Review of the Teaching Learning Based Optimization Algorithm

Aruna

Department of Computer Science and Engineering,
GNDU Regional Campus Jalandhar, India
arunasharma94@gmail.com

Dr. Sheetal Kalra

Department of Computer Science and Engineering,
GNDU Regional Campus Jalandhar, India
sheetal.kalra@gmail.com

Abstract: The Teaching Learning Based Optimization (TLBO) algorithm is a recent nature based optimization algorithm which has attracted a lot of attention from the researchers due to its high potential in solving the optimization problems. The algorithm has proved itself worthy for many applications in different disciplines of engineering, technology and science such as mechanical design, thermal engineering, electrical engineering, artificial intelligence, physics, chemistry, biotechnology, computer engineering and economics. The algorithm takes its inspiration from the natural teaching-learning phenomenon of a classroom. It finds the best solution among the various possible solutions. One of the major characteristics of the algorithm is that it requires only common control parameters for its operation and does not require any algorithm-specific-parameter. This adds to the efficiency of the algorithm as the errors caused by the improper tuning of the specific parameters are removed. The presented paper reviews the TLBO algorithm and its potential.

Keywords: Optimization, Teaching Learning Based Optimization Algorithm

1. Introduction

Optimization techniques are used to find the optimal or near optimal solution to the problems. Constants efforts of researchers have contributed to the evolution of numerous optimization algorithms. In general, it is believed that nature's ways are the most optimized ones. That is why many optimization algorithms take their inspiration from various natural phenomena. In fact, most of the population based optimization algorithms are inspired from nature. They can be classified into two important categories: Evolutionary Algorithms and Swarm Intelligence based algorithms. Genetic Algorithm (GA) [1], Bacterial Foraging Algorithm (BFO) [2] are some of the well-recognized nature inspired Evolutionary Algorithms. Some of the well-known Swarm Intelligence based optimization algorithms are Ant Colony Optimization (ACO) [3] and Artificial Bee Colony (ABC) algorithm [4]. The swarm intelligence and evolutionary algorithms are efficient but their performance depends upon some algorithm-specific parameters such as GA uses mutation rate and crossover rate, ABC uses number of bees etc. These specific parameters are used in addition to the common controlling parameters such as population size and number of generations. The improper tuning of these algorithm specific parameters has a negative impact on the effectiveness of the algorithm. This issue was addressed by Rao et al. in [5] and the TLBO was introduced. The TLBO is a nature based optimization algorithm which does not require any algorithm specific parameters. The common controlling parameters such as the population size and the number of generations are sufficient for its operation. TLBO is inspired from the natural teaching learning process of a classroom. The algorithm has outperformed many existing optimization algorithms in terms of the number of evaluations. TLBO was initially proposed for the mechanical design problems but later it found its applications in many fields of science and engineering and has gained a lot of reputation from researchers in such a short span of time. For the applications with large number of parameters, TLBO is proved to be very efficient. It has shown potential to solve the combinatorial optimization problems too which are considered as the most complex optimization problems. In the presented paper, we study the working and potential of the algorithm.

1.1 Organisation of the Paper

In the presented paper, section 1 introduces the TLBO algorithm in brief. Section 2 explains the working of the algorithm in detail. Section 3 describes the related work done by various researchers to empower the algorithm.

Section 4 discusses the algorithm's potential to solve different optimization problems and finally the paper is concluded in section 5.

2. TLBO Algorithm

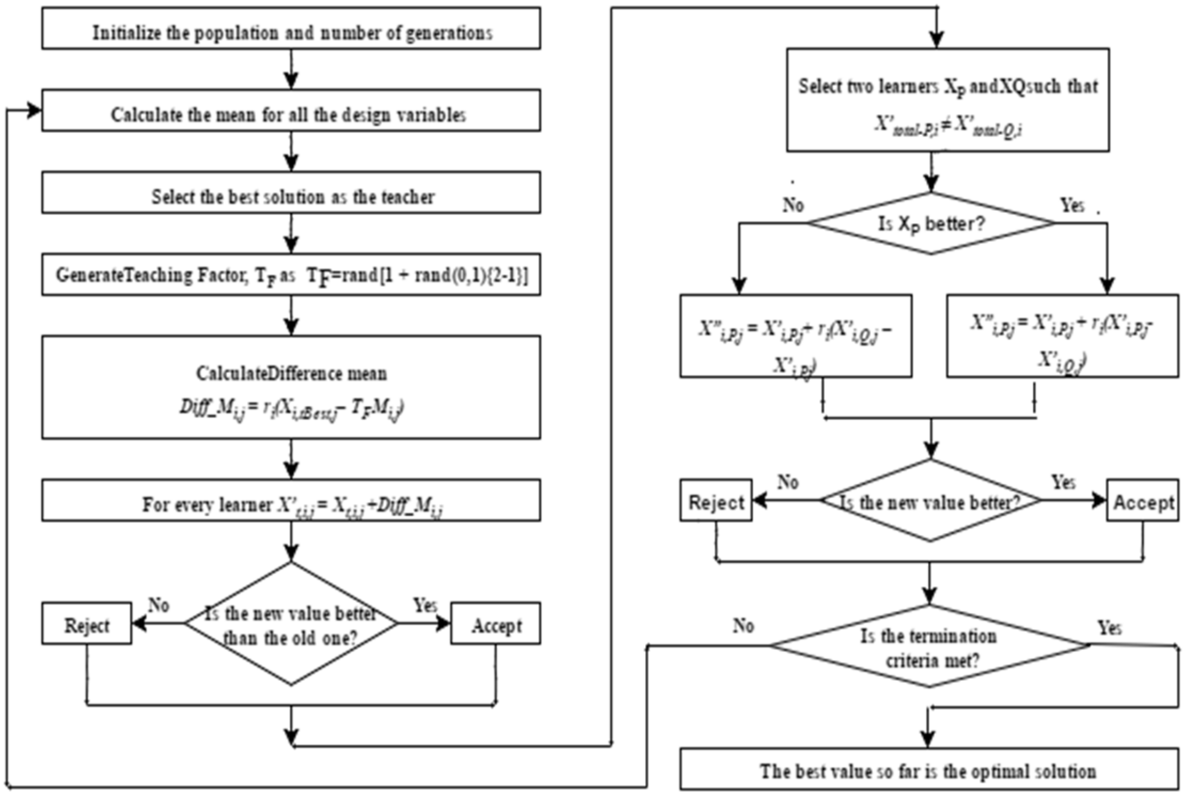

Fig 1: Flowchart for the TLBO Algorithm

As mentioned earlier TLBO algorithm is inspired from the teaching-learning process of a classroom. TLBO considers the possible solutions to the problem as the learners. The best solution is considered as the teacher. A new teacher is selected for each iteration. The number of learners is referred as the population size. The design variables or the parameters of the problem are represented by the subjects that the learners study. The value of the parameters is said to be the knowledge possessed by the learner in that particular subject. The idea of the algorithm is to improve the knowledge of the learners and thus, improving the value of the parameters which leads to the optimal solution. The algorithm works in two phases: the teacher phase and the learner phase. The learners try to enhance their knowledge in both the phases. Fig 1 shows the flowchart of the TLBO. During the teacher phase, the learners interact with the teacher to enhance their knowledge. During the learner phase, the knowledge is enhanced by interaction with the fellow learners. This section explains the working of the TLBO in detail. First of all the population is initialized randomly. Let t be the population size (i.e. population size, t=1,2,3,….,n). Assume s to be the number of subjects i.e. the design variables (i.e. design variables, s=1,2,3,….,m). During any i^{th} iteration, for the j^{th} subject, the mean is calculated and is denoted as $M_{i,j}$. $X_{tBest,i}$ of the population and is designated as the teacher for the i^{th} iteration. At the start of every iteration, the mean and the teacher change.

2.1 Teacher Phase

In the real world, the knowledge of the students of a classroom is affected by the quality of the teacher. The teacher phase of TLBO is inspired from this phenomenon. The best solution is elected as the teacher for the iteration. This teacher will try to improve the mean, $M_{i,j}$, of the class. For this purpose, the TLBO calculates the difference mean ($Diff\_M_{i,j}$) as :-

$$Diff\_M_{i,j} = r_i(X_{i,tBest,j} - T_F M_{i,j})$$

Where r_i is a random number whose range is in between 0 and 1. $X_{i,tBest,j}$ is the value of the teacher in subject j for the i^{th} iteration. T_F is the teaching factor. Its value can either be 1 or 0. Where 1 represents a situation where the learner learned all the knowledge from the teacher and 0 represents a situation where he learned nothing. It must be noted that the teaching factor, T_F, is not an algorithm specific parameter because its value is generated as:

$$T_F = rand[1+rand(0,1)\{2-1\}]$$

The knowledge of the t^{th} in the i^{th} iteration for the j^{th} subject ($X_{t,i,j,}$) is modified with the help of the calculated difference mean. The modified value is denoted as $X'_{t,i,j}$ and is calculated as:

$$X'_{t,i,j} = X_{t,i,j} + Diff\_M_{i,j}$$

The updated values are accepted if and only if they are better than the existing ones. The better value is decided on the basis of the type of problem. For a maximization problem, the higher value is considered better and for the minimization problem, a lower value is considered better. The updated values are fed as input to the learner phase.

2.2 Learner Phase

In real world classroom, the students can enhance their knowledge by interacting with their fellow students. TLBO uses this concept. The learners interact with each other to improve their knowledge. The learners with lower knowledge are benefitted by this. In this phase two learners P and Q are selected such that, $X'_{total-P,i} \neq X'_{total-Q,i.}$ i.e. their knowledge is not equal. Then, TLBO compares these values.
For a maximization problem,

If $X_{total-P,i} > X_{total-Q,i}$,

$$X''_{i,P,j} = X'_{i,P,j} + r_i(X'_{i,P,j} - X'_{i,Q,j})$$

Else if $X_{total-Q,i} > X_{total-A,i}$,

$$X''_{i,P,j} = X'_{i,P,j} + r_i(X'_{i,Q,j} - X'_{i,P,j})$$

For a minimization problem,

If $X_{total-P,i} < X_{total-Q,i}$,

$$X''_{i,P,j} = X'_{i,P,j} + r_i(X'_{i,Q,j} - X'_{i,P,j})$$

Else if $X_{total-Q,i} < X_{total-P,i}$

$$X''_{i,P,j} = X'_{i,A,j} + r_i(X'_{i,Q,j} - X'_{i,P,j})$$

Where $X''_{i,P,j}$ is the updated value which is accepted if and only if it is better than the existing value. The accepted values are fed as input to the next iteration. The algorithm is iterated until the termination criterion is met. The best value obtained at the termination is the optimal solution. The results [5] show that the number of functional evaluations required by TLBO is lesser as compared to many other optimization algorithms. TLBO leads many of them by a considerable margin in terms of the number of functional evaluations.

3. Related Work

Rao et al. [5] in 2011, presented the TLBO algorithm for the mechanical design problems. They tested it on different benchmark functions and compared its performance to other existing optimization algorithms. The results obtained proved that TLBO requires lesser number of functional evaluations than other algorithms. The algorithm was taken positively by many researchers but Cˇrepinšek et al. [6] differed in the opinion. They raised questions over the correctness of the formula and over the parameter-less control. They claimed that the algorithm uses a parameter, teaching factor, so it cannot be accepted as a parameter less algorithm. These questions were addressed by Rao and Patel [7]. It was explained that the TLBO does not claim to be a parameter-less algorithm. Rather it claims to be a specific-parameter-less algorithm. It was also stated that the teaching factor is not a specific parameter because its value is computed randomly and is not passed as input to the algorithm. Thus, it cannot be stated as an algorithm specific parameter. The other issues expressed by Cˇrepinšek were also clarified. Also, Elitist TLBO was introduced which uses the method of elitism i.e. at the end of every generation the worst solution is replaced by the elite solution. The duplicate solutions are modified with mutation if they exist. Later Rao and Patel introduced Improved TLBO (I-TLBO) [8]. The I-TLBO improved performance by introducing four new concepts: multiple teachers, adaptive teaching factor, learning through tutorial and self-motivated learning. The concept of multiple teachers prevents the immature converging of the algorithm. The adaptive teaching factor allows the learners to gain partial knowledge from the teacher whereas, in the basic TLBO, they could either learn everything or nothing at all. Self-motivated learning was also inspired from the natural teaching-learning phenomenon where a student may inspire himself to gain knowledge. Learning through tutorials allows learners to enhance their knowledge by discussion with teachers and fellow students. TLBO was applied by Roy [9] in short term hydrothermal scheduling problem. Niknam et al. modified TLBO [10] to present a better formulation of the reserve constrained dynamic economic dispatch of thermal units. Satapathy et al. introduced Orthogonal TLBO (OTLBO) [11] which is based on orthogonal design. OTLBO was found to be effective in terms of speed, stability and quality of the final solutions. This approach aimed at making the TLBO faster. Baykasoğlu et al. [12] tested the performance of TLBO on combinatorial Optimization problems: Flow shop and Job shop scheduling. The scheduling problems are considered one of the most complicated combinatorial optimization problems. The experimental results depicted the effectiveness of TLBO on the scheduling problems. Chen et al. [13] proposed an improved version of TLBO by introducing methods for local learning and self-learning. These improvements increased the searching ability of the TLBO. This version also achieved good performance. Umbarkar et al. [14] presented a solution to the classic 0/1 knapsack problem using the hybrid TLBO-GA algorithm. Zou et al. proposed LETLBO [15] i.e. TLBO with Learning Experience of other learners. This provided more learning methods for the learners and thus, increased the performance of the TLBO. LETLBO was proved efficient for many global optimization problems. Derakhshan et al. [16] used TLBO in optimizing the smart grids. Chen et al. [17] presented TLBO with variable population scheme and applied the same to Artificial Neural Network (ANN). [18] By Rao covers all the aspects of the algorithm. A recent review [19] by Rao presents an easy tutorial for the beginners and studies the applications of the TLBO. The literature of TLBO clearly indicates that the algorithm is being widely accepted and used. It is having potential to solve problems related to many fields of engineering and science. We sum up the literature review in the following table.

Table 1

Contribution of Researchers

S. No.	Author	Contribution
1	Rao et al.	Introduction of the TLBO to solve the constrained mechanical design problems
2	Črepinšek et al.	A note on the TLBO
3	Rao and Patel	Introduction of Elitist TLBO for solving complex constrained optimization problems
4	Rao and Patel	Introduction of Improved TLBO for solving unconstrained optimization problems
5	Roy, Provas Kumar	TLBO for short-term hydrothermal scheduling problem
6	Niknam et al.	Introduction of modified TLBO for reserve constrained dynamic economic dispatch
7	Satapathy et al.	Introduction of Orthogonal TLBO based on orthogonal design
8	Baykasoğlu et al.	Testing of TLBO on combinatorial optimization problems: Flow Shop and Job Shop scheduling problems
9	Chen et al.	Introduction of improved TLBO to solve global optimization problems
10	Umbarkar et al.	Solving 0/1 Knapsack Problem Using Hybrid TLBO-GA Algorithm
11	Zou et al.	TLBO with learning experience of other learners and its application
12	Derakhshan et al.	The optimization of demand response programs in smart grids with TLBO
13	Chen et al.	TLBO with variable-population scheme and its application for ANN and global optimization
14	Rao, R. Venketa	Covering of all the aspects of the TLBO algorithm in detail in the form of a book
15	Rao, R. Venkata	Review of the TLBO and its application

4. Discussion

From the wide range of literature available on TLBO, we can deduce that the TLBO is accepted worldwide for different applications. Except for a few contradictions, the algorithm has received appreciation from researchers around the globe. The raised contradictions were successfully addressed and were proved to be wrong. TLBO was established as a specific parameter less algorithm. The high number of variants and the dynamic set of applications justify that the algorithm has high potential to solve the optimization problems. Its application in solving the combinatorial optimization problems is highly remarkable and should be explored more in future. Many researchers have contributed to improve the performance of the TLBO. The algorithm is proving itself to be very efficient. The lesser functional evaluations and the lack of algorithm specific parameters results in its high efficiency. There is no conflict over the potential of the algorithm. The power of the algorithm is expected to grow with time. It will be interesting to see the performance of the TLBO in new domains. Also, the research should also incline towards improving the performance of the TLBO.

5. Conclusion

TLBO is a recent population based optimization algorithm. The algorithm has established itself as the star of the optimization algorithms. Many versions of the algorithm have been proposed and have been widely applauded. Both TLBO and its modified versions have been applied in various applications in different domains. The modified versions have added to the power of the TLBO. The algorithm is simple to implement and understand. Also, it operates without algorithm-specific parameters. The number of functional evaluations required is lesser than many other optimization algorithms. These are the major characteristics of the algorithm. The algorithm has proved itself efficient for numerous optimization problems. In future, it is hoped that both the TLBO and its variants will find their use in more complex optimization problems.

References

[1] Whitley, Darrell. "A genetic algorithm tutorial." *Statistics and computing* 4, no. 2 (1994): 65-85.

[2] Brabazon, Anthony, Michael O'Neill, and Seán McGarraghy. "Bacterial foraging algorithms." In *Natural computing algorithms*, pp. 187-199. Springer Berlin Heidelberg, 2015.

[3] Dorigo, Marco, Mauro Birattari, and Thomas Stutzle. "Ant colony optimization." *IEEE computational intelligence magazine* 1, no. 4 (2006): 28-39.

[4] Karaboga, Dervis, and Bahriye Basturk. "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm." *Journal of global optimization* 39, no. 3 (2007): 459-471.

[5] Rao, Ravipudi V., Vimal J. Savsani, and D. P. Vakharia. "Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems." *Computer-Aided Design* 43, no. 3 (2011): 303-315.

[6] Črepinšek, Matej, Shih-Hsi Liu, and Luka Mernik. "A note on teaching–learning-based optimization algorithm." *Information Sciences* 212 (2012): 79-93.

[7] Rao, R., and Vivek Patel. "An elitist teaching-learning-based optimization algorithm for solving complex constrained optimization problems." *International Journal of Industrial Engineering Computations* 3, no. 4 (2012): 535-560.

[8] Rao, R. Venkata, and Vivek Patel. "An improved teaching-learning-based optimization algorithm for solving unconstrained optimization problems." *Scientia Iranica* 20, no. 3 (2013): 710-720.

[9] Roy, Provas Kumar. "Teaching learning based optimization for short-term hydrothermal scheduling problem considering valve point effect and prohibited discharge constraint." *International Journal of Electrical Power & Energy Systems* 53 (2013): 10-19.

[10] Niknam, Taher, Rasoul Azizipanah-Abarghooee, and Jamshid Aghaei. "A new modified teaching-learning algorithm for reserve constrained dynamic economic dispatch." *IEEE Transactions on power systems* 28, no. 2 (2013): 749-763.

[11] Satapathy, Suresh Chandra, Anima Naik, and K. Parvathi. "A teaching learning based optimization based on orthogonal design for solving global optimization problems." *SpringerPlus* 2, no. 1 (2013): 1.

[12] Baykasoğlu, Adil, Alper Hamzadayi, and Simge Yelkenci Köse. "Testing the performance of teaching–learning based optimization (TLBO) algorithm on combinatorial problems: Flow shop and job shop scheduling cases." *Information Sciences* 276 (2014): 204-218.

[13] Chen, Debao, Feng Zou, Zheng Li, Jiangtao Wang, and Suwen Li. "An improved teaching–learning-based optimization algorithm for solving global optimization problem." *Information Sciences* 297 (2015): 171-190.

[14] Umbarkar, A. J., P. D. Sheth, and S. V. Babar. "Solving 0/1 Knapsack Problem Using Hybrid TLBO-GA Algorithm." In *Proceedings of Fourth International Conference on Soft Computing for Problem Solving*, pp. 1-10. Springer India, 2015.

[15] Zou, Feng, Lei Wang, Xinhong Hei, and Debao Chen. "Teaching–learning-based optimization with learning experience of other learners and its application." *Applied Soft Computing* 37 (2015): 725-736.

[16] Derakhshan, Ghasem, Heidar Ali Shayanfar, and Ahad Kazemi. "The optimization of demand response programs in smart grids." *Energy Policy* 94 (2016): 295-306.

[17] Chen, Debao, Renquan Lu, Feng Zou, and Suwen Li. "Teaching-learning-based optimization with variable-population scheme and its application for ANN and global optimization." *Neurocomputing* 173 (2016): 1096-1111.

[18] Rao, R. Venkata. "Teaching-Learning-Based Optimization Algorithm." In *Teaching Learning Based Optimization Algorithm*, pp. 9-39. Springer International Publishing, 2016.

[19] Rao, R. "Review of applications of TLBO algorithm and a tutorial for beginners to solve the unconstrained and constrained optimization problems." *Decision Science Letters* 5, no. 1 (2016): 1-30.