})$ is better than $f(X_{i,old})$
End

The detailed description of proposed TLBO algorithm is given in Algorithm 3. The main steps of proposed algorithm are summarized as below and flowchart is illustrated in Fig. 1.

Algorithm 3: Algorithmic steps of TLBO algorithm

Step 1: Initialize the number of learners (X), number of dimension (D) and other algorithmic parameters of TLBO algorithm.
Step 2: Evaluate the positions of learners (X) and compute the fitness function F(X).
Step 3: Determine the best learner and it can be acted as Teacher.
Step 4: Compute the mean of all learners (X) and denoted as Mean
Step 5: While(stopping condition is not met)
Step 6: Apply teacher phase of TLBO algorithm (Algorithm 1)
Step 7: Apply learner phase of TLBO algorithm (Algorithm 2)
Step 8: Update the Teacher and the mean
Step 9: End While
Step 10: Obtain final optimal solution

5 Results

This section describes the results of proposed TLBO algorithm using benchmark test functions of CEC'14. These functions are combination of uni-modal and multi-modal test functions that are highly trapped in local optima. The proposed algorithm is implemented in Matlab 2010 (a) environment using window based operating system having core i7 processor and 8 GB RAM. The results of proposed algorithm are taken on average of 30 independent runs for each test functions. Mean and standard deviation are taken as performance parameters to compare the performance of proposed algorithm and other algorithms. The mean parameter demonstrates the efficiency of algorithms, whereas standard deviation parameter illustrates the robustness of algorithms. The experiment is performed using real dimension i.e.30 for all benchmark functions i.e. F_1-F_{16}. The performance of proposed algorithm is compared with other state of art algorithms like PSO, GA, BA, FPA, ABC, FA, BBO, HS and TLBO. Table 1-2 depict

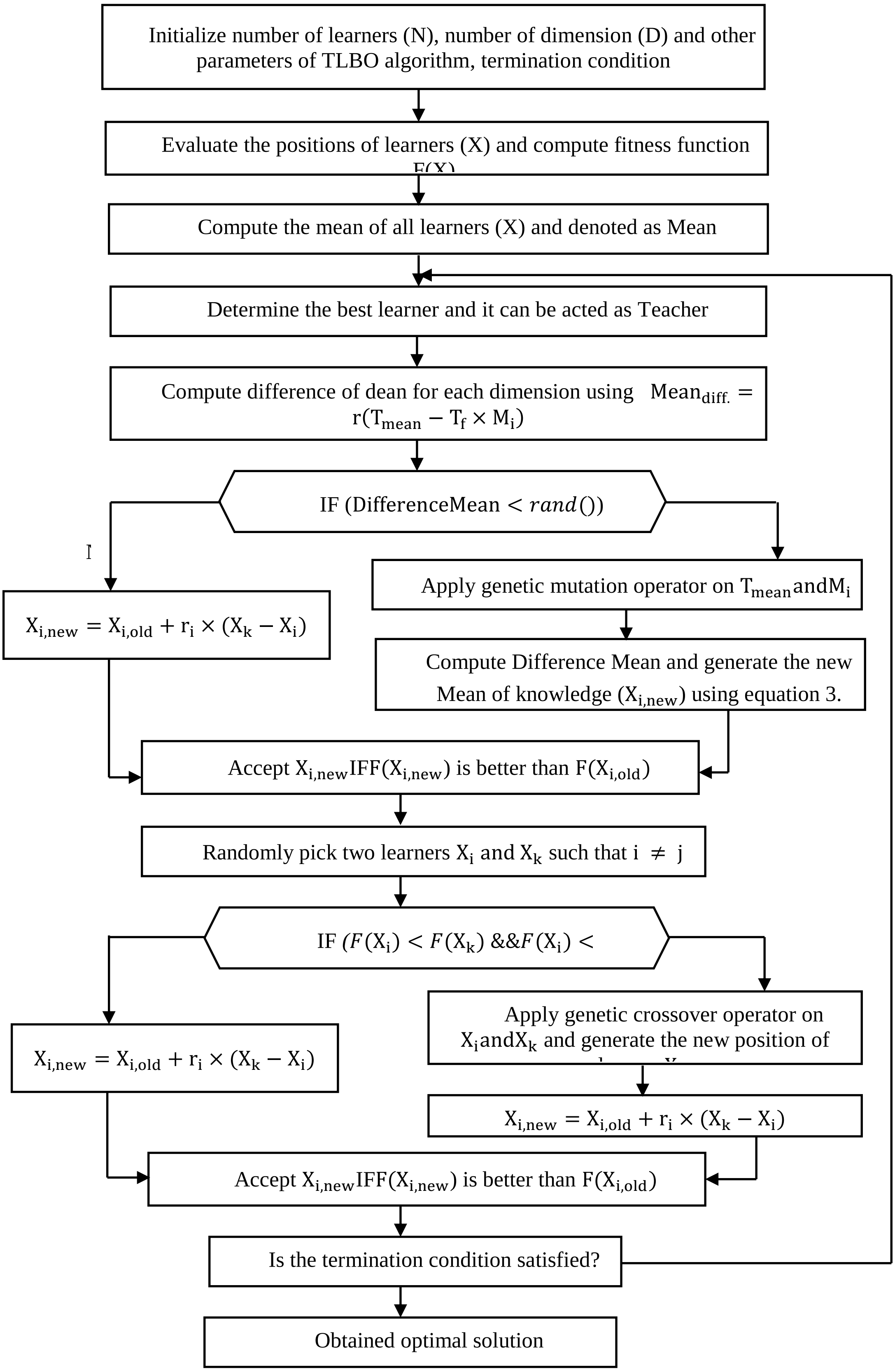

Figure 1: Flowchart of the proposed TLBO algorithm.

Table 1: List of test functions used for experimentation.

No.	**Function Name**	**Definition**	**Parameter**
F_1	Sphere	$F_1(x) = \sum_{i=0}^{D} x_i^2$	[-100, 100]
F_2	Rosenbrock	$F_2(x) = \sum_{i=1}^{D} 100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2$	[-30,30]
F_3	Rastrigin	$F_3(x) = \sum_{i=1}^{D} (x_i^2 - 10\cos(2\pi x_i) + 10)$	[-5.12, 5.12]
F_4	Griewank	$F_4(x) = \frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	[-600, 600]
F_5	Ackley	$F_5(x) = 20 + e - 20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right)$	[-32, 32]
F_6	Step	$F_6(x) = \sum_{i=0}^{D} (x_i + 0.5)^2$	[-100, 100]
F_7	Schwefel	$F_8(x) = 418.9828D - \sum_{i=1}^{D}\left(x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)\right)$	[-500, 500]
F_8	Schaffer	$F_9(x) = 0.5 + \frac{\sin^2(x_i^2 - x_i^2) - 0.5}{[1 + 0.001(x_i^2 - x_i^2)]^2}$	[-100, 100]
F_9	Powell	$F_{10}(x) = \sum_{i=1}^{D/4} (x_{4i-3} + 10x_{4i-2})^2 + 5(x_{4i-1} - 10x_{4i})^2 + (x_{4i-2} + 10x_{4i-1})^4 + 10(x_{4i-3} + 10x_{4i})^4$	[-4, 5]
F_{10}	Zakharov's	$F_{10}(x) = \sum_{i=0}^{D} (x_i)^2 + \left(\frac{1}{2}\sum_{i=0}^{D} ix_i\right)^2 + \left(\frac{1}{2}\sum_{i=0}^{D} ix_i\right)^4$	[-5, 10]
F_{11}	Michalewicz	$F_{11}(x) = \sum_{i=1}^{D} \mathrm{Sin}x_1\left(\sin\left({ix_i}^2/\pi\right)\right)^{20}$	[0, π]
F_{12}	Quartic	$F_{12}(x) = \sum_{i=1}^{D} ix_i^4 + \mathrm{rand}(0,1)$	[-1.28, 1.28]

Table 2: Benchmark test functions from CEC'14 suite.

Function No.	Functions	Search Range	Global Optimum
F_{13}	Rotated High Conditioned Elliptic Function	[-100, 100]	100
F_{14}	Rotated Bent Cigar Function	[-100, 100]	200
F_{15}	Rotated Discus Function	[-100, 100]	300
F_{16}	Shifted and Rotated Rosenbrock's Function	[-100, 100]	400

Table 3: Results of proposed TLBO and other existing algorithm with test functions F_1-F_6.

Algorithm	Parameter	Function					
		F_1	F_2	F_3	F_4	F_5	F_6
PSO	average	3.00E-04	2.59E+01	3.58E-01	1.05E-01	5.21E-02	4.00E-04
	std.	1.50E-03	1.63E-01	6.98E-01	4.62E-02	4.06E-02	2.60E-03
GA	average	8.38E-01	4.53E+01	1.00E+00	8.61E-01	7.93E-01	7.87E-01
	std.	5.14E-01	2.16E-01	6.92E-01	6.48E-02	3.22E-01	5.64E-01
BA	average	1.00E+00	3.90E+01	4.27E-01	8.21E-01	1.00E+00	1.00E+00
	std.	1.00E+00	1.56E+01	1.00E+00	8.14E-02	1.00E+00	1.00E+00
FPA	average	4.28E-01	3.69E+01	5.92E-01	1.00E+00	3.17E-01	2.76E-01
	std.	8.26E-02	1.76E+01	3.54E-01	2.09E-02	7.36E-02	1.97E-01
ABC	average	6.00E-04	2.35E+01	3.29E-01	1.51E-02	9.63E-02	1.46E-02
	std.	1.00E-04	1.36E+01	4.25E-02	1.24E-02	7.86E-02	3.50E-03
FA	average	3.79E-02	1.72E+02	2.29E+01	1.05E-01	2.05E+00	3.11E-01
	std.	5.35E-02	1.30E+02	7.14E+00	5.45E-02	3.57E-01	1.18E-01
BBO	average	2.40E-03	5.91E+01	7.08E-02	1.89E-01	1.01E-01	1.71E+00
	std.	4.56E-04	1.27E+00	5.56E-02	3.36E-02	5.13E-02	3.71E-01
HS	average	5.22E-04	1.90E+02	1.69E+01	1.60E-01	1.09E+00	4.37E+00
	std.	3.29E-05	5.16E+01	2.66E+00	5.34E-02	1.36E-01	9.83E-01
TLBO	average	0	26.6567	1.87E−12	0	3.55E−15	2.74E−09
	std.	0	2.94E−01	6.66E−12	0	8.32E−17	5.36E−09
Proposed TLBO	average	0	23.9648	1.983 E-12	0	3.39 E−15	2.56E−11
	std.	0	3.26E−01	3.68E-12	0	6.53E−16	4.98E−13

Table 4: Results of proposed TLBO and other existing algorithm using test functions F_5-F_8.

Algorithm	Parameter	Functions					
		F_7	F_8	F_9	F_{10}	F_{11}	F_{12}
PSO	average	9.82E+03	3.86E+02	5.13E-01	6.14E-10	-2. 96847	4.36E-03
	std.	6. 412E+02	1.13E+02	3.46E-03	1.35E-11	6.52E-01	5.71E-04
GA	average	4.62E+04	8.30E+02	5.40E-01	5.50E-10	-5.86E+00	2.35E-01
	std.	1.59E+03	3.93E+02	7.31E-03	7.62E-10	9.16E-01	6.71E-02
BA	average	2.76E+02	1.14E+02	8.25E-02	9.83E-14	-4.54E+00	4.13E-03
	std.	1.12E+02	8.61E+01	1.83E-02	4.86E-14	7.16E-01	7.87E-03
FPA	average	3.53E+02	8.62E+01	7.92E-02	5.22E-14	-3.86E+00	3.86E-03
	std.	1.26E+03	8.07E+01	3.82E-02	4.80E-14	8.35E-01	1.55E-03
ABC	average	2.79E+04	2.35E+01	3.29E-01	1.51E-02	9.63E-02	1.46E-02
	std.	2.10E+01	1.36E+01	4.25E-02	1.24E-02	7.86E-02	3.50E-03
FA	average	3.79E+02	1.72E+02	2.29E+01	1.05E-01	2.05E+00	3.11E-01
	std.	5.35E+01	1.30E+02	7.14E+00	5.45E-02	3.57E-01	1.18E-01
BBO	average	1.38E+02	7.50E-01	2.46E+02	1.30E-03	-3.92E+00	2.00E-05
	std.	1.14E+02	3.86E-02	6.47E+01	1.85E-03	1.31E+00	3.14E-06
HS	average	4.59E+02	1.53E-01	2.83E+02	1.03E-11	-4.32E+00	8.44E-04
	std.	5.86E+01	3.10E-02	1.06E+02	1.31E-12	1.06E+00	2.21E-05
TLBO	average	124.1484	0.0066	0.0066	4.64E-14	-4.352678	3.25E-04
	std.	2.60E+02	4.50E-03	4.50E-03	2.34E-14	1.44E-02	1.59E-04
Proposed TLBO	average	104.526	0.0058	0.0052	8.35E-16	-3.73415	5.14E-03
	std.	4.13E+01	3.66E-03	4.48E-03	1.42E-16	2.43E−2	2.86E-03

Table 5: Performance comparison of proposed algorithm and other meta-heuristic algorithms with extended benchmark functions of CEC'14.

Algorithm	Parameter	Functions			
		F_{13}	**F_{14}**	**F_{15}**	**F_{16}**
PSO	Average	9.78E+04	1.69E+03	5.73E+02	4.04E+02
	Std	2.82E+03	7.32E+02	1.92E+02	1.46E+01
GA	Average	9.02E+05	7.34E+03	1.18E+03	2.13E+03
	Std	3.16E+08	3.18E+03	2.68E+02	1.67E+03
BA	Average	3.46E+03	9.84E+02	3.74E+02	4.27E+02
	Std	1.73E+02	3.11E+02	1.38E+02	2.43E+01
FPA	Average	4.41E+03	7.63E+02	3.48E+02	4.19E+02
	Std	2.26E+02	2.73E+02	100%	1.78E+01
ABC	average	1.02E+03	5.35E+02	2.14E+02	3.52E+02
	std.	7.94E-05	1.47E+02	5.64E+01	1.24E+02
FA	average	3.79E+03	4.87E+02	2.30E+02	3.75E+02
	std.	9.91E+01	1.49E+02	7.14E+01	6.85E+01
BBO	average	1.73E+03	4.38E+02	4.09E+02	3.90E+02
	std.	4.36E+01	9.13E+01	5.88E+01	4.73E+01
HS	average	9.23E+02	3.19E+02	2.68E+02	2.16E+02
	std.	1.33E+02	2.66E+01	6.69E+01	5.35E+01
SFLP	average	1.09E+03	2.98E+02	3.28E+02	2.57E+02
	std.	1.08E+02	3.15E+01	5.32E+01	3.79E+01
TLBO	Average	3.82E+03	7.42E+02	3.26E+02	4.08E+02
	Std	2.58E+02	2.42E+02	1.42E+02	1.96E+01
Proposed TLBO	Average	3.27E+03	5.24E+02	3.04E+02	3.41E+02
	Std	1.92E+02	2.16E+02	1.98E+02	7.05E+01

the various unimodal and multi-modal test functions taken from CEC, 14. Table 1 shows the normal benchmark function of the CEC'14, whereas Table 2 contains the some extended benchmark function of CEC'14.

Table 3 demonstrates the results of proposed algorithm and other algorithm like PSO, GA, BA, FPA, ABC, FA, BBO, HS and TLBO using test functions F_1-F_4.These functions are widely adopted to investigate the performance of newly developed algorithms. It is observed from the results that the proposed TLBO algorithm achieves global optimum value for rosenbrock and rastrigin functions within specified number of iterations. It is seen that the performance of proposed algorithm and TLBO algorithm is same for sphere and griewank functions. Further on the analysis of standard deviation parameter, it is observed thatproposed TLBO algorithm obtains minimum standard deviation value in comparison to other algorithms being compared. Its reveals that the proposed algorithm provides more stable result for solving benchmark test functions.

Table 4 illustrates the experimental results of proposed algorithm and other algorithm for standard benchmark functions F_7-F_{12}. It is seen that proposed algorithm obtains global optimum values i.e. minimum values among all other compared algorithm using most of functions. It is observed that significant difference occurs between the performance of the proposed algorithm and rest of algorithms being compared. On the analysis of standard deviation parameter, it is stated that again the proposed algorithm gets minimum value for standard deviation parameter among all other algorithms. This indicates that the proposed algorithm provides more stable results for solving these functions. From tables 3-4, it is stated that the proposed algorithm is an effective and efficient algorithm for solving bench mark test function and this algorithms also provides more stable results in comparison to other algorithms being compared. Table 5 demonstrates the comparison of the proposed TLBO algorithm and other meta-heuristic algorithms with the extended benchmark functions (F_{13}-F_{16}) of the CEC'14. To show the effectiveness of the proposed algorithm four well known benchmark functions are taken from the extended benchmarks functions set of CEC'14. It is observed that the proposed algorithm obtains better optimum value as compared to other algorithms being compared. Hence, it can be concluded that the proposed algorithm is one of the efficient algorithm for solving global optimization problems.

Figs. 2-3 show the convergence pattern i.e. cost function of proposed TLBO and original TLBO algorithm using rastrigin and rosenbrock functions. From these, it is also stated that the convergence of the TLBO algorithm is significantly improved.From Fig. 2, it is seen that the proposed algorithm requires less number of iterations to converge than TLBO algorithm. Further, it is also observed that proposed algorithm obtains minimum cost than original TLBO algorithm. On analysis of Fig. 3, it is noted that the proposed algorithm converges fast than the original TLBO algorithm. It is also noticed that there is the significant difference between the initial solution obtained through proposed algorithm and original TLBO algorithm. Finally, it is concluded that the proposed modifications not only improve the performance of TLBO algorithm, but also enhance the convergence rate of algorithm.

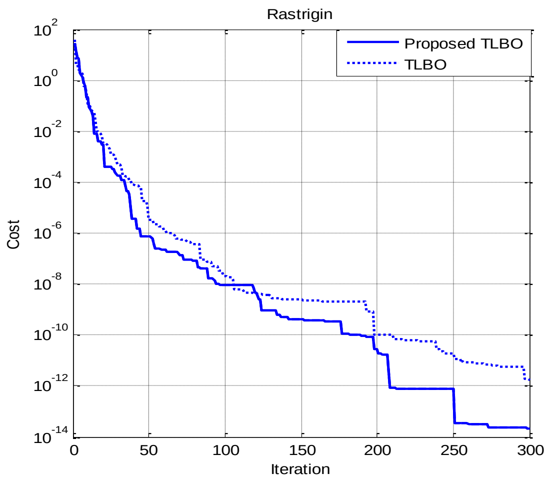

Figure 2 shows the convergence of TLBO and Proposed TLBO algorithm for rastrigin function

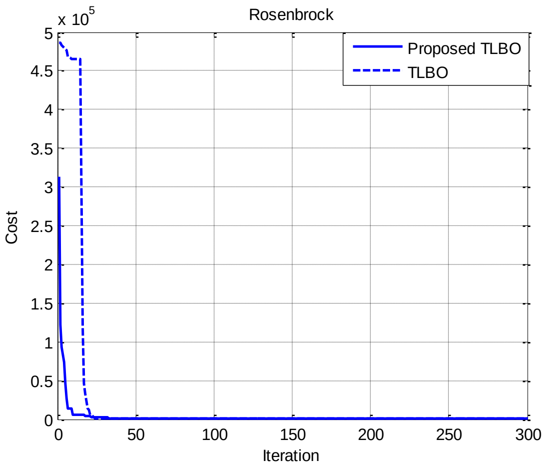

Figure 3: shows the convergence of TLBO and Proposed TLBO algorithm for rosenbrock function

6 Conclusion

In this work, a new variant of TLBO algorithm is presented for solving the global optimization problems. For improving the performance of TLBO algorithm, two modifications are incorporated into teacher and learner phases of TLBO algorithm. These modifications are genetic crossover and mutation operators and the aim of these operators to generate diverse population and to improve searching ability and convergence rate of TLBO algorithm. The genetic crossover operator is applied in learner phase for determining the good learner from the set of learners. The aim of genetic mutation operator is to minimize the knowledge gap between teacher and learners. So, this operator is applied in teacher phase of TLBO algorithm to generate diverse population. The performance of the proposed algorithm is evaluated using a set of benchmark test functions using mean and SD parameters and the results are compared with some of state of art algorithm available in literature. From experimental study, it is seen that the performance of the proposed algorithm is better than other algorithms being compared. It is also observed that proposed algorithm provides state of art results with most of benchmark test functions.

7 Future work

In future research work, the proposed TLBO algorithm is adopted for solving single objective and multi-objective constrained optimization problems. Further, neighborhood search mechanism is introduced to explore good candidate solution and also for improving convergence rate. In teaching learning process, selection of teacher also impact on the performance of learners. In future work, the effect of number of teachers will be evaluated on the fitness value of objective function. Apart from above, the capability of TLBO algorithm will explore in different research problems such as classification, feature selection, document clustering, parameter optimization of ANN and SVM techniques etc.

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