

# Improvement of Teaching-Learning-Based-Optimization

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**Abstract**—Teaching-Learning-Based-Optimization is an optimization algorithm that simulates the teaching process. In the standard Teaching-Learning-Based-Optimization there are some problems such as precocity and low optimization accuracy. Through daily discovery, students' learning effect is better when there are exercise lessons than when there are no exercise lessons. Students who study toward teacher on one's own learn better than students who do not. Therefore, this paper proposes a teaching mode that combines exercise lessons and one-to-one to improve the Teaching-Learning-Based-Optimization.

## 1 Introduction

Many phenomena in nature are closely related to human life and social progress, the survival of the fittest is the process of finding the best, such as Ant Colony Optimization Algorithm, Particle Swarm Optimization and other bionic population optimization algorithms. Not only the animals in nature have survival of the fittest, but also in human life, the first place in each class is also the "optimal solution" in a class. This is the Teaching-Learning-Based-Optimization (TLBO) proposed by Indian scholar Rao in 2011. At the beginning of a collective, an optimal solution is selected as a "teacher", and the optimal solution is sought in the subsequent stages of teacher teaching and student learning.

There are also some problems in the TLBO, such as precocity and low solution accuracy. Therefore, many scholars have proposed different improvements[1-10]. For example, OBLSATLBO proposed by Wang Peichong[7] is based on the TLBO. It adds teachers' self-learning mechanism and student's selective absorption of knowledge; Liu Yin[9] proposed a TLBO based on differential optimization using adaptive teaching factor.

## 2 Standard Teaching-Learning-Based-Optimization (TLBO)

This paper assumes that the class has a total of  $N$  students, they are  $X = \{X_1, X_2 \dots X_N\}$ . The maximum number of iterations is  $it_{max}$ . The optimal solution sought is the minimum. This paper assumes that the adaptability of all students in the class at the  $i$ -th iteration is:  $Grai(i) = \{Grai_1, Grai_2 \dots Grai_N\}$ .

When  $t = 0$ , it is the adaptability of the classmates at the beginning of the class, from which the best individual is selected as the teacher, and initialization is completed at the same time:  $Grai(0) = \{Grai_0, Grai_0 \dots Grai_0\}$

### 2.1 Teaching phase

$Grai_{mean}$  is the average adaptability of all students in the class, During the teaching phase, students learn from the difference between  $Grai_{mean}$  and the teacher  $Grai_{tea}$ . If student  $X_j$  (this student is not the teacher) learns well in the teaching phase, that is, the adaptability after learning phase is better than the original adaptability.  $Grai'_j$  is the new adaptability ( $i$  represents the  $i$ -th iteration).

Otherwise, the original adaptability  $Grai_j$  is retained as the adaptability of the student. The process is as follows:

$$Grai_{mean} = \frac{1}{N} \sum_{i=1}^N Grai_i \quad (1)$$

$$Grai'_j = Grai_j + rand(1) \times (Grai_{tea} - TF \times Grai_{mean}) \quad (2)$$

$$TF = round(1 + rand(1)) \quad (3)$$

$rand(1)$  is a random number on the interval(0,1).

$TF$  is a teaching factor, and  $round$  is a round to the nearest integer (if it is 0.5, it is rounded to the larger integer). Since  $rand(1)$  is in the range of (0,1), the teaching factor  $TF$  can only be 1 or 2.

### 2.2 Learning phase

This phase is learning and communication between students without teacher. In this phase, two students  $X_M$

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and  $X_N$  are randomly selected, their adaptability are  $Grai_M$  and  $Grai_N$ , and  $X_t$  learns from the better in  $Grai_M$  and  $Grai_N$ , the adaptability after learning is assumed as  $Grai_t''$ .

$$Grai_t'' = Grai_t' + rand(1) \times (\min\{Grai_M, Grai_N\} - Grai_t') \quad (4)$$

Similarly, if  $Grai_t''$  is better than  $Grai_t'$ ,  $Grai_t''$  is the new adaptability, if not,  $Grai_t'$  is retained.

### 3 Improvement of TLBO

In daily teaching, teaching phase and learning phase are traditional teaching methods, but the teaching effect is relatively insufficient. In our learning process, both teachers and students will try some new learning methods. Teachers will learn by themselves to improve teaching level, students will join cram school, learn from each other, etc.

Similar to our usual exercise lessons, teachers will arrange some homework after the teaching phase, students will learn and complete the homework after class, and the teacher will explain the homework in the next lessons. After such a cycle, the students' knowledge will be more consolidated and reward better results.

At the same time, in some university teachings, some teachers teach more than a hundred students (we call them large classes), and some classes can only accommodate about 30 people (we call them small classes) because of the small classroom. From the perspective of the final learning effect, the learning effect of the small class is significantly better than that of the large class. Through

observation, it is found that in the small class, students will ask the teacher more frequently about the aspects they do not understand. Because of the small number of students, teachers can also basically take into account each student. In the large class, the proportion of students who ask the teacher about the aspects they do not understand is relatively small.

Therefore, on the basis of the standard TLBO, the consolidation of the exercise lesson and the one-to-one teaching phase are added: after the teaching phase and the learning phase, this paper adds the teacher's double teaching and one-to-one teaching phase to improve TLBO, one-to-one is mean that all students learn from the teacher individually. In this algorithm, it is not considered that the teacher cannot take full account of all students.

The entire improved TLBO process is as follows:

#### 3.1 Teaching phase

In the standard TLBO, the value of the teaching factor  $TF = round(1 + rand(0,1))$  is only 1 or 2, and each student has a different ability of learning from the teaching phase. Therefore, this paper modified the generation function of teaching factor  $TF$ , which is called CFTLBO (Change  $TF$  Teaching-Learning-Based-Optimization). In this paper, the generation function of the teaching factor is set to  $TF = 1 + rand(1)$ . When  $TF = 1 + rand(1)$ , the value of  $TF$  is randomly selected between (1,2). The test results are shown in Table 1. Each data in Table 1 is an average of 50 experiments ( $N=50$ ).

**Table 1.** The value of optimal solutions for TLBO between CFTLBO, DTTLBO, OTOTLBO and CDOTLBO

iteration	TLBO	CFTLBO	DTTLBO	OTOTLBO	CDOTLBO
500	$4.2376e^{-110}$	$5.7415e^{-111}$	$1.4065e^{-119}$	$3.0475e^{-242}$	0
1000	$7.4378e^{-222}$	$4.2676e^{-223}$	$6.2733e^{-241}$	0	0
500	$5.8031e^{-110}$	$6.0658e^{-111}$	$2.7562e^{-119}$	$6.8432e^{-242}$	0
1000	$4.5852e^{-223}$	$3.8532e^{-224}$	$9.0462e^{-241}$	0	0
500	$4.8426e^{-110}$	$2.8044e^{-111}$	$6.0363e^{-119}$	$2.4512e^{-242}$	0
1000	$8.0046e^{-222}$	$1.7345e^{-224}$	$3.6353e^{-241}$	0	0
500	$6.9073e^{-110}$	$5.2357e^{-112}$	$5.2674e^{-119}$	$7.3523e^{-242}$	0
1000	$1.5479e^{-222}$	$7.2657e^{-223}$	$4.2689e^{-242}$	0	0

In TLBO, the series of values of the optimal solution sought by TLBO when iterating 500 times is near  $e^{-110}$ , and the series of values of the optimal solution sought by CFTLBO is near  $e^{-111}$ ; when the number of iterations is 1000, the series of TLBO optimal solutions Near  $e^{-222}$ , and the series of the CFTLBO optimal solution is near  $e^{-223}$ 、 $e^{-224}$ . Under these two kinds of iterations, CFTLBO only leads by an order of magnitude multiple of

e, so CFTLBO can only show a little optimization advantage.

#### 3.2 Learning phase

In this phase, students still learn from each other. Two students are randomly selected for learning. If the adaptability after learning is better, the new adaptability is used to replace the original one, otherwise the original adaptability is maintained.

### 3.3 Exercise lesson phase

In this phase, the teacher arranges homework during the teaching phase, so he needs to take class again. This process is similar to the teaching phase, which is called as DTTLBO (Double Teaching Teaching-Learning-Based-Optimization) in this paper. It also calculates the average

adaptability of all students in the class  $Grai'_{mean}$ . During the teaching phase, students learn through the difference between the teacher  $Grai'_{tea}$  and the average adaptability of the classmates. In the exercise lesson phase, keep the teaching factor as  $TF = round(1 + rand(0,1))$  in TLBO.

$$Grai'_{mean} = \frac{1}{N} \sum_{i=1}^N Grai'_i \quad (5)$$

$$Grai''_j = Grai'_j + rand(1) \times (Grai'_{tea} - TF \times Grai'_{mean}) \quad (6)$$

Through experiments, the optimization results are shown in Table 1.

From the Table 1 above, it can be seen that the value of the optimal solution sought by DTTLBO at 500 iterations are near  $e^{-119}$ , and the value of the optimal solution sought by TLBO are near  $e^{-110}$ , with a difference of about 9 orders of magnitude multiple of e; when the number of iterations is 1000, the series of the DTTLBO optimal solution is near  $e^{-241}$ , and the series of the TLBO optimal solution is near  $e^{-222}$ , which differs by about 19 orders of magnitude multiple of e. Therefore, the optimization effect of DTTLBO is more significant.

### 3.4 One-To-One Teaching

In the first three phase, the teacher will change as the number of iterations increases. Therefore, in this phase, Student  $X_i$  learns one-to-one from the optimal solution at the exercise lesson phase, the survival of the fittest is the same as before, this paper calls this phase as OTOTLBO (one-to-one Teaching-Learning-Based-Optimization).

$$Grai''_i = Grai'_i + rand(1) \times (Grai'_{tea} - Grai'_i) \quad (7)$$

Table 1 shows the results obtained by retaining the standard teaching factor  $TF$  and adding one-to-one teaching without the exercise lesson phase, and the optimization results obtained by the CDOTLBO (Change  $TF$  and Double teaching and One to one Teaching-Learning-Based-Optimization), which is a combination of the three improvement methods.

From Table 1, it can be seen that the value of the optimal solution sought by OTOTLBO at 500 iterations is near  $e^{-242}$ , and the value of the optimal solution sought by TLBO is near  $e^{-110}$ , with a difference of more than 130 orders of magnitude multiple of e; when the number of iterations is 1000, the series of the DTTLBO optimal solution is 0, and the series of the TLBO optimal solution is near  $e^{-222}$ , It can be seen from this effect that after

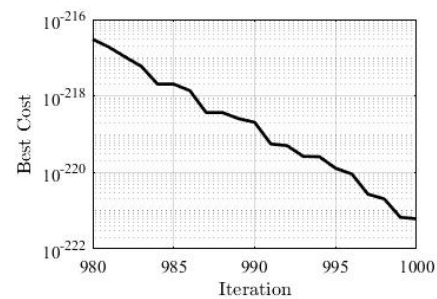
adding one-to-one teaching phase, the effect of optimizing is more significant.

From the data in Table 1, it is found that the optimization effect of CDOTLBO after combination has improved very much compared to the standard TLBO.

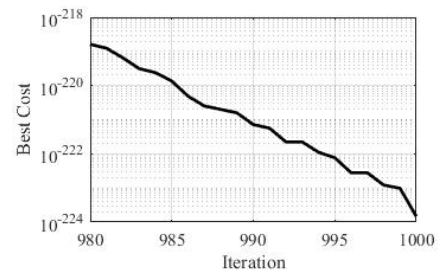
## 4 Simulation results

This paper improves on the standard TLBO, and obtains three improvements: CFTLBO, DTTLBO, OTOTLBO, and comprehensively obtains CDOTLBO.

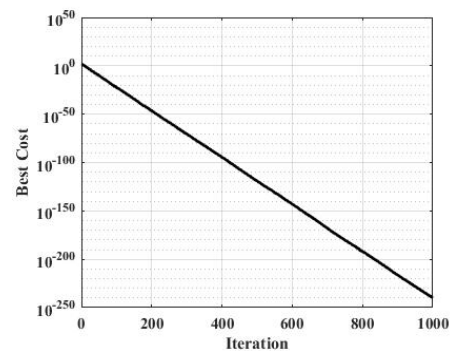
The test method in this paper is to use MATLAB to write code for simulation. The relationship between the optimal solution and the number of iterations in various improvements is shown in Figures 1 to 5 respectively. The effect of changing the  $TF$  is not obvious in the simulation diagram. Therefore, Figure. 1 and Figure. 2 have selected positions with the number of iterations of 980-1000.



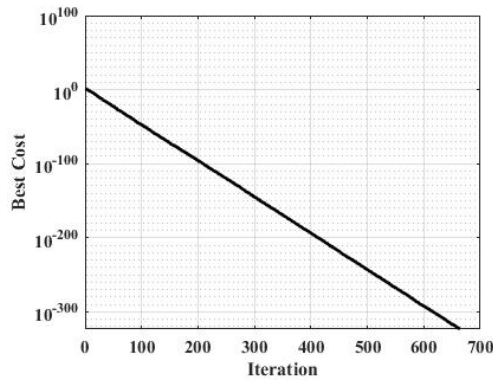
**Figure 1.** The relationship between the number of iterations of TLBO and the optimal solution.



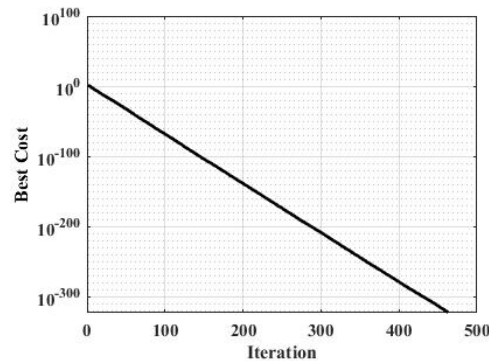
**Figure 2.** The relationship between the number of iterations of CFTLBO and the optimal solution.



**Figure 3.** The relationship between the number of iterations of DTTLBO and the optimal solution.



**Figure 4.** The relationship between the number of iterations of OTOTLBO and the optimal solution.



**Figure 5.** The relationship between the number of iterations of CDOTLBO and the optimal solution.

It can be seen from Figures 1 and 2 that the optimization accuracy of CFTLBO after 1000 iterations is slightly better than that of standard TLBO. The optimization results are not yet become 0 when the number of iterations is 1000. In Figure 3, When the number of iterations is 1000, the optimization results is near  $10^{-250}$ . In Figure 4, when the number of iterations is 600-700, the optimization result is 0, indicating that the optimization effect of OTOTLBO has a greater advantage than the previous two. Figure 5 is the final result, when the number of iterations is 450, The optimization result has been less than  $10^{-300}$ , and in the course of the experiment, it was found that when the number of iterations is about 470, the optimization result has become 0.

## 5 Conclusion

This paper has proposed an improved teaching optimization algorithm called CDOTLBO, which is improved on the basis of TLBO. It is experimentally obtained that CDOTLBO has a higher optimization accuracy. After the TLBO was created, some scholars found some better method based on it. This algorithm has also been widely used in general[11-15], such as multi-shop collaborative comprehensive scheduling based on hybrid teaching optimization algorithm proposed by Liao Bufan[15].

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## References

1. Yan Miaomiao, Liu Sanyang. Multi-class interactive teaching optimization algorithm [J]. Computer Engineering and Applications, 2019, 55 (09): 10-16 + 64.
2. He Jieguang, Peng Zhiping, Lin Weihao, Cui Delong. A teaching optimization algorithm for rectangular neighborhood structure [J]. Acta Electronica Sinica, 2019, 47 (08): 1768-1775.
3. Zhai Junchang, Zhao Zhen, Zhang Ping. Improved teaching-learning optimization algorithm [J]. Computer Technology and Development, 2019, 29 (08): 37-41. K. Elissa, "Title of paper if known," unpublished.
4. Ping Liangchuan, Sun Ziqiang. Improvement and Application of Teaching Optimization Algorithms [J]. Computer Engineering and Design, 2018, 39 (11): 3531-3537.
5. Yu Kunjie, Wang Xin, Wang Zhenlei. Improved teaching optimization algorithm and its application [J]. Chemical Industry and Engineering Progress, 2014, 33 (04): 850-854.
6. Li Rongyu, Liang Dong, Qi Guihong. Elite teaching optimization algorithm based on adaptive feedback mechanism [J]. Journal of System Simulation, 2018, 30 (08): 2950-2957.
7. Wang Peizong. Teaching optimization algorithm with self-learning mechanism and annealing selection [J]. Computer Engineering and Science, 2016, 38 (04): 706-712.
8. Chen Debao, Wei Hua, Zou Feng, Wang Jiangtao, Yang Yijun, Li Yi, Fang Zhenguo. Simulated annealing teaching optimization algorithm [J]. Application Research of Computers, 2014, 31 (12): 3553-3556.
9. Liu Yin, Li Dan. A teaching and learning optimization algorithm based on differential evolution [J]. Wireless Internet Technology, 2018, 15 (20): 100-102.
10. Yang Run, Mao Jichen. Research on teaching and learning optimization algorithm based on parallel teaching in small classes [J]. Journal of Software, 2018, 17 (10): 93-96.
11. Cui Dongwen. Application of multi-group teaching optimization algorithm-neural network-support vector machine combination model in runoff prediction [J]. Progress in Water Resources and Hydropower Science and Technology, 2019, 39 (04): 41-48 + 84.
12. Li Ruiguo, Zhang Hongli, Wang Ya. Parameter identification of chaotic system based on improved

- teaching optimization algorithm [J]. Computer Engineering and Design, 2016, 37 (01): 195-200.
13. Li Yueyu, Cui Dongwen, Gao Zengwen. Random forest prediction model based on multi-group teaching optimization and its application [J]. Yangtze River, 2019, 50 (07): 83-86 + 91.
  14. Lei Deming. Low-carbon flexible job shop scheduling based on a new teaching optimization algorithm [J]. Control and Decision, 2017, 32 (09): 1621-1627.
  15. Liao Bufan, Lei Qi, Wu Wenlie, Song Yuchuan, Guo Weifei. Multi-shop collaborative comprehensive scheduling based on hybrid teaching optimization algorithm [J / OL]. China Mechanical Engineering: 1-11 [2020-01-15]