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TEACHING OPTIMIZATION ALGORITHM AND SIMULATION ANALYSIS BASED ON SELF-LEARNING MECHANISM AND MULTI-CLASS INTERACTION

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Abstract. Teaching optimization algorithm is an intelligent optimization algorithm applied in the education. At the same time, it can solve complex optimization problems in other fields such as traffic flow optimization and logistics optimization. In response to the weak development ability, a teaching optimization algorithm based on self-learning mechanism is proposed by referring to general reverse learning methods. Meanwhile, a multi class interactive teaching optimization algorithm is proposed by combining clustering and partitioning methods based on Euclidean distance. By combining the two algorithms, a personalized and collaborative learning teaching environment is provided. When the function dimension is 30, the average function evaluations for the teaching optimization algorithm based on self-learning mechanism on unimodal function f_1 is only 3859. On the multimodal function f_2, the average function evaluations for this algorithm are only 4735, which is 2057 and 1367 less than the other two algorithms, respectively. Meanwhile, the success rates of this algorithm are all 100%. In addition, on the unconstrained function f_6, the multi class interactive teaching optimization algorithm tends to converge when the function evaluations are 0.1×10^4. Traditional teaching optimization algorithms tend to converge only at 1.0×10^4. The two improved algorithms proposed in the study have better solution accuracy and stability, providing a reliable method reference for solving modern complex engineering problems.

Key words: TLBO algorithm; Self study mechanism; Multi class interactive; Cluster partitioning

1. Introduction. Optimization problems are closely related to people's lives, mainly referring to finding the best solution to achieve one or more functional indicators from many different solutions on the basis of meeting certain conditions. The method used to solve optimization problems is called optimization method. As the name suggests, it is a type of method used to solve optimization problems based on various theories or principles. There are many optimization methods, all based on different theories and principles to solve optimization problems. In the context of the information age, many fields such as image processing, signal processing, production scheduling, pattern recognition, task allocation, mechanical design, and automatic control have developed rapidly. Optimization methods have played an irreplaceable role in solving optimization problems in various fields. From this, it can be seen that optimization methods are of great significance to people's lives. They can effectively plan and utilize existing resources on complex and large-scale problems, providing irreplaceable guidance value for people. Moreover, the larger the scale of the problem to be solved, the greater the contribution of optimization methods [1]. Since the introduction of intelligent optimization algorithms, they have solved significant challenges that were previously difficult to overcome in many fields such as industrial optimization design, electronics, and communication due to their simplicity, versatility, and ease of parallel processing. Among them, the Teaching-Learning-Based Optimization algorithm (TLBO) is a novel algorithm that compares student grades to fitness values based on school teaching principles. This algorithm imitates the way that schools improve students' grades, abstracting the teaching and learning processes of teachers and students into teaching and learning stages. However, the research on TLBO algorithm is still in the early stages. It has problems such as low accuracy and insufficient local search ability [2-3]. To address these issues, a teaching optimization algorithm based on the self-learning mechanism (SLTLBO) is introduced. On the basis of teacher self-learning and diversified learning methods for students, the aim is improve the convergence performance and search ability. A multi class interactive teaching optimization algorithm (MCITLBO) combining clustering partitioning method is proposed to improve the local search ability of the population and enhance population diversity. The main content includes four parts. The first part provides a review of the application and corresponding improvement methods of the TLBO algorithm. The second part provides a detailed introduction to

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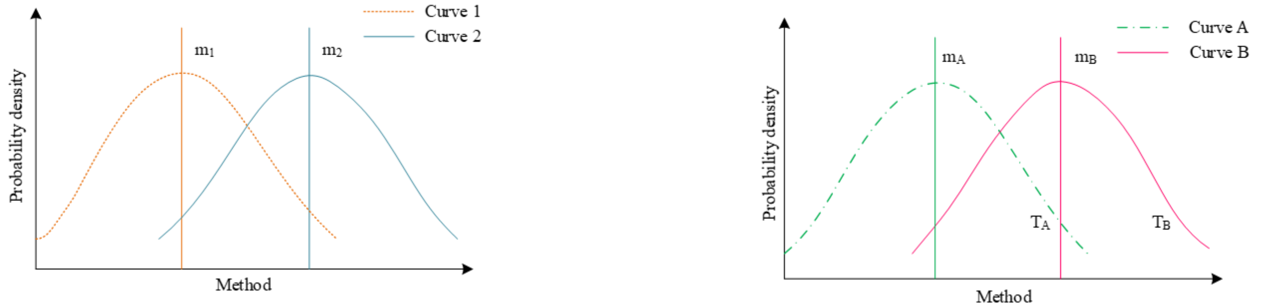
the TLBO algorithm and the improved algorithms. The first section introduces the TLBO algorithm model and the complexity analysis. The second section proposes SLTLBO and provides detailed implementation steps of the algorithm. The third section proposes the MCITLBO algorithm and introduces the specific implementation steps. The third part mainly conducts simulation experiments and analysis on the two improved algorithms proposed in the research. The fourth part discusses the experimental results and proposes future prospects.

2. Related works. The TLBO algorithm is based on the principles of teaching by teachers and learning by students in schools. Starting from the reality of teaching, this algorithm has high solving accuracy and good convergence performance. Since its proposal, it has quickly attracted the interest of a large number of scientific researchers. Many scholars have conducted extensive research on this algorithm from multiple perspectives, proposing a large number of effective improvement algorithms, and applying them to many fields such as pattern recognition, function optimization, clustering problems, machine learning, scheduling problems, etc. Chen W et al. proposed the TLBO algorithm and the satin bowerbird optimization algorithm to optimize the adaptive neural fuzzy inference system model for landslide susceptibility evaluation. The proposed exhibited higher AUROC values and lower RMSE values [4]. Ghoneim S S M et al. proposed a new optimization method for transformer fault diagnosis. By using the TLBO algorithm to establish an optimization model, high-precision fault diagnosis is achieved. The results show that this method outperforms other existing DGA techniques in diagnostic accuracy [5]. Shukla A K et al. developed an algorithm using adaptive exponential distribution of inertia weights and changing position update equations to improve the TLBO algorithm with local optimal problems. The logistics map generates a uniformly distributed population, further improving the quality of the initial population. The results show that the method is superior in solution quality, convergence speed, and classification accuracy [6]. Gao N et al. proposed an embedding rib strategy to broaden the sound absorption region of porous materials. The results show that the composite element structure based on the TLBO algorithm has ultra wide high sound absorption characteristics. The average sound absorption coefficient in the range of 0-10 kHz is 0.937 [7]. Arashpour M et al. proposed a hybrid machine learning model and a teaching based optimizer approach for reliable prediction of individual learning performance. The results show that using the TLBO algorithm to perform feature selection and ANN structure determination can reliably predict students' exam scores [8].

Reverse learning is a machine learning method that learns optimal behavioral strategies through the interaction between intelligent agents and the environment. In reverse learning, intelligent agents continuously adjust their behavioral strategies by observing environmental conditions and receiving reward signals, in order to maximize long-term cumulative rewards. Clustering algorithm is an unsupervised learning method used to partition a set of data into different categories or clusters. The goal of clustering algorithms is to find intrinsic patterns and structures in data, group similar data points together, and maximize the differences between different groups. Currently, reverse learning and clustering algorithms are widely used in fields such as data mining and image analysis. Yildiz B S et al. proposed a grasshopper optimization method based on elite reverse learning for engineering design problems. It has significant performance advantages in engineering design problems such as welding beam design, car collision, and multi clutch discs [9]. Khishe M designed an improved chaotic ant colony algorithm to solve the slow convergence speed and low exploration ability. The results show that the algorithm ranks first among 27 numerical test functions. It achieves the fourth highest score in the percentile challenge [10]. Wang S et al. developed an improved ant lion optimization algorithm based on reverse learning for region analysis of complex images in image segmentation. This algorithm determines the optimal threshold by maximizing the objective function. The exponentially increasing time complexity when the number of thresholds increases is effectively addressed. The results show that the fitness value and peak signal-to-noise ratio of this algorithm are significantly better than other algorithms [11]. Ghazal T M found that the K-means clustering algorithm needs to be optimized in execution time. Therefore, different mathematical measurement methods are proposed to evaluate different datasets and cluster numbers. The results show that the Manhattan distance measurement method achieves the best execution time results [12]. Zhao P et al. introduced a clustering method relying on network distance and graph partitioning to better solve the detection problem of urban hotspots. The taxi unloading event is represented as a linear element in the spatial environment of the road network. The Jaccard distance is used to measure the similarity of road segments. The results show that this method has higher accuracy in identifying urban hotspots [13].



(a) Distribution of teaching effectiveness among different teachers

(b) Distribution of learning outcomes among different students

Fig. 3.1: Distribution of grades in different situations

In summary, domestic and foreign researchers have conducted extensive research on reverse learning algorithms and clustering algorithms. However, few scholars have applied it to the optimization of TLBO algorithms. Therefore, the SLTLBO algorithm and MCITLBO algorithm are designed by combining general reverse learning methods and new clustering partitioning methods based on Euclidean distance (ED). It is expected to improve the solving ability of the TLBO.

3. Teaching optimization algorithm based on self-learning mechanism and multi class interaction. The TLBO algorithm has advantages such as fewer control parameters and ease of understanding. Currently, it is a research focus in the scientific research. However, it has premature convergence, low solving accuracy, and poor stability. This chapter first introduces a general reverse learning method. Then the SLTLBO algorithm is designed to address this issue. At the same time, a clustering partitioning method based on Euclidean distance is used to design the MCITLBO algorithm to improve the convergence performance and solving ability of the TLBO.

3.1. Model construction and complexity analysis of teaching optimization algorithms. The TLBO algorithm can be applied to optimize the teaching process. It can also solve complex optimization problems in other fields. In the TLBO algorithm, it is assumed that there are two teachers, Teacher 1 and Teacher 2, who respectively teach the same subject in two classes. The students in both classes have similar levels of proficiency. Student grades exhibit a normal distribution. After a period of teaching, the distribution of grades between the two classes is shown in Figure 3.1a. In the figure, curve 1 stands for the distribution of grades in the class taught by Teacher 1. Curve 2 stands for the distribution of grades in the classes taught by Teacher 2. m_1 and m_2 represent the average of the two, respectively. The grades of the classes taught by Teacher 2 are better, indicating that Teacher 2 has better teaching effectiveness. To play the guiding role of the optimal individual, the teacher with the best performance should be selected as the leader. That is, the individual with the best fitness value should be selected as the teacher [15].

The distribution of grades before and after the teaching and learning stages is shown in Figure 3.1b. In the figure, curve A represents the student's performance before learning. Curve B represents the student's academic performance after learning. m_A and m_B represent the average of the two, respectively. From the graph, through learning and teacher guidance, students' individual grades have also improved. Therefore, after learning, both the average grade of the class and the individual grades of the students have improved. The original teacher may not be competent for the teaching work of the class. A new teacher needs to be selected for the next round of teaching work. Through this cycle, the solution represented by each student will be continuously updated until the termination condition is met [16]. The optimization problems involved are represented in equation

(3.1).

$$\min imize\, f(X_i), X_i = (x_1, x_2, ..., x_D) \in S = \prod_{j=1}^{D} [L_j, U_j] \tag{3.1}$$

In equation (3.1), X_i represents the decision variable of the iF-th D dimension, that is, the i-th student. $f(X_i)$ represents the fitness value function, which is the student's score. S is the decision space. D represents the dimension. L_j and U_j represents the lower and upper bounds of the j-th dimensional variable. During the teaching phase, the average score of students is shown in equation (3.2).

$$M_k = \frac{(\sum_{i=1}^{NP} X_{i,1}, \sum_{i=1}^{NP} X_{i,2}, ..., \sum_{i=1}^{NP} X_{i,D})}{NP} \tag{3.2}$$

In equation (3.2), NP represents the number of students. The selected teacher is shown in equation (3.3).

$$T_k = \min \{f(X_i)\,|i = 1, 2, ..., NP\} \tag{3.3}$$

In equation (3.3), k is the number of iterations. The basis for teachers to impart knowledge includes students' average grades and their own differences. The gap calculation is shown in equation (3.4).

$$Difference\_Mean_i = r_i(T_k - T_{F_i} M_k) \tag{3.4}$$

In equation (3.4), r_i is 0 or 1. $T_F$represents the teaching factor. T_{F_i} is shown in equation (3.5).

$$T_{F_i} = round\,[1 + rand(0, 1)] \tag{3.5}$$

The update calculation of individual is shown in equation (3.6).

$$X_{new} = X_{old} + Difference\_Mean \tag{3.6}$$

In equation (3.6), X_{old} and X_{new} represent individual students before and after the update, respectively. If X_{new} exceeds X_{old}, it is replaced. During the learning stage, student $X_j$is randomly selected. If there is $f(X_i) < f(X_j)$, it is calculated in equation (3.7).

$$X_{new,i} = X_{old,i} + r_k(X_i - X_j) \tag{3.7}$$

If there is $f(X_i) > f(X_j)$, the calculation is shown in equation (3.8).

$$X_{new,i} = X_{old,i} + r_k(X_j - X_i) \tag{3.8}$$

The population initialization is shown in equation (3.9).

$$P(t) = \{X_i(t)\,|x_{i,j}(t) = rand \cdot (U_j - L_j) + L_j, 1 \le i \le NP,\ 1 \le j \le D\} \tag{3.9}$$

Time complexity and spatial complexity are used to measure the execution efficiency of the TLBO algorithm. The time complexity calculation is shown in equation (3.10).

$$T(D) = O(\max\_iter \times 2 \times NP \times D) \tag{3.10}$$

In equation (3.10), $\max\_iter$ represents the maximum number of cycles. The spatial complexity is shown in equation (3.11).

$$S(D) = O((\max\_iter + 2 \times NP) \times D) \tag{3.11}$$

The time complexity and spatial complexity of the TLBO algorithm are linearly related to the size of the problem. As the scale of the problem increases, the execution time and required memory space of the algorithm can grow relatively quickly.

3.2. Teaching optimization algorithm based on self-learning mechanism. In traditional TLBO algorithms, students mainly improve themselves by learning from other students and retaining or updating individuals in a survival of the fittest manner. But it limits students' diversity and selectivity in learning methods, leading to a rapid decrease in population diversity. Therefore, the SLTLBO algorithm is proposed. In this algorithm, teachers act an important leading role in the evolution of the entire population. Excellent individual teachers can help the entire population approach the optimal solution faster. To more effectively utilize the guiding role of individual teachers in population evolution, a general reverse learning method is introduced to achieve individual teachers' self-learning [17-18]. Specifically, firstly, in the k-th iteration, the individual with the best fitness value is selected as the teacher individual T_k. Next, the general inverse solution $\overline{T}_k$ is calculated and evaluated. When $f(\overline{T}_k) < f(T_k)$ is met, replace T_k with $\overline{T}_k$ and teach. In the TLBO algorithm, after obtaining knowledge from teachers, students can not only learn from other students again, but also improve their academic performance through self-learning. As the iterations increases, the search area shrinks. The similarity of individuals in the population will gradually increase. However, this learning method has low efficiency, which is prone to trapping the population into local optima. To better simulate the learning process in real life, the learning stage is modified. Students engage in diversified learning through three methods, seeking advice from teachers in a probabilistic manner, learning from other classmates, and self-learning, thereby enhancing the diversity of the population. A random number between (0, 1) is generated during the learning phase. When $0 < rand < \frac{1}{3}$ is reached, students will seek advice from the teacher, as shown in equation (3.12).

$$X_{newi} = X_i + rand(T_k - X_i) \tag{3.12}$$

When $\frac{1}{3} \leq rand \leq \frac{2}{3}$ is reached, students seek advice from other students. When $\frac{2}{3} < rand < 1$ is reached, students adopt a general reverse learning method for self-learning. The specific calculation is shown in equation (3.13).

$$\overline{x_j} = \begin{cases} x_j^* + rand\left[(a+b)/2 - x_j^*\right], & if\,(a+b)/2 < x_j^* \\ (a+b)/2 + rand\left[x_j^* - (a+b)/2\right], & else \end{cases} \tag{3.13}$$

In equation (3.13), $X = (x_1, x_2, ..., x_D)$ represents a point in the D-dimensional space. $x_j \in [a_j, b_j], j = 1, 2, ..., D$. X^* represents the reverse point of X. The general reverse point definition of X is represented by equation (3.14).

$$\overline{X} = (\overline{x_1}, \overline{x_2}, ..., \overline{x_D}) \tag{3.14}$$

When $f(X_{newi}) < f(X)$ is reached, X is replaced with X_{newi}. In the proposed SLTLBO algorithm, the teacher who plays a dominant role in algorithm convergence no longer only selects the optimal population, but improves their own ability through general reverse learning methods, which can not only enhance the convergence performance of the algorithm, but also to a high extent avoid the population falling into local "valleys"; Students are no longer blindly learning from random individuals, with a single and inefficient learning method. Instead, they imitate the real teaching environment by establishing three learning methods: self-learning, learning from other classmates, and seeking advice from teachers. This diversifies the learning methods of students, increases the utilization of population neighborhood information, and enhances the development ability of algorithms. The SLTLBO algorithm is shown in Figure 3.2.

3.3. Teaching optimization algorithm based on multi class interaction. The TLBO algorithm is a method of improving students' academic performance by optimizing their learning process. It is mainly calculated based on two parameters, population size and iteration number. To effectively improve the stability performance and optimization accuracy of the TLBO algorithm, a MCITLBO algorithm is further proposed. Firstly, a new clustering method is adopted to divide the initial population into multiple subgroups based on ED to effectively utilize the neighborhood information and enhance the local search ability. Then, after the teaching stage, the school selects excellent teachers to guide students with poor grades. The worst individual (WI) in each subgroup learns from the best individual (BI) in that subgroup, accelerating the evolution of the WI towards the best direction. Finally, after the learning stage, based on the principle of student mobility, an

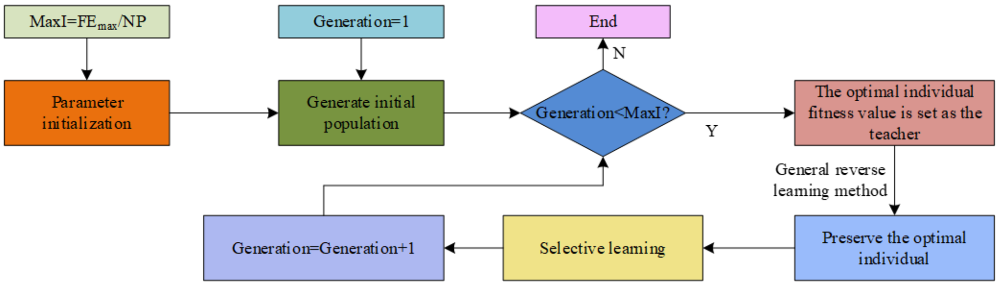


Fig. 3.2: SLTLBO The flow of the algorithm

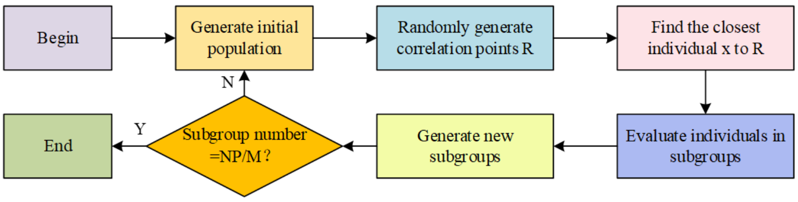


Fig. 3.3: Flowchart of a Novel Clustering and Partitioning Method Based on Euclidean Distance

individual is randomly generated for each subgroup to learn from two individuals in other subgroups, effectively maintaining population diversity [19]. The main implementation steps of the new clustering partitioning method based on ED are shown in Figure 3.3.

The advantages of clustering and partitioning methods based on ED are as follows. Firstly, compared to classical clustering and partitioning methods, it has lower complexity and shorter runtime. Secondly, the clustering partitioning method based on Euclidean distance can select individuals from each sub region during the learning stage, thereby better utilizing the local information of the population. The algorithm can more accurately find the optimal solution and converge more stably. In real life, schools will take measures to help poorer students improve their academic performance. One of them is to organize the best teachers to provide them with after-school tutoring. After the teaching stage, the worst performing students communicate with the best performing students in the entire class, thereby accelerating the improvement of their grades [20]. The WI learns from the BI as shown in equation (3.15).

$$x_{new,i} = x_{old,i} + rand(T_k - x_{old,i}) \tag{3.15}$$

When $x_{new,i}$ is superior to $x_{old,i}$, then $x_{new,i}$ is accepted. At the same time, to promote student interaction and information exchange between different classes and increase population diversity, a student x_{M1} is randomly selected from each class. It communicates with students from two other classes. The specific update method is shown in equation (3.16).

$$\begin{cases} x_{new,M_1} = x_{old,M_1} + rand(x_{M_2} - x_{M_3}), & if\ f(x_{M_2}) < f(x_{M_3}) \\ x_{new,M_1} = x_{old,M_1} + rand(x_{M_3} - x_{M_2}), & if\ f(x_{M_2}) > f(x_{M_3}) \end{cases} \tag{3.16}$$

MCITLBO When x_{new,M_1} is superior to x_{old,M_1}, x_{new,M_1} is accepted. In the early stages of algorithm iteration, the diversity of the algorithm population is good, and the establishment of information exchange between populations ensures that each class searches within the feasible domain under the guidance of the optimal teacher in the population. The algorithm has good exploration and development capabilities. As the number of iterations gradually increases, the population gradually approaches the optimal solution, individual differences gradually shrink, and population diversity gradually decreases. Population evolution puts higher

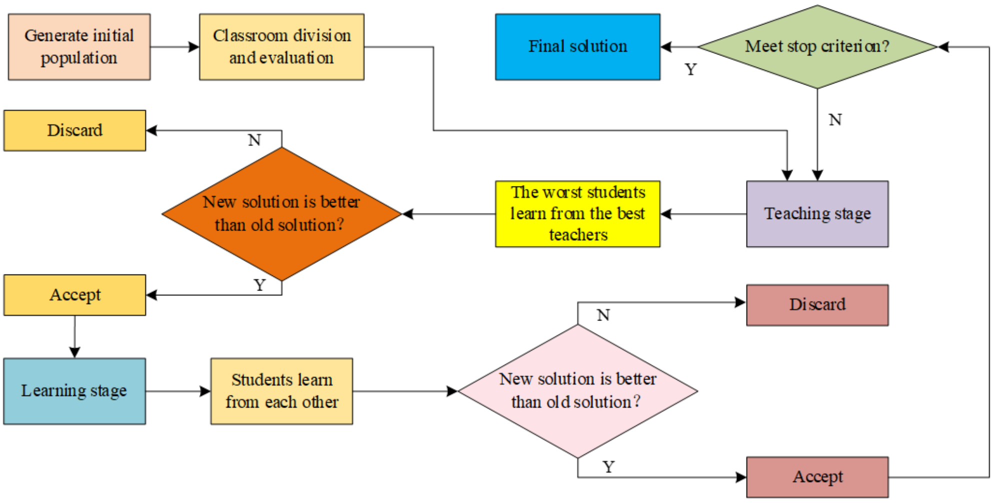


Fig. 3.4: Flowchart of MCITLBO algorithm

requirements on the algorithm's local search ability. Due to the delay in the evolution of each class in the multi class teaching mode and the learning method of random communication between students in each class, it can effectively enhance population diversity and improve the algorithm's optimization ability. Therefore, MCITLBO can fully maintain a balance between the two search abilities in evolution, improving the search performance of TLBO. According to the description of the multi class interactive TLBO, the flowchart of the MCITLBO is displayed in Figure 3.4.

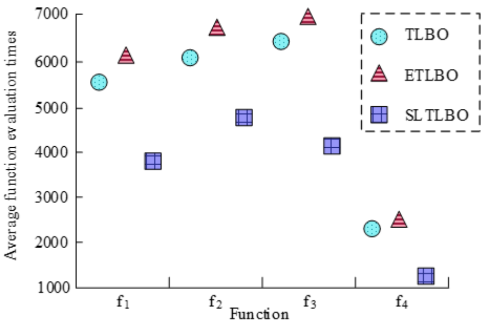
In the multi class teaching mode, there is random communication between students in each class, as well as enhanced population diversity, which can effectively improve the optimization ability. Therefore, the MCITLBO algorithm can balance the two search abilities, thereby improving the search performance. In addition, the SLTLBO algorithm focuses on the learning process of individual learners. It mainly adjusts the teaching content and learning path based on the individual learning characteristics and needs of students, so that each student can receive suitable learning support. In contrast, the MCITLBO algorithm fully considers the interaction and cooperation between different classes. By analyzing the learning situation and interactive behavior of multi class learners, the allocation of teaching resources and the organization of teaching activities are optimized. By combining the two, a personalized and collaborative learning teaching environment can be better provided.

4. Simulation analysis based on SLTLBO and MCITLBO algorithms. To verify the performance advantages of the optimized TLBO, this chapter conducts simulation experiments on the SLTLBO algorithm and the MCITLBO algorithm. In the experiment of SLTLBO algorithm, multiple test functions are used and performance simulation analysis is conducted from multiple dimensions. In the experiment to validate the MCITLBO algorithm, the performance simulation analysis is conducted using population distribution and experimental results on unconstrained functions.

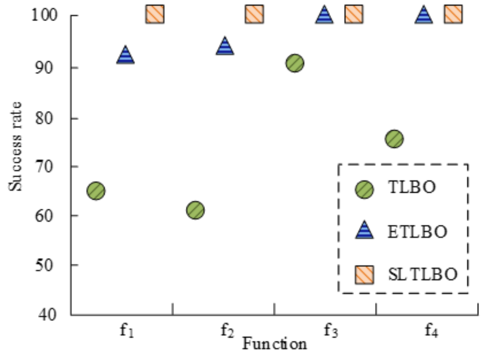
4.1. Analysis of teaching optimization algorithms based on self-learning mechanism. To verify the performance advantages of the SLTLBO, the Enhanced Teaching-Learning Based Optimization Algorithm (ETLBO) and TLBO are experimentally compared. Function evaluation is an important means of evaluating algorithm performance and optimizing algorithm design, which refers to quantifying and evaluating the performance of algorithms in solving optimization problems. By systematically evaluating functions, algorithms can be better understood and improved, thereby improving the efficiency and quality of problem solving. The test functions used include unimodal function f_1, multimodal function f_2, the rotation function f_3 of unimodal function f_1, and the rotation function f_4 of multimodal function f_2. The optimal value for all functions is 0.

Table 4.1: The specific case of each function

Function	Name	Value range	Acceptable solution
f1	Sum square	[-10,10]	1E-8
f2	Ackley	[-32.768,32.768]	1E-6
f3	Rotated sum square	[-10,10]	1E-8
f4	Rotated ackley	[-32.768,32.768]	2



(a) The average number of successful function evaluations for each algorithm



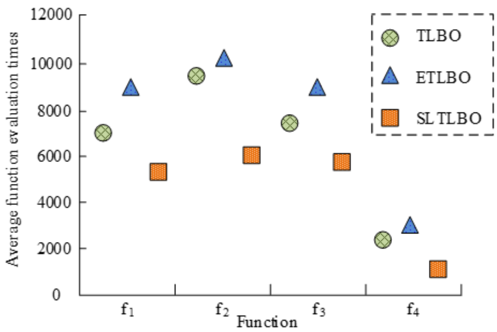
(b) The success rate of each algorithm's operation

Fig. 4.1: Running results of various algorithms in 30 dimensional situation

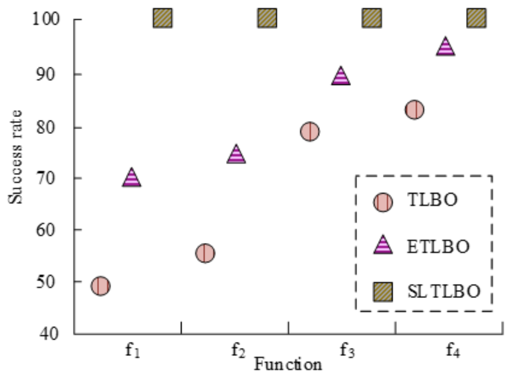
The specific situation of each function is displayed in Table 4.1.

The experimental environment is a Windows 7 system with a 3.2GHz CPU, 2GB RAM, and MATLAB 2016a. The population size is 50. The dimensions of the function include 30 and 50. The maximum function evaluations are 300000. To ensure the effectiveness of the experiment, each function is run independently 50 times. When the algorithm converges to an acceptable solution, it represents the successful operation of the algorithm. Success rate is an important indicator in function evaluation, used to measure the degree of success of algorithms in solving optimization problems. It represents the probability that the algorithm can find the optimal solution or approach the optimal solution. The success rate is usually expressed as a percentage, calculated by dividing the number of times the algorithm has successfully found or approached the optimal solution by the total number of experiments, and multiplying by 100. For a specific optimization problem, a higher success rate means that the algorithm performs better in solving the problem. A high success rate algorithm can find the optimal solution or approach the optimal solution more frequently, while a low success rate algorithm may often fall into local optima or find poorer solutions. When the dimension is 30, the average function evaluations and success rates of each algorithm are shown in Figure 4.1. From Figure 4.1, on the unimodal function f_1, the average function evaluations for the SLTLBO algorithm are only 3859. Compared to the ETLBO algorithm and TLBO algorithm, it has decreased by 2293 and 1634, respectively. On the multimodal function f_2, the average function evaluations for the SLTLBO algorithm are only 4735. Compared to the other two algorithms, it reduces 2057 and 1367 respectively. On the rotation function f_3, the average function evaluations for the SLTLBO algorithm are 4022. The ETLBO algorithm is as high as 6831. On the rotation function f_4, the average function evaluations for the SLTLBO algorithm are only 1204. At the same time, the success rates of the SLTLBO algorithm are all 100%. When the function dimension is 30 dimensions, the SLTLBO algorithm has a lower function evaluations and a higher success rate compared to the other two algorithms.

When the dimension is 50, the average function evaluations and success rates of each algorithm are shown



(a) The average number of successful function evaluations for each algorithm



(b) The success rate of each algorithm's operation

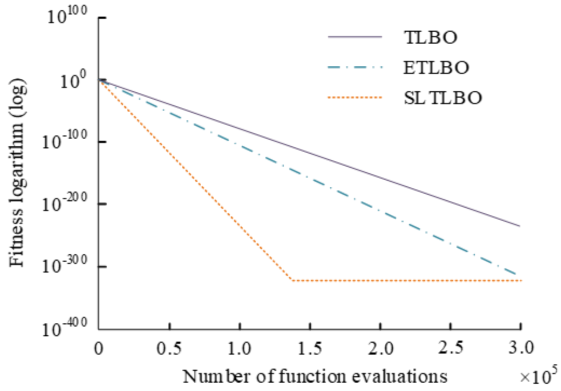
Fig. 4.2: Running results of various algorithms in 50 dimensional situation

in Figure 4.2. From Figure 4.2, the SLTLBO algorithm outperforms other algorithms in the average function evaluations on each function. Among them, on the unimodal function f_1, the average function evaluations for the SLTLBO algorithm are 5093. On the multimodal function f_2, the average function evaluations for the SLTLBO algorithm is only 5929. On the two rotation functions, the average function evaluations for the SLTLBO algorithm are 4813 and 1368, respectively. Meanwhile, the success rate of the algorithm on each function is 100%. When the dimension is 50, the SLTLBO algorithm still has lower function evaluation times and better operational stability.

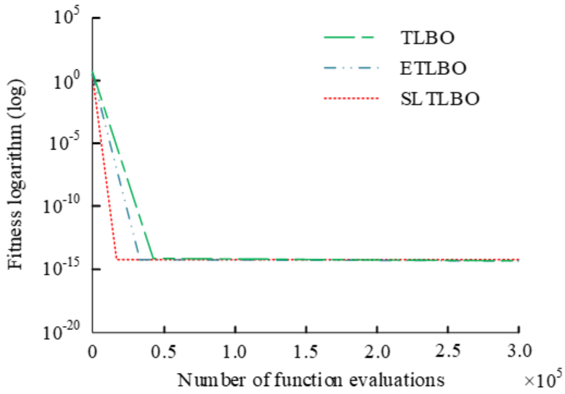
The convergence of each function under different algorithm optimizations is shown in Figure 4.3. In Figure 4.3, the SLTLBO algorithm outperforms other algorithms in convergence across various functions. Among them, the SLTLBO algorithm converges faster on the unimodal function f_1. On the multimodal function f_2, the SLTLBO tends to converge when the function evaluations are 0.15×10^5. The ETLBO tends to converge when the function evaluations are 0.31×10^5, while the TLBO tends to converge at 0.43×10^5. On the rotation function f_3, the SLTLBO algorithm tends to converge at 1.4×10^5. On the rotation function f_4, the SLTLBO tends to converge at 0.14×10^5, while the ETLBO tends to converge when the function evaluations are 0.32×10^5. The TLBO tends to converge when the function evaluations are 0.43×10^5. This indicates that the SLTLBO algorithm has more significant convergence performance.

From an overall perspective, the optimization performance of each algorithm is compared. At a significance level of 0.05, the double tailed t-test results of each algorithm compared to SLTLBO are analyzed. Figure 4.4 displays the results. In Figure 4.4, "+", "-", and "=" respectively represent that the SLTLBO is superior, inferior, or equal to the algorithm being compared. From Figure 4.4, the SLTLBO algorithm outperforms the other two algorithms in various functions with dimensions of 30 and 50, respectively. It is only inferior to the ETLBO algorithm on the rotation function f_4. The SLTLBO algorithm has significant performance advantages.

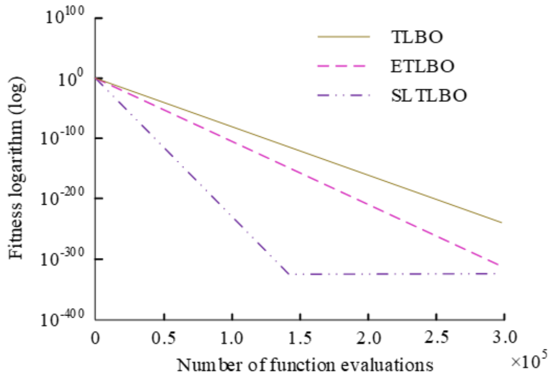
To verify the performance advantages of the MCITLBO, population diversity is used as a performance evaluation indicator. It is compared with the TLBO algorithm. The 2D Sphere function is used as the test function. TLBO and MCITLBO are used to optimize them, thereby obtaining the population distribution of each algorithm under different evolutionary algebras. Among them, the optimal value of the function is 0, the optimal solution is [0,0], and the search space is $[100,100]^2$. The population size is NP=100. The iteration is max Gen=100. The population distribution of each algorithm evolving to the 100th generation is shown in Figure 4.5. In Figure 4.5, MCITLBO has a faster optimization speed, reducing the search space to $[-2\times10^{-25},2\times10^{-25}]^2$. At the same time, compared to the TLBO algorithm, the population distribution of MCITLBO is more dispersed, indicating that the MCITLBO algorithm has better population diversity.



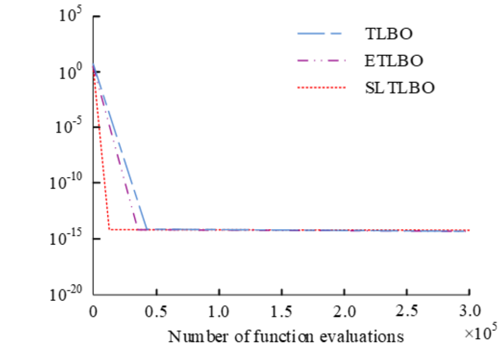
(a) The fitness convergence curve of function f1



(b) The fitness convergence curve of function f2

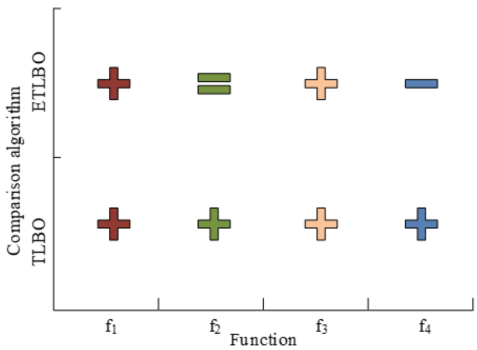


(c) The fitness convergence curve of function f3

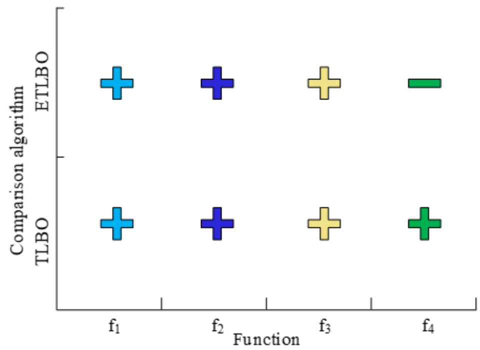


(d) The fitness convergence curve of function f4

Fig. 4.3: Convergence of various functions under optimization by different algorithms

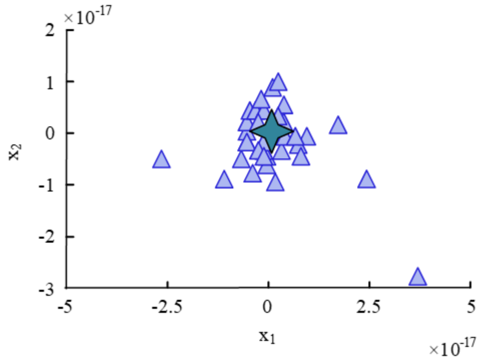


(a) Performance comparison results under 30 dimensional conditions

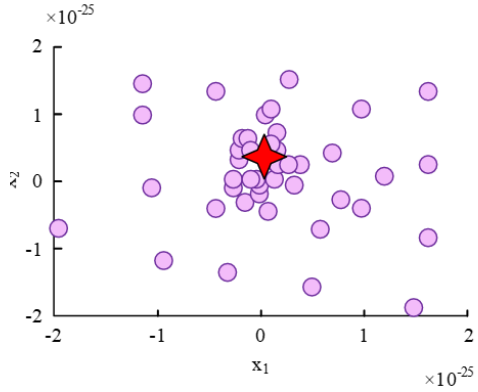


(b) Performance comparison results under 50 dimensional conditions

Fig. 4.4: Analysis of teaching optimization algorithms based on multi class interaction



(a) Population distribution results of TLBO algorithm



(b) Population distribution results of MCITLBO algorithm

Fig. 4.5: The population distribution of various algorithms evolving to the 100th generation

Table 4.2: The specific situation of two unconstrained functions

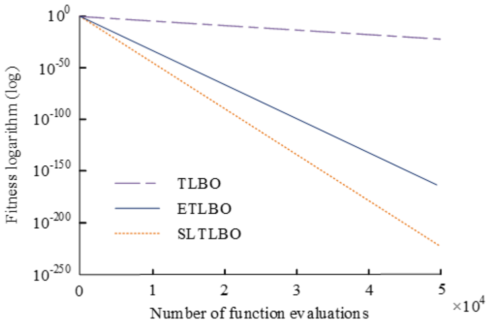
Function	Variable range
$f_5(x) = \sum_{i=1}^{D} x_i^2$	(-100,100)
$f_6(x) = \sum_{i=1}^{D-1}[100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2]$	(-10,10)

The convergence performance of MCITLBO algorithm is verified. The TLBO and ETLBO are selected for performance comparison. The unconstrained test functions f_5 and f_6 are used for comparison. The specific situation of the two unconstrained functions is shown in Table 4.2.

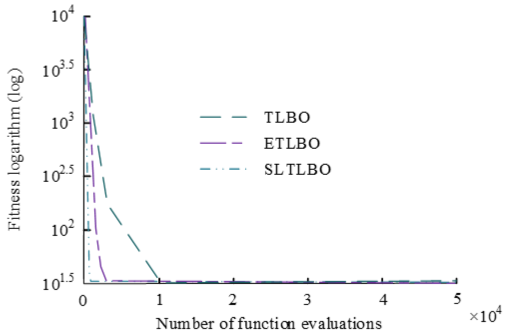
The function evaluations of the experiment are 50000 times, and the dimension is 30. Meanwhile, the subgroup in the MCITLBO algorithm is M1=5. The individual in each subgroup is M2=20. The population size of other algorithms is 50. The convergence curves of each algorithm on unconstrained functions are shown in Figure 4.6. From Figure 4.6, on function f_5, when the function evaluations are 5000, the fitness logarithm of MCITLBO algorithm is the lowest, indicating it has faster convergence speed. Meanwhile, on function f_6, the MCITLBO tends to converge when the function evaluations are 0.1×10^4. The TLBO only tends to converge at 1.0×10^4. The MCITLBO has a significantly faster decline rate in fitness values on f_5 and f_6 compared to other algorithms, with the fastest convergence speed and higher optimization accuracy.

The runtime of the algorithm on unconstrained test functions is further validated. The MCITLBO and TLBO algorithms independently run 50 times on function f_5. The average CPU consumption time is recorded. The runtime of different algorithms on various functions with dimensions of 30 and 100 is shown in Figure 4.7. In Figure 4.7, when the dimension is 30, the average running time of the MCITLBO algorithm on function f_5 is 1.03s. The ratio to the TLBO algorithm is 1.19. When the dimension is 100, the average running time of the MCITLBO algorithm on function f_5 is 2.86s. The ratio to the TLBO algorithm is 1.16. From this, as the dimension of the function increases, the complexity of each algorithm increases and the running time increases. However, the running time ratio of MCITLBO algorithm to TLBO has decreased. As the complexity of the fitness function increases, the proportion of operators in the entire running time decreases. In addition, MCITLBO can provide higher solution accuracy, and the runtime ratio to TLBO algorithm is relatively low. Therefore, the MCITLBO algorithm has stronger feasibility.

5. Conclusion. The TLBO algorithm is currently widely used for solving optimization problems in various fields. In response to the low solution accuracy and weak local search ability, SLTLBO algorithm and MCITLBO

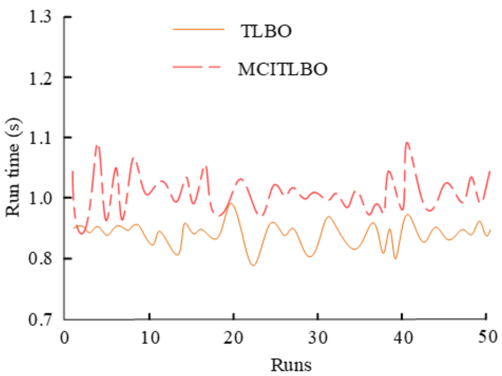


(a) The fitness convergence curve of function f5

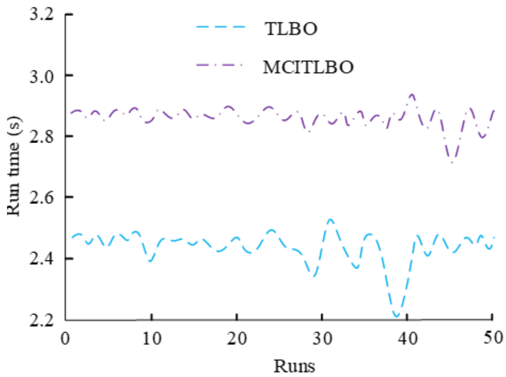


(b) The fitness convergence curve of function f6

Fig. 4.6: Convergence curves of various algorithms on unconstrained functions



(a) Running time of different algorithms in 30 dimensions



(b) Running time of different algorithms in 50 dimensions

Fig. 4.7: The running time of different algorithms in different dimensions

algorithm are introduced to improve the algorithm performance. In the experiment testing the SLTLBO algorithm, when the dimension is 50, the average function evaluations of the SLTLBO algorithm on the unimodal function f_1 are 5093. On the multimodal function f_2, the average function evaluations for the SLTLBO are 5929. On the two rotation functions, the average function evaluations for the SLTLBO are 4813 and 1368, respectively. Meanwhile, the success rate of the algorithm on each function is 100%. In the performance experiment to verify the MCITLBO, the optimization speed of the MCITLBO is faster. It reduces the search space to $[-2\times10^{-25},2\times10^{-25}]^2$ when it iterates to 100 times. At the same time, compared to the TLBO algorithm, the population distribution of MCITLBO is more dispersed, indicating that the MCITLBO algorithm has better population diversity. In addition, when the dimension is 30, the average running time of the MCITLBO algorithm on function f_5 is 1.03s. The ratio to the TLBO algorithm is 1.19. When the dimension is 100, the average running time of the MCITLBO algorithm on function f_5 is 2.86s. The ratio to the TLBO algorithm is 1.16. The two improved algorithms proposed have significant performance advantages and stronger feasibility in solving engineering problems. However, the research does not consider the balance between the global and local search capabilities. Therefore, further improvement is needed.

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