J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 9017--9033

Journal of Combinatorial Mathematics
and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Design of a multi-objective optimization model of blended teaching for the improvement of music teachers' teaching ability

Yufeng Li[1,✉]

[1] *College of Music, Bohai University, Jinzhou, Liaoning, 121000, China*

ABSTRACT

Teaching optimization algorithm is a new type of group intelligence algorithm, which simulates the teaching process of teachers, and this paper improves the algorithm to realize the improvement of music teachers' teaching ability. Aiming at the shortcomings of the teaching optimization algorithm which is easy to mature prematurely, has low solution accuracy and converges to the local optimum, this paper proposes a teaching optimization algorithm which integrates the improved Tennessee whisker search. The algorithm combines Tent mapping and inverse learning strategy to initialize the population and improve the quality of the initial population. Tennessee whisker search is performed on teachers to improve their teaching ability. Incorporating the hybrid variation operator into the individual student variation formula allows the algorithm to quickly jump out of the local optimum dilemma. The experimental results show that the hybrid teaching optimization algorithm based on BASTLBO proposed in this paper has good solution accuracy and robustness in finding the optimum on different types of optimization problems. The algorithm in this paper can achieve better teaching ability results than the unimproved TLBO algorithm and the teaching optimization algorithm incorporating the hippocampus strategy, and the objective function on two different indexes is reduced by 8.75% and 7% compared with that of the TLBO algorithm, respectively, and the hybrid teaching multi-objective optimization model designed in this paper has stronger practicality.

Keywords: Tennessee whisker search, Tent mapping, population initialization, pedagogical optimization algorithms, music teachers' pedagogical competence

1. Introduction

With the rapid development of information technology, the field of education has also ushered in unprecedented changes. The blended teaching model has emerged, which combines traditional

✉ Corresponding author.
E-mail address: 13941614083@163.com (Y. Li).
Received 20 February 2024; Revised 15 April 2024; Accepted 20 November 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-495

classroom teaching with modern information technology to provide students with a more flexible and efficient way of learning. Music, as an emotional and creative art discipline, can also be integrated into the concept of blended learning to bring a new experience for students' music learning [1-2].

First of all, blended teaching emphasizes students' personalized learning, through the organic combination of online platform and offline classroom, students can independently choose the learning content and methods according to their own learning progress and interests. In the music classroom, students can learn music theory, such as music theory, harmony, etc. on the online platform, and consolidate what they have learned through practical sessions offline. Secondly, blended teaching integrates teaching resources, and teachers can make full use of online resources, such as video, audio, etc., to enrich the teaching content and improve teaching efficiency and teachers' teaching ability. At the same time, the online platform can provide students with instant feedback, help students correct their mistakes in time, and improve the learning effect [3-6]. In addition, under the blended teaching mode, teachers and students interact more frequently, which helps to stimulate students' interest in learning and cultivate their independent learning ability. Blended teaching also helps to encourage students to carry out innovative learning, through the integration of online platforms and offline classrooms, students can be exposed to more musical styles and works, broaden their horizons, and improve their innovative ability. In the music classroom, students can try to create their own musical works and develop music creation ability [7-8].

Literature [9] proposes the application of a blended learning approach in the teaching of Oriental music and investigates its impact on the improvement of students' SATM ability. Experiments based on students from several schools showed a significant improvement in students' performance under the blended learning model. Literature [10] emphasizes the great potential of technology in education and discusses the results of using an online music education program in a blended learning environment, a program that can provide high quality music learning resources to schools in remote areas. Literature [11] aims to explore music teachers' experiences and perceptions of blended learning. A multi-case study approach was used to survey music teachers in different schools. The results showed that teachers agreed with the educational effects of blended learning, but expressed concerns about motivational factors and teacher education, and made related recommendations. Literature [12] aimed to find out how student teachers learn the music theory needed by music teachers, and the results pointed out the advantages of blended learning and the application of blended learning by students, but students did not find every blended element useful. Literature [13] describes a survey conducted by two pre-service teachers on their students' understanding of BL. After a long period of data collection, the results showed that most of the students had very little understanding of BL prior to this, and that there was a qualitative improvement based on the BL experience. Literature [14] examined a number of research themes including the effectiveness of music learning in a blended learning environment, and by launching a survey with a number of students, it was emphasized that student performance improved in the blended environment and that students rated the blended learning environment highly. Literature [15] aimed to document the experience of teaching music in a blended, face-to-face and online synchronous environment during the epidemic. Embodying the voice of a practicing teacher, teaching and learning in a blended environment informs music teachers. Literature [16] identifies the problems of teaching music in the preschool program in higher education and initiates a study of teaching music in the preschool program in higher education based on the blended teaching model, with the aim of achieving the goal of training comprehensive and applied music teachers in preschool education. Literature [17] reveals the application and positive impact of ICT in music education, and points out that this process is faced with many challenges, such as “improving teachers' information literacy”, and puts forward corresponding measures and future development direction. Literature [18] takes libraries as the research object and discusses the blended learning strategy of preschool music education. It emphasized that online and offline blended teaching is conducive to the provision of high-quality early childhood education, and suggested that colleges and universities should strengthen the training of online educators. Literature [19] compared the effects of online music learning and blended music learning during the new crown. A comparative experiment based on college students pointed out that personalized blended learning was more effective than online learning. It provides a reference for designing and implementing online or blended music courses.

The Teaching-Learning-Based Optimization (TLBO) algorithm has a strong local search capability, but it is unable to perform a fine-grained local search on the space where it is located. In this paper, Tent mapping and backward learning mechanism are introduced into TLBO algorithm to increase the diversity of the population, and Tennessee whisker search is used to make the search approach the optimal solution quickly. In the TLBO algorithm, the use of Cauchy function and Gaussian function is adopted to reduce the running time of the algorithm, and at the same time to ensure that the algorithm can jump out of the local. The BASTLBO algorithm was tested with sixteen different test functions to show that it has good performance in finding the optimal solution. Then the BASTLBO algorithm is used to optimize the teaching ability of music teachers. The results of simulation experiments are utilized to confirm the effectiveness of the BASTLBO algorithm.

2. Multi-Objective Teaching Competency Enhancement Model for Music Teachers

2.1. Types of Teaching Competency Enhancement for Music Teachers

Teaching ability improvement can be divided into teachers' teaching ability, students' learning quality and teaching management quality according to the main body. From the type of teaching, it can be divided into theoretical teaching ability and practical teaching ability. From the feedback type of teaching ability, the quality can be divided into teaching reward and teaching punishment.

2.2. Common indicators

With reference to the common teaching competence index system of Chinese universities, the following indicators are summarized, in which each first-level indicator can be divided into three second-level indicators.

Indicator 1 Teaching Ideology (T_1): including targeting characteristics (t_{11}), cultivating qualities (t_{12}), student body (t_{13});

Indicator 2 Teaching attitude (T_2): including teacher's morality (t_{21}), classroom discipline (t_{22}), lecture program (t_{23});

Indicator 3 Teaching content (T_3): including clear basic knowledge (t_{31}), highlighting important and difficult knowledge (t_{32}), looking forward to the cutting-edge trend of the discipline (t_{33});

Indicator 4 Teaching methods (T_4): including diversification of teaching methods (t_{41}), use of modern technology (t_{42}), focus on the development of students' abilities (t_{43});

Indicator 5 Teaching organization (T_5): including strict requirements (t_{51}), good classroom order (t_{52}), teaching according to progress (t_{53});

Indicator 6 Teaching effect (T_6): including the degree of students' mastery (t_{61}), students' interest in knowledge (t_{62}), students' application ability (t_{63});

2.3. Modeling

Each indicator takes on a different value at different universities or for different programs. First assume that there are N subjects denoted respectively as $C_1, C_2, \ldots, C_N$ any subject C_i teaching ability $E(C_i)$ can be expressed in the form shown in equation (1):

$$E(C_i) = \sum_{i=1}^{6} \alpha_{ij} = T_j(C_i) \tag{1}$$

In equation (1), $T_j(C_i)$ represents the subject C_i, the conclusion on the j rd level indicator, α_{ij} represents the weight coefficient of C_i on the j th level indicator, $\alpha_{i,1}$ is a predetermined value in relation to a specific course or situation, and there $\sum_i = 1^6 \alpha_{ij} = 1$. $T_i(C_i)$ can be expressed as shown in equation (2).

$$T_j(C_i) = \sum_{k=1}^{3} \beta_{jk}(C_i)\, t_{jk}(C_i) \tag{2}$$

In equation (2), $\beta_{jk}(C_i)$ represents the weight of subject C_i on the k th secondary indicator of the j rd primary indicator, and there $\sum_k = 1^2 \beta_k = 1, t_k(C_i)$ represents the conclusion of subject C_i on the k th secondary indicator of the j th primary indicator. At this point the expectations of the teacher, the main implementer of teaching, for outcome R can be expressed in the form shown in equation (3).

$$R = \begin{cases} \max \quad \sum_{i=1}^{k} \alpha_{1/}\left(\sum_{k=1}^{3} \beta_{jk}(C_1) t_{jk}(C_1)\right) \\ \max \quad \sum_{i=1}^{k} \alpha_{3/}\left(\sum_{k=1}^{3} \beta_{jk}(C_2) t_{jk}(C_2)\right) \\ \quad\quad \cdots\cdots \\ \max \quad \sum_{i=1}^{k} \alpha_{N}\left(\sum_{k=1}^{3} \beta_{jk}(C_N) t_{jk}(C_N)\right) \end{cases} \tag{3}$$

Equation (3) indicates that the teacher's expectation of the result is that all indicators reach the maximum value, i.e., there are N expressions maximized at the same time, and the problem belongs to a typical multi-objective optimization problem. This paper adopts the single-objective optimization transformation method, using linear weighting and means of formula (3), when the final result SCORE can be expressed as the form shown in formula (4).

$$SCORE = \sum_{i=1}^{N} \gamma_i \sum_{j=1}^{6} \alpha_{ij} \left(\sum_{k=1}^{3} \beta_{jk}(C_i) t_{jk}(C_i)\right) \tag{4}$$

In Eq. (4), γ_i indicates the weight of the conclusion of subject C, with $\sum_{i=1}^{\wedge} \gamma = 1$. According to the description of Eqs. (1)~(4), it is easy to prove the final result $SCORE \in [0,100]$.

There are three kinds of weight coefficients in the model proposed in this paper, which are $\alpha_{ij}, \beta_{jk}(C_i)$ and γ, where $\alpha_{ij}, \beta_{jk}(C_i)$ are set uniformly, i.e., $\alpha_{ij} = 1/6, \beta_{jk}(C_i) = 1/3$. In the following, we focus on the setting of γ, and in setting the weights of different subjects, we should firstly reduce the weights of the subjects that have a large deviation from the mean, and the codified rate of difference is expressed as shown in Equation (5).

$$\frac{|E(C_i)-\sum_{i=1}^{N}E(C_i)/N|}{\sum_{i=1}^{N}E(C_i)/N}>\zeta \tag{5}$$

Equation (5), the left indicates the subject C_i conclusion of the deviation rate, ζ indicates the deviation rate of the threshold, when the deviation rate exceeds ζ indicates that the subject error may be larger, then reduce the weight of the subject. Do not prevent the conclusion of χ subjects to meet the inequality (5), χ subjects of the proportion of φ, the larger the deviation value of the proportion of the subject is lower, then one of the subject C, the weight γ. As shown in Equation (6).

$$\gamma_v=\frac{|E(C_p)-\sum_{i=1}^{N}E(C_i)/N|}{\sum_{p=1}^{N}|E(C_p)-\sum_{i=1}^{N}E(C_i)/N|}\varphi \tag{6}$$

The weights of the other subjects, γ, will evenly split the remaining total weight $I-\phi$, expressed as shown in Equation (7).

$$\gamma_i=\frac{1-\varphi}{N-\chi} \tag{7}$$

3. Instructional optimization algorithms incorporating improvements in the search for aspen whiskers

3.1. *Teaching Optimization Algorithm*

The TLBO algorithm [20] is simple to implement and its best features are simple setting of algorithm parameters, fast convergence and high search accuracy. The TLBO algorithm requires only 2 control parameters to be set - population size, maximum number of iterations. Therefore, the teaching optimization algorithm has received widespread attention and is used in many fields.

The specific implementation steps of TLBO algorithm are as follows:

Step 1: Initialize the number of students P_n, the maximum number of iterations $G_{\max}$, the number of courses D_n, and the upper and lower bounds of course grades (U_L, L_L); a student j has a grade of $X^j=(x_1^j,x_2^j,\cdots,x_{D_n}^j), j=1,2,\ldots,P_n$ in each subject

Step 2: Initialize the population, i.e., all students and teachers form a class, expressed in the following matrix:

$$Class=\begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_{D_n}^1 \\ x_1^2 & x_2^2 & \cdots & x_{D_n}^2 \\ \vdots & \vdots & & \vdots \\ x_1^{P_n} & x_2^{P_n} & \cdots & x_{D_n}^{P_n} \end{bmatrix} \tag{8}$$

where the column means of the matrix represent the average scores of all students in different courses M_i.

Step 3: Assume that the distribution of students' performance in the class satisfies a normal distribution with distribution function $f(X)=\frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-(x-\mu)^3}{2\sigma^2}}$, σ^2 is the variance, and μ is the performance mean. Select the student with the best performance (optimal fitness value) in the class as the teacher $X_{teacher}$.

Step 4: The first stage of the algorithm - the teaching process. The students' performance is relatively low, and their mean score is Mean, and the best performing T_A at this point serves as the teacher. After a certain period of time, the student's performance will be raised to a level close to the teacher's performance $Mecm_B$. At this point, it is difficult for teacher T_A to take on the role of teaching, and the teacher is replaced by T_B, who has the best performance at this point in the algorithm. In the first process, the improvement of students' performance is mainly realized by the difference between the teacher's performance and the students' average score. To wit:

$$Different_m ean_i = r_i(X_{teucher} - T_F \cdot M_t) \tag{9}$$

where r_i is a random number in the range [0, 1]; and the teaching factor $T_i = round[1 + rand(0,1)\{2-1\}]$, which is a random value between 1 or 2.

An update formula for the teaching process is derived:

$$X_{new} = X_{old} + Different\_mean_i = X_{old} + r_i(X_{teacher} - T_F \cdot M_i) \tag{10}$$

Step 5: The second phase of the algorithm I a learning process, any two students are selected to communicate, report, discuss, etc., so that the current student acquires more knowledge from the better classmates and thus improves his/her grade. Randomly select two students X_i and X_j, when X_i after the teaching process after the grade X_i' is better than X_j after the teaching process after the grade X_j', using the following formula to update the current grade becomes X_{mew}:

$$X_{new} = X_{old} + r_i(X_i - X_j) \tag{11}$$

Otherwise, if X_j has a better grade X_j', after the teaching process, the grade is updated using the following formula:

$$X_{new} = X_{old} + r_i(X_j - X_i) \tag{12}$$

The updated score cannot be taken as the final score and a comparison of fitness values is required to determine it. If and only if the fitness value of X_{new} is better than that of X_{old}, the update operation is performed on X_{old}, otherwise the original value is retained.

Step 6: If the termination condition is satisfied then end and output the final result. Otherwise return to step 4.

The flowchart of the basic TLBO algorithm is shown in Fig. 1.

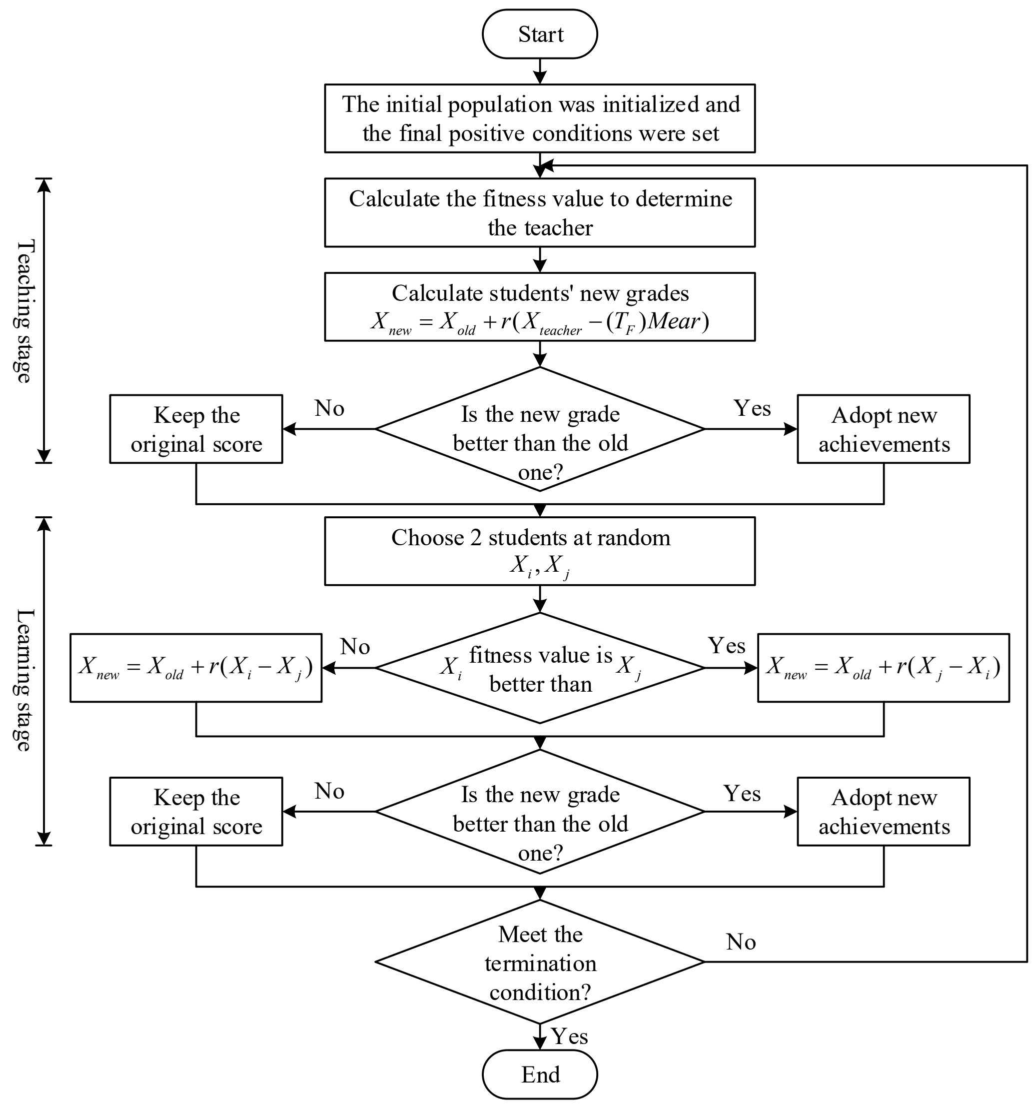

Fig. 1. Flowchart of basic teaching optimization algorithm

3.2. Population initialization strategies

In order to enhance the diversity of the population, the population initialization strategy [21] is integrated with the pedagogical optimization algorithm, and in the BASTLBO algorithm, the Tent mapping is first used to generate the chaotic initial population, then the inverse population is generated by backward learning, and finally, the chaotic initial population and its inverse population are sorted, and the solution with the better fitness value is selected from them to form the initial population.

The formula for Tent mapping to generate chaotic particle sequences is defined as follows:

$$x_{id}^{t+1} = \begin{cases} 2x_{id}^{t}, x_{id}^{t} \in [0, 0.5] \\ 2(1 - x_{id}^{t}), x_{id}^{t} \in (0.5, 1.0] \end{cases} \tag{13}$$

where x_{id}^{t} denotes the chaotic variable of the tnd iteration particle i in the d th dimensional component, $t = 1, 2, \cdots, T, d = 1, 2, \cdots, D$.

The chaotic sequence composed of t chaotic variables $Y_t = (Y_{t,1}, Y_{t,2}, \cdots, Y_{t,D})$ can be obtained by iterating T times, and then after the inverse mapping, the t initial solution $X_t = (X_t, 1, X_{t,2}, \cdots, X_{t,D})$ can be obtained, which is denoted as the population X.

$$X_{t,d} = X_{\min} + Y_{t,d} * (X_{\max} - X_{\min}) \tag{14}$$

where $X_{\max}$ and $X_{\min}$ come from the range of values $[X_{\min}, X_{\max}]$ of the search space.

As an effective method to improve the search capability of stochastic search algorithms, the inverse learning (OBL) strategy is based on the principle that if there exists a point $x = (x_1, x_2, \cdots, x_D), x_i \in [a_i, b_i]$ in a D-dimensional space then its inverse point is $x^* = (x_1^*, x_2^*, \cdots, x_D^*)$, where $x_i^* = a_i + b_i - x_i, i \in [1, D]$. Thus the inverse population OX is computed from the population X:

$$OX = X_{\max} + X_{\min} - X \tag{15}$$

Population X and reverse population OX are merged to obtain a new population, i.e., $X_{\text{new}} = \{X \cup OX\}$. Then the objective function values of X_{new} are calculated and sorted, from smallest to largest in case of very small value optimization, and from largest to smallest in case of very large value optimization, and then the top N individuals with the best fitness values are selected as the initial population.

3.3. Improvement of the search for tenebrous whiskers

One obvious disadvantage of the TLBO algorithm is the lack of a learning mechanism for the individual teacher, i.e., the teacher does not search for optimality further, and does not perform a fine-grained local search of the space in which he or she is located. And the tenebrae whisker search (BAS) algorithm [22] is different from other optimization algorithms, which happens to require only one individual, does not need to know the specific form of the function and gradient information can be achieved to efficiently search for the optimal, the amount of operation is small, and the search for the optimal speed is fast. The BAS algorithm process is as follows:

1) Because of the random orientation of the head of the aspens, the vector of the left whisker pointing to the right whisker of the aspens is denoted as:

$$b = \frac{rands(k,1)}{\| rands(k,1) \|} \tag{16}$$

where $rands(k,1)$ denotes the generation of a k-dimensional random vector.

2) Set the step size of the asp δ, which is decreasing in a linear manner, and t is the current number of iterations, then the step size of the asp move at the tth iteration is:

$$\delta^t = eta_\delta^* \delta^{t-1} \tag{17}$$

where eta_δ is the step decreasing coefficient.

3) Set the distance between the two whiskers of the tenebrous oxen d, also decreasing in a linear manner, with a decreasing factor of eta_d. The distance between the two whiskers at the tth iteration is:

$$d^t = eta\_d * d^{t-1} \tag{18}$$

4) The left and right whiskers of the tenrecs are positionally updated:

$$\begin{cases} x_l = x^t + d^t * b \\ x_r = x^t - d^t * b \end{cases} \tag{19}$$

In the formula, the left whisker x_l and the right whisker x_r are k-dimensional vectors, and x^l denotes the position of the center of mass of the tenebrae at the tth iteration.

5) Calculate the fitness values $f(x_l)$ and $f(x_r)$ of the left and right whiskers x_l and x_r, and judge the forward direction of the aspis according to the relationship between their sizes:

$$x^t = x^{t-1} - \delta^t * b * \mathrm{sign}[f(x_l) - f(x_r)] \tag{20}$$

where sign is the sign function.

6) Calculate the fitness value after the movement of the aspen.

7) Determine whether it meets the end of iteration condition, if it meets, end the iteration, otherwise repeat 1) to 6) until it meets the condition.

Although the principle of the BAS algorithm is simple and the convergence speed is fast, the ability of individual tensors to find the optimal in the high-dimensional space is still lacking, and it is easy to fall into the local optimum, and it is necessary to improve it. Therefore, the quadratic interpolation operator is introduced:

$$x_{ik} = \frac{1}{2} \times \frac{(x_{lk}^2 - x_{bk}^2) f(x_r) + (x_{bk}^2 - x_{rk}^2) f(x_l) + (x_{rk}^2 - x_{lk}^2) f(x_b)}{(x_{lk} - x_{bk}) f(x_r) + (x_{bk} - x_{rk}) f(x_l) + (x_{rk} - x_{lk}) f(x_b)} \tag{21}$$

where k denotes the dimension and x_b is the current global optimal solution.

Using the quadratic fit function method, at each update of the aspen position, a new solution x_i different from the current solution x^t can be obtained by using quadratic interpolation, comparing their fitness values, and if $f(x_i) < f(x^t)$, replacing the current aspen position with the new position generated by the quadratic interpolation, or else keeping the current position.

Although the improved BAS algorithm has increased the ability of high-dimensional optimization search, the optimal point searched by the algorithm is not necessarily the global optimal point. Therefore, two termination conditions should be set for BAS to ensure the overall search efficiency of the algorithm: the first one is the accuracy of the solution; considering that in the process of solving some problems, the BAS algorithm may iterate many times even if the accuracy requirement is low, so the second one is to set a fixed number of iterations. When the precision reaches the requirement or the number of iterations reaches the set value, the search is completed and the obtained points are directly applied to replace the teacher individuals.

3.4. Mixed variability of students

From the probability distribution characteristics of Gaussian variation, Cauchy variation itself and the application effect in other optimization algorithms, it can be seen that Gaussian variation can give the algorithm a better local search ability, and Cauchy variation has a strong global exploration ability, so it can be combined with the characteristics of the two, and through the mixed variation to make the teaching-learning optimization algorithm adaptive to regulate the effect of mutual learning between students. Random vectors obeying the mixed-variance distribution are introduced into the individual student update formula, as shown in equation (22).

$$x_i^{new} = \begin{cases} x_i^{old} + rand(x_i^{old} - x_j^{old}) + (\alpha(t) + \gamma(t)) * rand, f(x_i) < f(x_j) \\ x_i^{old} + rand(x_j^{old} - x_i^{old}) + (\alpha(t) + \gamma(t)) * rand, f(x_j) < f(x_i) \end{cases} \tag{22}$$

In the process of algorithmic generation selection, stronger local search ability is needed in the early stage so that the algorithm can quickly converge to the neighborhood of the global optimum and save the algorithm optimization search time. In the later stage, in order to make TLBO escape from the bound of local extremes and avoid premature convergence, it is necessary to strengthen the global exploration ability of the algorithm, so the TLBO algorithm focuses on Gaussian variation in the early stage and Cauchy variation in the later stage. $\alpha(t)$ and $\gamma(t)$ with the iterative process are calculated as follows:

$$\alpha(t) = \left(1 - \frac{t}{T}\right) \times G(0,1) \tag{23}$$

$$\gamma(t)=\frac{t}{T}\times C(0,1) \tag{24}$$

where t is the current number of iterations, T is the maximum number of iterations of the algorithm, $G(0,1)$ is the standard Gaussian distribution, and $C(0,1)$ is the Cauchy distribution.

3.5. Steps of the BASTLBO algorithm

Step 1: Starting with individual $X_0(0)$, iterate to obtain chaotic population X, and population X iterates to obtain its inverse population OX. Order $X_{\text{new}}=\{X\bigcup OX\}$, calculate the objective function value of X_{new} and sort it, and select the first N individuals with the best fitness value to form the initial population POP(0).

Step 2: Calculate the fitness value, select the best individual, set as teacher $x_{teacher}$, and calculate the class mean x_{mean}.

Step 3: Perform Tennessee whisker search for teacher individual $x_{teacher}$. Set the initial parameters related to the improved BAS algorithm, the number of iterations $t=0$, perform the tenno iteration, and determine whether the termination condition of the BAS algorithm is satisfied, if yes, go to the next step, otherwise continue the iteration.

Step 4: Update the individual teacher $x_{teacher}=x^t$.

Step 5: Perform teacher's “teaching” behavior.

Step 6: Perform mutual “learning” behavior of students.

Step 7: If the BASTLBO algorithm satisfies the end condition, then output the optimal solution X_{gbest} and end the algorithm, otherwise return to step 2.

4. Experimental simulation tests

In order to check the performance of this paper's algorithm, it is simulated with seven other excellent algorithms DIHS, HIS, RCGHS, TLBO, ITLBO, MTLBO, and TLBO-GC on 16 different types of standard test functions. Among them, F1 to F3 are single-peak functions,, F4 are hybrid functions, F5 to F12 are complex multi-peak functions, and F13 to F16 are shift operations on four classical multi-peak functions, and these different types of standard functions can test the generalization of the algorithms well.

Figures 2 and 3 show the average convergence curves of eight algorithms for 30 independent runs on two different functions, respectively. From the convergence curve graph, it is easy to see that the convergence curve of this paper's algorithm for the two complex optimization functions shows a downward trend, and the convergence effect is significantly better than other algorithms, indicating that the global search ability of this paper's algorithm is stronger, and it is not easy to fall into the local optimum.

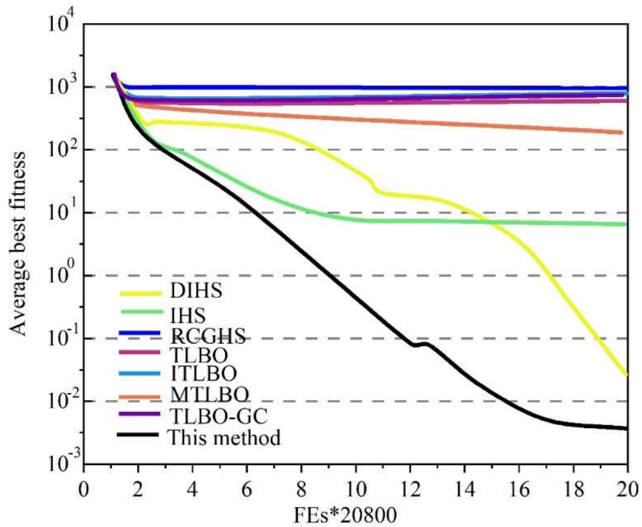

Fig. 2. Schaffer shift function

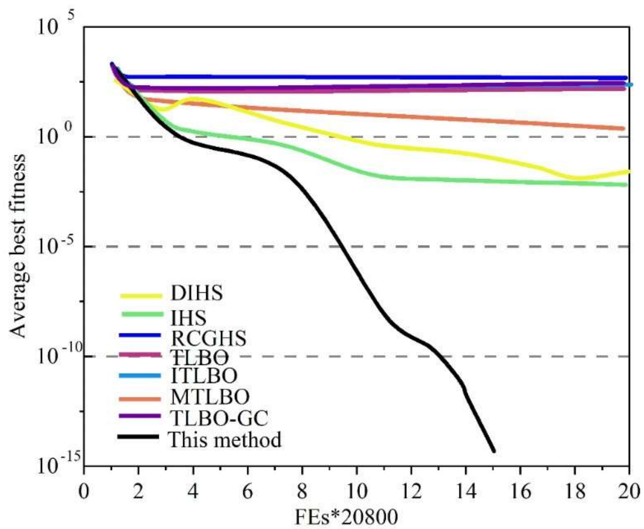

Fig. 3. Rastrigin shift function

In order to test the difference between the proposed algorithm and the comparison algorithm, Table 1 shows the P-value value of the Wilcoxon signed-rank test of the results of 30 independent runs of the proposed algorithm and the seven comparison algorithms on 16 test questions, and "-", "+" and "≈" indicate that the performance of the comparison algorithm is "poor", "good" and "equivalent" compared with the proposed algorithm (NaN indicates that there is no difference in the performance of the algorithm). The seven comparison algorithms are not superior to the proposed algorithm in the test problems, DIHS is comparable to the proposed algorithm in 6 problems, IHS algorithm is comparable to the proposed algorithm in 7 problems, and RCGHS, TLBO and ITLBO algorithms are comparable to the proposed algorithm in 6 problems. It can be seen that there are significant differences between the proposed algorithm and the comparison algorithm in most of the test problems, which has obvious statistical significance.

Table 1. Wilcoxon rank test of the p-value (D=100)

Function	DIHS	IHS	RCGHS	TLBO	ITLBO	MTLBO	TLBO-GC
F1	6.35E-05	6.35E-05	NaN	NaN	NaN	6.35E-05	NaN
F2	6.35E-05	6.35E-05	NaN	NaN	NaN	6.35E-05	NaN

F3	1.76E-04	1.76E-04	1.76E-04	1.78E-04	1.78E-04	1.78E-04	1.78E-04
F4	6.13E-05	1.77E-03	1.77E-04	1.73E-04	1.78E-04	2.72E-01	1.78E-04
F5	8.74E-05	8.42E-05	1.23E-04	9.16E-05	9.16E-05	7.58E-05	1.19E-04
F6	NaN	3.65E-01	NaN	NaN	NaN	7.79E-02	NaN
F7	1.81E-04	1.83E-04	1.88E-04	1.89E-04	1.83E-04	1.83E-04	1.83E-04
F8	6.34E-05	6.32E-05	NaN	NaN	NaN	6.39E-05	NaN
F9	NaN	1.41E-02	NaN	3.68E-01	NaN	6.39E-05	7.79E-02
F10	1.73E-03	2.11E-01	1.82E-04	1.84E-04	1.84E-04	1.84E-04	1.84E-04
F11	NaN	NaN	6.33E-05	6.33E-05	6.33E-05	6.33E-05	6.33E-05
F12	NaN	NaN	6.36E-05	6.36E-05	NaN	6.36E-05	6.36E-05
F13	1.73E-03	2.13E-01	1.81E-04	NaN	1.81E-04	1.81E-04	NaN
F14	3.64E-01	NaN	6.38E-05	6.38E-05	6.38E-05	NaN	6.38E-05
F15	4.52E-01	8.38E-03	NaN	1.12E-04	1.12E-04	1.12E-04	1.12E-04
F16	1.25E-01	1.85E-04	1.85E-04	1.85E-04	1.85E-04	1.85E-04	1.85E-04
-	10	9	10	10	10	13	12
+	0	0	0	0	0	0	0
$\approx$	6	7	6	6	6	3	4

In order to further analyze the dynamic selection strategy designed by the algorithm in this paper, single-peak and complex multi-peak functions were selected for testing, respectively. Figure 4 shows, and Figure 5 shows the dynamic selection probability change curves of single-peak and complex multi-peak functions, respectively. The dynamic selection strategy can dynamically choose the appropriate update strategy to meet the needs of different evolutionary stages according to the characteristics of the optimization problem and the specific performance of the two optimization algorithms in the iterative process. For a single-peak function such as Sphere function, the TLBO algorithm dominates the whole optimization process due to its good convergence ability, and the selection probability is significantly higher than that of the HS algorithm. For complex multi-peak functions like Schwefel2.26 function, global search is required in the early stage of evolution due to the existence of multiple local minima, and the HS algorithm obtains a higher selection ratio because of its stronger global search capability, which can quickly locate the effective region of the optimal solution. As the iteration proceeds, the selection probabilities of the two algorithms slowly converge and alternate. In the later part of the iteration, the selection probability of the TLBO algorithm increases, and it mainly performs fine search to improve the accuracy of the solution. During the iteration process, both algorithms maintain a certain selection ratio, and the HS algorithm is able to maintain the diversity of the population, while the TLBO algorithm is able to accelerate the convergence speed and improve the accuracy of the solution.

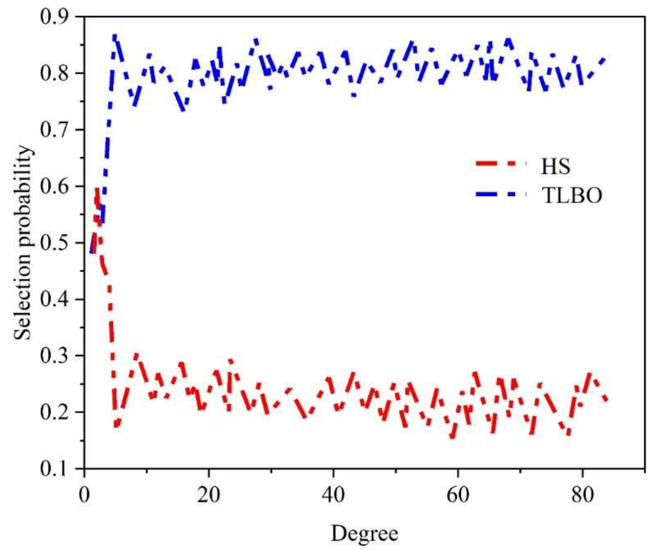

Fig. 4. Schaffer function

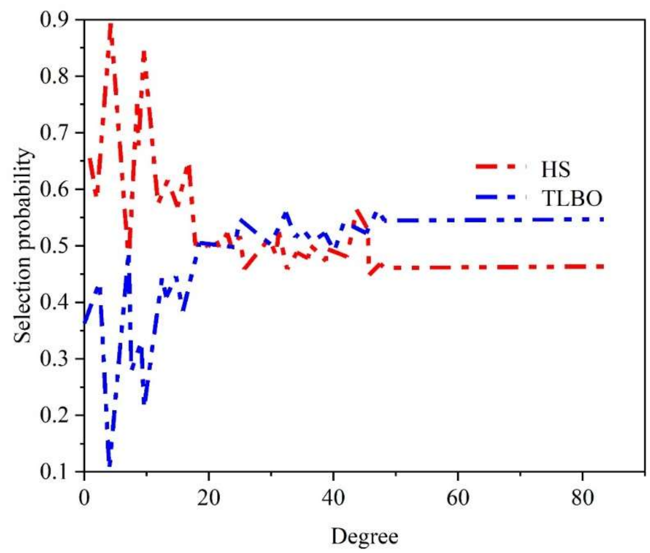

Fig. 5. Rastrigin shift function

5. Analysis of the effectiveness of the enhancement of teaching capacity

Based on the BASTLBO algorithm to optimize the design of music teachers' multi-objective teaching ability, under the same conditions, the most representative indicators of music teachers' teaching ability enhancement, i.e., teaching methods and teaching effects were selected to optimize the teaching ability by combining the TLBO algorithm and BASTLBO algorithm, respectively; the optimization curves of the teaching methods and the teaching effects were shown in Figures 6 and 7, respectively, and the optimization results were compared with the optimization results of the integration of the hippocampus strategy of teaching optimization algorithm (SHOTLBO) for comparison, and the results are shown in Table 2.

In the teaching method optimization curve, the BASTLBO algorithm reaches its target function value of 6.3758 after 15 iterations, while the TLBO algorithm reaches its target function value of 6.987 after 20 iterations.The BASTLBO algorithm's iterative speed is still superior to the TLBO algorithm in the optimization curve of the teaching effect, and it quickly reaches its target function value of 6.4152, while the TLBO algorithm is relatively slower to reach its objective function value of 6.8979.In conclusion, the BASTLBO hybrid algorithm outperforms the basic TLBO algorithm in optimizing the results under different loading scenarios, and the optimization results are more desirable.

In terms of teaching methods, the objective functions of TLBO algorithm, SHOTLBO algorithm, and BASTLBO algorithm are 6.9870, 6.4987, and 6.3758, respectively, which indicates that the BASTLBO algorithm optimizes a better result, 8.75% less than the TLBO algorithm and 1.89% less than the SHOTLBO algorithm. In terms of teaching effect, the objective function of TLBO algorithm, SHOTLBO algorithm and BASTLBO algorithm are 6.8979, 6.4951, 6.4152 respectively, and the BASTLBO algorithm optimizes the better result, which is reduced by 7% compared to the TL-BO algorithm, and 1.23% compared to the SHOTLBO algorithm, indicating that the BASTLBO algorithm has the characteristic of high efficiency in searching .

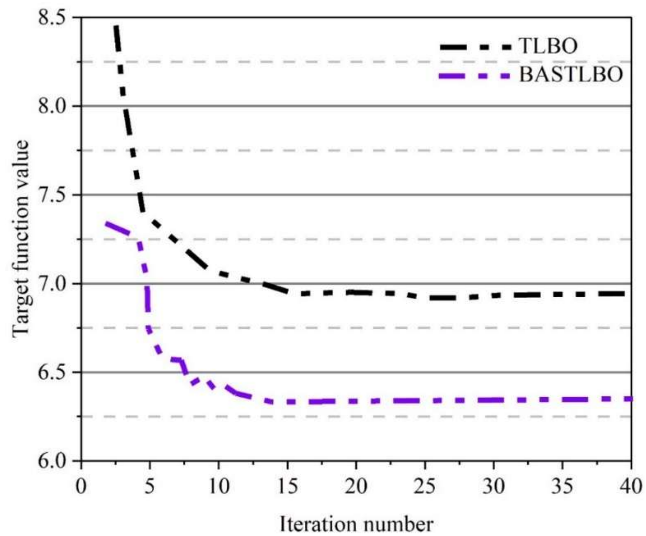

Fig. 6. Optimization curve of teaching method

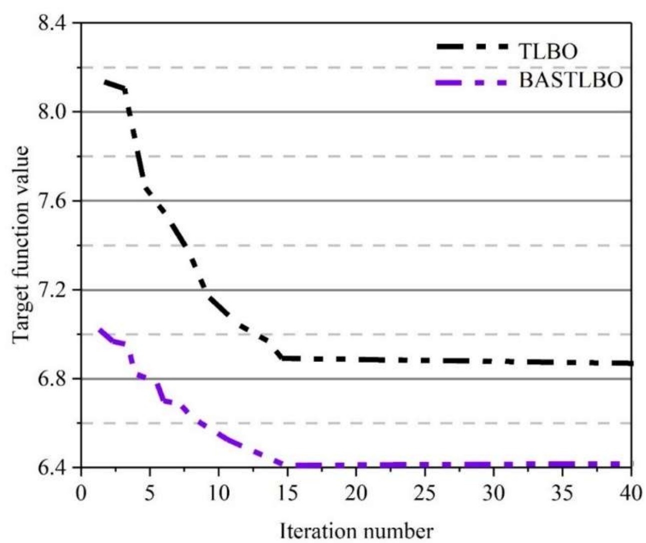

Fig. 7. Teaching effect optimization curve

Table 2. Optimized result

Optimization aspect	Algorithm		
	TLBO	SHOTLBO	BASTLBO
Teaching method	6.9870	6.4987	6.3758
Teaching effect	6.8979	6.4951	6.4152

6. Conclusion

In this paper, based on the basic teaching-learning algorithm, we combine the Tennessee whisker search algorithm with it and propose a hybrid BASTLBO algorithm, which improves the convergence speed of the teaching-learning algorithm.

The algorithm in this paper draws on the strengths of the two algorithms, BAS and TLBO, and complements their strengths with high solution accuracy, excellent stability performance, and the ability to achieve better results on many different types of optimization problems. The algorithm of this paper and the seven comparison algorithms run independently on 16 functions. None of the seven comparative algorithms is better than this paper's algorithm on 16 functions, DIHS, RCGHS, TLBO and ITLBO algorithms are comparable to this paper's algorithm on 6 problems, and IHS algorithm is comparable to this paper's algorithm on 7 problems. The significant difference in performance between this paper's algorithm and the seven proposed comparative algorithms proves that this paper's algorithm is more suitable for solving the multi-objective optimization model for improving the teaching ability of music teachers.

The BASTLBO hybrid algorithm can achieve better computational results than the basic TLBO algorithm and SHOTLBO hybrid algorithm, and the objective function is reduced by 8.75% and 7% respectively compared with the TLBO algorithm in two different teaching ability improvement indexes, which indicates that the BASTLBO algorithm designed in this paper can be applied to the improvement of music teachers' teaching ability, and the hybrid teaching multi-objective optimization model designed in this paper has more satisfactory optimization results. objective optimization model designed in this paper has more satisfactory optimization results.

Funding

This work was supported by

Project type: Ministry of Education Industry-University Cooperation and Collaborative Education Project.

Project name: Design and Practice of Hybrid Teaching System for the Teaching Ability Improvement of Music Teachers.

Project Number: 230806424212238

References

[1] Liu, L. (2024). Problems and Development Strategies of Music Education in Primary and Secondary Schools Based on Network Information Technology. Journal of Electrical Systems, 20(1).

[2] Montgomery, A. P., Mousavi, A., Carbonaro, M., Hayward, D. V., & Dunn, W. (2019). Using learning analytics to explore self-regulated learning in flipped blended learning music teacher education. British Journal of Educational Technology, 50(1), 114-127.

[3] Maharaj, A., & Gill, A. (2023). Technology in Music Education. Canadian Journal of Learning and Technology, 49(2), 1-15.

[4] Liang, Q. (2020, December). Review of the Technology Application in Music Teaching and Learning. In 2020 International Conference on Information Science and Education (ICISE-IE) (pp. 311-314). IEEE.

[5] de León, L. P., & Castro, P. L. (2014). ICT in career guidance. A case study of a "blended learning" career guidance programme for music students. Procedia-Social and Behavioral Sciences, 116, 2049-2058.

[6] Haning, M. (2016). Are they ready to teach with technology? An investigation of technology instruction in music teacher education programs. Journal of Music Teacher Education, 25(3), 78-90.

[7] Jenkins, L. E., & Crawford, R. (2016). The impact of blended learning and team teaching in tertiary pre-service music education classes. Journal of University Teaching & Learning Practice, 13(3), 5.

[8] Ling, S. I. (2023). Music Technology in the 21st Century of Global Music Education: Opportunities and Challenges. In the 14th Asia-Pacific Symposium for Music Education Research (APSMER 2023) (pp. 242-251).

[9] Edward, C. N., Asirvatham, D., & Johar, G. (2019). The impact of teaching Oriental music using blended learning approach: An experimental study. Malaysian Journal of Learning and Instruction, 16(1), 81-103.

[10] Crawford, R. (2017). Rethinking teaching and learning pedagogy for education in the twenty-first century: blended learning in music education. Music Education Research, 19(2), 195-213.

[11] Kim, J. H. (2021). Music teachers' understanding of blended learning in Korean elementary music classes. Music Education Research, 23(3), 311-320.

[12] Hietanen, L., & Ruismäki, H. (2017). The use of a blended learning environment by primary school student teachers to study music theory. The European Journal of Social & Behavioural Sciences, 19(2), 2393-2404.

[13] Jenkins, L. E., & Crawford, R. (2021). Pre-service music teachers' understanding of blended learning: Implications for teaching post COVID-19. Australian Journal of Teacher Education (Online), 46(7), 86-96.

[14] Jiemsak, R. (2021, November). The Efficiency of Music Learning in a Blended Learning Environment of Undergraduate Students In Phranakhon Si Ayutthaya Rajabhat University. In 2021 6th International STEM Education Conference (iSTEM-Ed) (pp. 1-4). IEEE.

[15] Beirnes, S., & Randles, C. (2023). A music teacher's blended teaching and learning experience during COVID-19: Autoethnography of resilience. International Journal of Music Education, 41(1), 69-83.

[16] Zhang, Y. (2021, November). Music teaching practice of preschool major in normal universities based on mixed teaching mode. In International Conference on Forthcoming Networks and Sustainability in the IoT Era (pp. 362-369). Cham: Springer International Publishing.

[17] Sun, H., Abramauskienė, J., Yao, Z., & Sun, B. (2024). The Transformation of Education Paradigm from the Perspective of Music Teachers: The Impact and Application of ICT. Art and Performance Letters, 5(2), 22-28.

[18] Longlong, C., & Luen, L. C. (2023). An In-Depth Blended Learning Strategies for Preschool Music Education in Higher Education. International Journal of Academic Research in Business and Social Sciences, 1(3), 12.

[19] Zhou, Y. (2024). Web-based music learning environment. Interactive Learning Environments, 32(7), 3566-3578.

[20] Zheng Senlin,Xu Haodong,Mukhtar Azfarizal,Hizam Md Yasir Ahmad Shah & Khalilpoor Nima. (2023). Estimating residential buildings' energy usage utilising a combination of Teaching–Learning– Based

Optimization (TLBO) method with conventional prediction techniques. Engineering Applications of Computational Fluid Mechanics(1),

[21] Kaushik Deepika & Nadeem Mohammad. (2023). Confluence metaheuristic: a novel initialization strategy for metaheuristic algorithms. Evolving Systems(2),429-454.

[22] Biao Yin,Liping Mo,Wei Min,Shan Li & Cunwei Yu. (2024). An improved beetle antennae search algorithm and its application in coverage of wireless sensor networks. Scientific reports(1),29372.