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A Multi-Objective Optimization Model for Hybrid Teaching to Improve Music Teachers' Teaching Abilities

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Abstract This paper focuses on the multi-dimensional characteristics of college music teachers' teaching ability, and constructs a four-dimensional evaluation index system containing professional ethics, practical ability, teaching and research ability, and expansion ability. In order to solve the multi-objective collaborative optimization problem, the constrained particle swarm algorithm (TBC-PSO) based on two-stage adaptive angular region division is proposed, which divides the whole optimization process into two stages of adaptive switching, and adopts different optimization strategies respectively. Through the balance of inter-group homogeneity and intra-group heterogeneity, the precise design of teaching ability improvement strategy is realized. The weights of the evaluation index system are determined, and a 16-week blended teaching experiment is carried out with a sample of 15 music teachers in a provincial university. The average value of teachers' teaching ability scores increased from 75.04 to 80.53 after the experiment, and all teachers' teaching ability scores exceeded 78, and 9 out of 15 teachers' comprehensive scores increased by more than 5 points, which verified the effectiveness of this paper's optimization scheme.

Index Terms music teachers, teaching ability, multi-objective optimization, TBC-PSO algorithm

I. Introduction

In order to cultivate a high-quality teaching force, the national education development plan requires strengthening the characteristics of teacher education, implementing the student-centered concept, and enhancing the development capacity of students, so as to improve the quality of curriculum teaching in the context of education in the new era [1]-[3]. Among them, the blended teaching mode is gradually being widely accepted and promoted by virtue of information technology integrating online and offline classrooms [4]. Taking the professional course of musicology as an example, the problems and coping strategies in the application of online and offline blended teaching mode are discussed in order to provide reference for improving the teaching of the professional theory course of musicology.

The application of blended teaching mode in musicology professional theory courses can not only make up for the shortcomings in traditional classroom teaching, but also enrich the content of classroom teaching, and at the same time, improve the initiative and enthusiasm of students' learning [5]-[7]. Compared with the traditional teaching mode, blended teaching emphasizes the teacher to guide students' independent learning by providing more learning styles and finer organizational design [8]. The role of teachers changes from traditional lecturers to designers and guides of teaching, and students change from passive recipients of knowledge to active explorers [9], [10]. In conclusion, the blended teaching mode can provide teachers with more resources and opportunities to improve the level of teachers' informatization teaching, and also can guide students to use network resources for independent learning, which is not only conducive to the professional development of teachers, but also conducive to students' personalized learning [11]-[14]. However, at present, some colleges and universities still have many problems in the design of blended teaching in music education, the development of online teaching platforms, the construction of online teaching resources, etc., and the teaching ability of teachers in the blended teaching mode needs to be further improved.

This paper firstly constructs a multidimensional evaluation index system to systematically portray the core elements of music teachers' teaching ability. The constrained single-objective optimization is carried out with the bi-objective method as the constraint processing method and the MOPSO algorithm as the search mechanism. The standard test function is used to test and verify the superiority of the proposed algorithm in solving multi-modal multi-objective optimization problems. The correlation weight calculation method is used to determine the weight allocation of the evaluation index system, and the weight coefficients of each index are calculated. The effectiveness of the proposed model in real teaching scenarios is examined through empirical analysis.

II. Design of Teaching Ability Enhancement Methods for Music Teachers under the Perspective of Multi-Objective Optimization

As a core component of art education, the quality improvement of music education is highly dependent on the systematic development of teachers' teaching ability. The teaching ability of music teachers in colleges and universities is not the embodiment of a single dimension of skills, but an organic whole covering multi-dimensional characteristics. There is a synergistic relationship between the dimensions of each ability, and there may also be conflicts due to resource constraints, so it is urgent to realize the efficient allocation of resources and balanced enhancement of ability through the multi-objective optimization method.

The enhancement of teaching ability is essentially a multi-objective synergistic optimization problem. How to construct a scientific multi-objective optimization model and seek an optimal solution between inter-group homogeneity and intra-group heterogeneity has become a key challenge in the study of music teachers' teaching ability enhancement. Aiming at the above problems, this study proposes a hybrid teaching multi-objective optimization model for music teachers' teaching ability improvement.

II. A. Construction of the evaluation index system of teaching ability

Using the literature method, this paper collects and organizes relevant literature and national policies, and combines initial expert interviews, music teachers' practical teaching experience and teaching needs to construct a teaching ability evaluation index system for college music teachers consisting of 4 first-level indexes, 8 second-level indexes and 17 third-level indexes. The design of specific indicators is shown in Table 1. The evaluation index system of teaching ability is divided into four dimensions: professional ethics, practical ability, teaching and research ability, and expansion ability, covering eight secondary indicators of teaching awareness, teaching ethics, teaching design ability, teaching implementation ability, teaching application ability, teaching innovation ability, music performance adjudication ability, and music activity guidance ability.

Table 1: Evaluation Index System of Teaching Ability

First-level indicator	Secondary indicator	Third-level indicator
Professional ethics(A1)	Teaching awareness(B1)	Teaching Understanding(C1)
		Teaching willingness(C2)
	Teaching ethics norms(B2)	Maintain a healthy teaching environment(C3)
		Protect students' personal information and privacy(C4)
Practical ability(A2)	Teaching design ability(B3)	Textbook analysis ability(C5)
		Teaching content design ability(C6)
	Teaching implementation ability(B4)	The ability to demonstrate and explain teaching(C7)
		Teaching organization and management ability(C8)
Teaching and research ability(A3)	Teaching application ability(B5)	Theoretical application ability(C9)
		The ability to produce teaching courseware(C10)
		Teaching integration ability(C11)
	Teaching innovation ability(B6)	Innovative ability in teaching ideas(C12)
		The ability to innovate teaching content(C13)
Expansion ability(A4)	Music performance judging ability(B7)	Referee grading improvement(C14)
		Music performance ability(C15)
	Music activity guidance ability(B8)	The ability to teach and guide music activities(C16)
		The ability to organize and guide music competitions(C17)

II. B. Multi-objective problem construction

In the real world there do not exist any single-objective problems, in other words, single-objective problems are defined mainly for the sake of simplicity. This means that most of the time a person just chooses to consider the most important objective and ignores the others, thus transforming a multi-objective problem into a single-objective problem. In addition, sometimes just one objective is chosen and one or more other objectives are considered as constraints. In both cases, the optimization process is simplified and redefined as single-objective optimization. Theoretically, most optimal grouping processes are multi-objective problems and solutions should be designed in a multi-objective framework.

Learning group formation, as a multi-objective optimization problem, is an essential and complex step in effective collaborative learning. The purpose of this study is to propose a method based on a heuristic search strategy to enhance the inter-group homogeneity and intra-group heterogeneity of learning groups in collaborative learning environments, which is capable of grouping an arbitrary number of pre-qualified learners with multiple characteristics into an arbitrary number of optimal inter-homogeneous and intra-heterogeneous learning groups. Here, P learning learners are grouped into Q groups, and the total sample of learners is represented by an array S, where subscripts denote the identity of the learners.

$$S=\{S_1,S_2,S_3,\ldots,S_P\} \tag{1}$$

Assume that each learner is evaluated and qualified with R features. The normalized features of each learner are represented as follows:

$$c(S_i)=\{C_1^i,C_2^i,C_3^i,\ldots,C_R^i\} \tag{2}$$

where C_r^i denotes the normalized score of learner i in feature r.

Normalization eliminates the effect of the magnitude of change in different features during the optimization process. Equation (3) is a linear transformation used to normalize the input features in the range 0 to 1:

$$C_r^i=\frac{C_r^i-Min(C_r)}{Max(C_r)-Min(C_r)} \tag{3}$$

where C_r^i denotes the input score of learner i in feature r before normalization, and $Min(C_r)$ and $Max(C_r)$ are the minimum and maximum values of feature r, respectively.

The focus of this paper is to group a certain number of learners into optimal inter-group homogeneous and intra-group heterogeneous learning populations according to a predetermined number of groups, where the number of groups and the number of learners assigned to each group should not change during the optimization process. The problem of learning group formation focuses on dividing learners into a number of pre-determined groups, each containing the same number of learners, i.e., P/Q. After the initial learning community formation, all learners should be accurately assessed based on one or more well-defined competencies. Therefore, a suitable fitness function needs to be defined that enables a careful grouping of learners based on inter-group homogeneity and intra-group heterogeneity.

Intergroup homogeneity and intragroup heterogeneity were quantified based on the difference between the mean value of each characteristic in the resulting group and the mean value of the same characteristic in the total sample of learners. The mean value of each characteristic in the total sample of learners was calculated and represented by the following array:

$$\overline{c}=\{\overline{c_1},\overline{c_2},\overline{c_3},\ldots,\overline{c_R}\} \tag{4}$$

where $\overline{c_r}$ is the mean of feature r in the total sample.

Then, the mean value of each feature for each group of learners is computed and represented by an appropriate array. For example, the following array represents the mean of the feature computed for the g th group:

$$\overline{c}(G_g)=\{\overline{c_1}(G_g),\overline{c_2}(G_g),\overline{c_3}(G_g),\ldots,\overline{c_R}(G_g)\} \tag{5}$$

where $\overline{c_r}(G_g)$ denotes the mean of the g th group of learner features r.

The total difference between the mean of each feature of learner i and the mean of the total sample of learners, i.e., the mean square error of the learning population, is constructed and can be calculated as follows:

$$MSE(Totai\ Groups)\,|\,i=\left(\frac{1}{R\times Q}\right)\sum\nolimits_{g=1}^{Q}\sum\nolimits_{r=1}^{R}(\overline{c_r}(G_g)-\overline{c_r})^2 \tag{6}$$

It can also be expressed more appropriately by calculating the total mean percentage deviation of learner i in the total sample of learners as follows

$$\begin{aligned}Error(Totai\ Groups)\,|\,i&=\frac{RMSE(Totai\ Groups)\,|\,i}{Max(Error)}\times 100\\&=\sqrt{\left(\frac{1}{R\times Q}\right)\sum\nolimits_{g=1}^{Q}\sum\nolimits_{r=1}^{R}(\overline{c_r}(G_g)-\overline{c_r})^2}\times 100\end{aligned} \tag{7}$$

where RMSE is the root mean square error and $Max(Error)$ denotes the maximum expected error for between-group homogeneity and within-group heterogeneity, which takes the value of 1 considering that all features are normalized between 0 and 1. According to Equation (7), between-group homogeneity and within-group heterogeneity are evaluated by the value that denotes the total mean deviation of all features in all groups from the mean of the total sample of learners.

Therefore, the learner group with a smaller percentage of total mean deviation is the more favorable solution. The previous statements clearly show that inter-group heterogeneity and intra-group heterogeneity are mainly captured by the values that reflect the average ability of all groups in a solution. Minimizing the overall error value of the learning population Eq. (7) does not guarantee that the error values of all the groups constituting the learner are minimized at the same time. In other words, when the optimization algorithm is arranged to evaluate each learning group by averaging the fitness values, it is set to be insensitive to the fitness values of the constructed learners.

Therefore, in order to obtain a globally optimal solution to the learning population formation problem, not only the total error of the learning population is considered, but also the error values of each feature on the learning population are considered separately. In other words, it is crucial to move from single-objective optimization to multi-objective optimization. In order to take this aspect into account, the percentage deviation of each learning population from the total sample of learners should be calculated separately. Equations (8)(9) calculate the mean square error and the total percentage deviation for the g th group.

$$MSE(G_g)\mid i=\left(\frac{1}{R}\right)\sum_{r=1}^{R}\left(\overline{c_r}(G_g)-\overline{c_r}\right)^2 \tag{8}$$

$$\begin{aligned}Error(G_g)\mid i&=\frac{RMSE(G_g)\mid i}{Max(Error)}\times 100\\&=\sqrt{\left(\frac{1}{R}\right)\sum_{r=1}^{R}(\overline{c_r}(G_g)-\overline{c_r})^2}\times 100\end{aligned} \tag{9}$$

II. C.Two-stage constrained particle swarm algorithm based on bi-objective approach

Realistic optimization problems are often constrained, and the effect of solving constrained optimization problems depends on a reasonable constraint processing mechanism on the one hand, and the advanced search mechanism on the other. Multi-objective optimization method as a constraint processing technology, is conducive to maintaining the diversity of the population and is not easy to fall into the local optimum.MOPSO algorithm, as one of the effective methods of multi-objective optimization, has the advantages of rapidity, convergence and so on, and can be used to solve constrained single-objective optimization problems. In this paper, a two-stage constrained particle swarm algorithm based on the bi-objective method is designed, with the bi-objective method as the constraint processing method and the MOPSO algorithm as the search mechanism for constrained single-objective optimization, and different optimization strategies are adopted for the different stages of the constraint process.

When performing angular region partitioning in the objective-constraint space, if the angular region partitioning is still performed with $(0,0)$ as the datum, the search for optimal individuals will be clustered on the objective axis due to the prerequisite requirement of the optimization that the constraints must be satisfied. No matter how small the angular division is, the entire target axis belongs to only one angular region. In this way, since the external archive concentration corresponds to the fact that only a small number of solutions are allowed to exist in each angular region, this results in a drastic reduction of the number of solutions located in the target axis as well as in the nearby regions, affecting the population diversity.

The optimal solution for constrained single-objective optimization is the one that does not violate the constraints and has the smallest objective value, located on the objective axis with $v(x)=0$ in the objective-constraint space. Considering the deep mining of the target axis region, the point $(1,1)$ in the normalized target-constraint space is used as the reference point for the angular regionalized partition. At this time, the whole target axis will be divided into more regions as the angle becomes smaller, which is more favorable to the search of feasible solutions. In addition, this angular regionalization method further expands the exploitation area, which is no longer limited to the feasible region, providing more opportunities for the search of the region near the constraint boundary.

In order to better guide the individuals of the population and promote the optimization process, the whole process is divided into two phases by combining the number of particles in the target-constraint region, and each phase adopts a different region division method. Considering the retention of infeasible solutions, two external archive sets, the primary external archive set (arc_p) and the secondary external archive set (arc_s), are established to jointly carry out the storage of solutions in the optimization process.

(1) Overall division of the objective-constraint space in the first stage

In the first stage, in the whole goal-constraint space, with the increasing number of particles in the region, the division of the region gradually increases until it reaches the upper limit of the total number of regions, and then stops the division. The number of total regions is $D \cdot i\left(D=2,3,\cdots,d\right)$.

$$\frac{(i-1)P}{i_{\max}} < P_{arc} \leq \frac{iP}{i_{\max}} \tag{10}$$

where, D is the number of initial division regions, i is the number of division times, P_{arc} is the total number of particles stored in the primary and secondary external archive sets, and the maximum capacity of the two external archive sets is set to 100. when $P_{arc} \geq 100$, the division of regions is stopped.

$$P_{arc} = P_{arc\_s} + P_{arc\_p} \tag{11}$$

where P_{arc_s} is the number of particles saved in the main external archive set, and P_{arc_p} is the number of particles saved in the secondary external archive set.

The whole target-constraint space is divided into regions, and an example of the adaptive angular region division of the first stage target-constraint space is shown in Fig. 1.

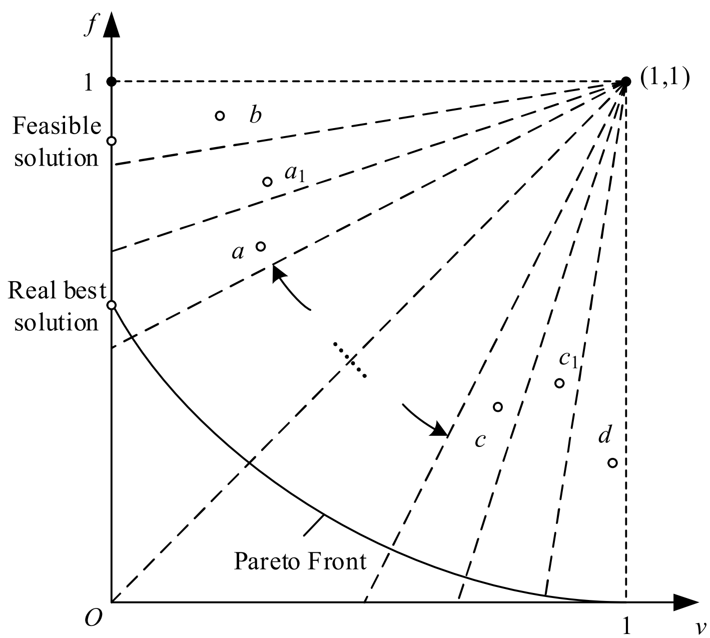

Figure 1: The first stage goal-constraint space adaptive Angle region division

(2) Local division of goal-constraint space in the second stage

When the first stage reaches the switching condition, it enters the second stage. The switching condition is: when P_{arc} reaches the upper limit or no new feasible region is added after n consecutive generations of updates. n is a set number of update generations, depending on the complexity of the optimization problem. Too large a value of n is detrimental to the convergence of the algorithm and affects the efficiency, while too small a value of n makes the search not deep enough.

When the first stage is switched to the second stage, the local search for the optimal solution is favored. Therefore, it is necessary to conduct an in-depth search for the region where the feasible solution is located on the target axis. The region where the particle with the smallest objective value in arc_p is located and the two neighboring regions along the direction of decreasing objective value are further divided. The above three regions are again divided equally into two regions each, so that there will be more particles that have the chance to be stored in arc_p and arc_s. Once a feasible solution with a smaller objective value is found, it will continue to be divided along the direction of decreasing objective value starting from the region where the particle is located in the same way, targeting the local angular region to strengthen the search.

If the current smallest target value particle gb_1 is $gbest\_1$, starting from the angular region where gb_1 is located, the two adjacent angular regions will be divided together for the second time along the direction of target value decrease on the target axis with $(1,1)$ as the reference point. After the local region enhanced search, if a feasible solution with a smaller target value is found, the division is continued in the above manner starting from the region where the new feasible solution is located, and an example of the second stage of local adaptive angular region division is shown in Fig. 2.

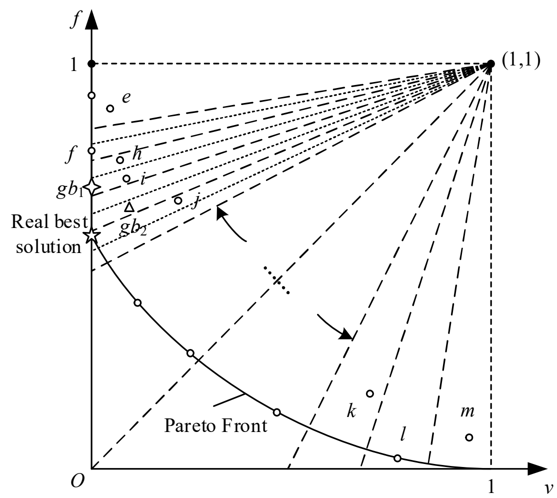

Figure 2: Local adaptive Angle region division in the second stage

III. Multi-objective Optimization of Blended Teaching for the Improvement of Music Teachers' Teaching Ability

III. A. Algorithm effectiveness analysis

To further validate the effectiveness of the TBC-PSO algorithm, it was subjected to optimization experiments on 10 test functions. The algorithm is set to have a maximum number of evaluations of 80,000, c1 and c2 are set to 1.85, and ω is set to 0.8375.

III. A. 1) Analysis of parameter values

This section investigates the effect of the size of the proportion of elite, general and inferior groups in the population, i.e., the size of Nelie:Nsecondary:Ninferiority, on the performance of the algorithm.

In this paper, it is hypothesized that the elite particles and inferiority particles only account for a small part of the whole population, so two division methods are adopted. (1) Equally dividing the proportion size of elite, general, and inferior groups in the population i.e., Nelie:Nsecondary:Ninferiority is 1:1:1. (2) Elite and inferior groups each account for the first 20% and the second 20% of the whole population, and the general group accounts for the remaining 60%, i.e., Nelie:Nsecondary:Ninferiority is 1:3:1. It is stipulated that the population size under the two different division methods is 1000. The average PSP values obtained by the algorithm after 50 runs under the two different ratios are shown in Fig. 3. when the ratio of Nelie:Nsecondary:Ninferiority is controlled at 1:3:1, the collaboration among the subpopulations is better and the algorithm performs better.

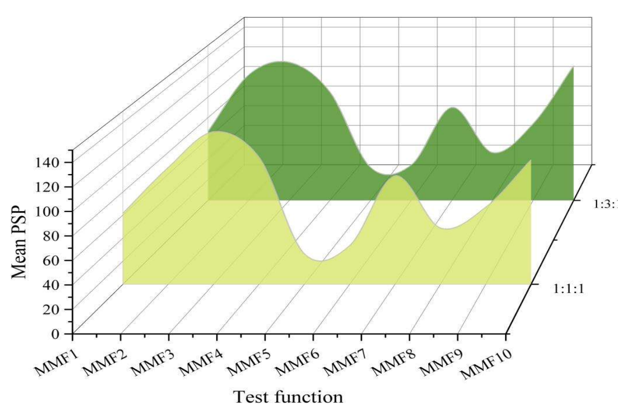

Figure 3: Mean PSP values obtained by the algorithms at two different ratios

III. A. 2) Control experiments

In order to verify the actual efficacy of the two-stage adaptive angular region delineation mechanism proposed in this paper played in the algorithm, 10 standard test functions were chosen to conduct controlled experiments on it. The rest of the algorithm is consistent throughout the experiment, except for this strategy. Here, the algorithm without the two-stage adaptive angular region delineation mechanism is denoted as TBC-PSO-N1, the algorithm with only the first-stage constrained optimization strategy is denoted as TBC-PSO-N2, and the algorithm with only the second-stage constrained optimization strategy is denoted as TBC-PSO-N3. The results obtained from the experiments are shown in Table 2.TBC-PSO significantly outperforms the other variants of the algorithm in terms of the mean value of PSP on each of the tested functions. Taking the MMF1 function as an example, the mean value of PSP for TBC-PSO is 61.3876, while that for TBC-PSO-N1, TBC-PSO-N2, and TBC-PSO-N3 are 50.2864, 58.3667, and 54.2975, respectively. It can be observed that the single-stage division mechanism is difficult to balance the global optimization and convergence accuracy due to the limitations of the search scope or local optimization seeking ability. The two-stage combined division strategy effectively balances the search efficiency and solution quality through the global exploration in the first stage and the locally enhanced search in the second stage, and is able to drive the algorithm's performance to a higher level, thus obtaining more desirable optimization results.

Table 2: PSP Mean Values of different algorithms

	TBC-PSO-N1	TBC-PSO-N2	TBC-PSO-N3	TBC-PSO
MMF1	50.2864	58.3667	54.2975	61.3876
MMF2	120.9742	131.4862	128.8465	139.2274
MMF3	63.2865	70.2864	67.2864	78.3653
MMF4	78.2754	89.3862	86.3862	94.2864
MMF5	66.3175	74.8621	70.2861	80.0826
MMF6	109.3861	116.2864	113.3896	121.3865
MMF7	79.0282	90.3862	87.3671	85.9371
MMF8	88.2456	98.3861	95.2864	104.8973
MMF9	117.2265	128.3863	125.4725	133.2871
MMF10	92.0843	103.3861	99.3862	109.4864

III. B. Allocation of weights in the evaluation indicator system

In this paper, the correlation weight calculation method is used to determine the weight allocation of the evaluation index system, which is used to explain the relationship between the indicators, and the weight coefficients of the indicators are obtained through calculation. For example, by applying formulas (12) and (13), the path coefficient is utilized to calculate the weight coefficient of each indicator.

$$W(F_m)=\frac{R(F_m)}{\sum_{m=1}^{n=4}R(F_m)}(m=1,2,3,4) \tag{12}$$

$$W(T_{mk})=\frac{R(T_{mk})}{\sum_{k=1}^{n1=k,n2=m}R(T_{mk})}(m,k=1,2,3,4) \tag{13}$$

$$W_{mk}=W(F_m)*W(T_{mk}) \tag{14}$$

The final results of the weight distribution of the evaluation index system obtained are shown in Table 3. In the first-level indicators, the teaching and research ability has the highest weight, reaching 0.326, followed by practical ability (0.255) and professional ethics (0.224). Expanding ability has the lowest weight, which is only 0.195. Among the secondary indicators, teaching innovation ability (0.166) and teaching implementation ability (0.160) have higher weights, indicating that innovative teaching practice and efficient classroom implementation are the focus of the current music teachers' ability improvement.

Table 3: Results of weight allocation

	First-level indicator	Secondary indicator	W(Tmk)	Wmk
Teaching ability evaluation	A1(0.224)	B1	0.214	0.103
		B2	0.235	0.121
	A2(0.255)	B3	0.218	0.103
		B4	0.246	0.160
	A3(0.326)	B5	0.237	0.152
		B6	0.248	0.166
	A4(0.195)	B7	0.197	0.096
		B8	0.203	0.099

III. C. Tests of empirical results

In order to verify the practical application effect of the proposed multi-objective optimization model, the study selected 15 in-service music teachers in the music school of a provincial university as experimental samples to carry out a 16-week blended teaching experiment. 15 music teachers adopted the blended teaching mode based on the multi-objective optimization model, and the results of the evaluation scores of the teaching ability before and after the experiment are shown in Tables 4 and 5, respectively, in which the V = (excellent, good, medium, passing, to be improved) five grades, differentiated by equidistant scoring method. and passing, to be improved) five grades, with equal difference scoring method to distinguish the degree of grade, excellent 90 points, good 80 points, medium 70 points, passing 60 points, to be improved 50 points. Before the experiment, the average value of teachers' teaching ability score was 75.04 points, and teachers' scores were mostly distributed in the range of 70-75 points, and there were individuals with lower scores, reflecting that teachers' teaching ability before the experiment was in the middle of the upper level as a whole, but the individual differences were more obvious. After the experiment, the average value of teachers' teaching ability scores increased to 80.53 points, all teachers' teaching ability scores exceeded 78 points, and 9 out of 15 teachers' comprehensive scores increased by more than 5 points. This indicates that the proposed model effectively promotes the overall improvement of teaching ability by accurately identifying the shortcomings of teachers' ability and implementing differentiated interventions.

Table 4: Teaching ability evaluation scores before the experiment

Number	Excellent	Good	Medium	Pass	To be improved	Comprehensive score
T1	0.0937	0.4896	0.1297	0.2870	0	73.9
T2	0.1284	0.5022	0.2084	0.1610	0	75.98
T3	0.1873	0.3972	0.1863	0.2292	0	75.426
T4	0.2011	0.3985	0.1571	0.2433	0	75.574
T5	0.2786	0.3946	0.1183	0.2085	0	77.433
T6	0.1392	0.6084	0.1735	0.0437	0.0352	77.727
T7	0.3861	0.1973	0.1775	0.2391	0	77.304
T8	0.1085	0.3972	0.1396	0.3547	0	72.595
T9	0.1936	0.3752	0.1284	0.3028	0	74.596
T10	0.1083	0.3376	0.1025	0.4516	0	71.026
T11	0.1196	0.2884	0.1184	0.4736	0	70.54
T12	0.2974	0.3395	0.1846	0.1785	0	77.558
T13	0.1173	0.5022	0.1132	0.2485	0.0188	74.507
T14	0.1933	0.5284	0.1297	0.1486	0	77.664
T15	0.3388	0.1086	0.1479	0.4047	0	73.815

Table 5: Teaching ability evaluation scores after the experiment

Number	Excellent	Good	Medium	Pass	To be improved	Comprehensive score
T1	0.3864	0.3126	0.1287	0.1723	0	79.131
T2	0.2903	0.4128	0.2206	0.0763	0	79.171
T3	0.4297	0.3328	0.1583	0.0792	0	81.13
T4	0.3964	0.4015	0.1029	0.0992	0	80.951
T5	0.3882	0.3521	0.1624	0.0973	0	80.312

T6	0.4017	0.3882	0.1097	0.1004	0	80.912
T7	0.3296	0.5028	0.0938	0.0738	0	80.882
T8	0.4283	0.4426	0.0833	0.0458	0	82.534
T9	0.3327	0.4341	0.1154	0.1178	0	79.817
T10	0.3108	0.4286	0.1083	0.1523	0	78.979
T11	0.3972	0.4389	0.1194	0.0445	0	81.888
T12	0.3364	0.3986	0.2085	0.0565	0	80.149
T13	0.3559	0.4298	0.2011	0.0132	0	81.284
T14	0.4021	0.3317	0.1625	0.1037	0	80.322
T15	0.3894	0.3197	0.2426	0.0483	0	80.502

IV. Conclusion

In this study, for the multi-objective synergistic demand of music teachers' teaching ability improvement in colleges and universities, a multi-objective optimization model containing a four-dimensional index system is constructed and an improved constrained particle swarm algorithm is proposed to realize the strategy optimization.

The mean value of PSP of TBC-PSO on each test function is significantly better than other variant algorithms. Taking the MMF1 function as an example, the PSP mean value of TBC-PSO is 61.3876, while that of TBC-PSO-N1, TBC-PSO-N2, and TBC-PSO-N3 are 50.2864, 58.3667, and 54.2975, respectively.The two-phase combination of the division strategy effectively balances the search efficiency and the solution quality through the global exploration in the first phase and the local enhanced search in the second phase. The search efficiency and the quality of the solution, which can drive the performance of the algorithm to a higher level, thus obtaining more desirable optimization results.

The empirical results show that before the experiment, the average value of teachers' teaching ability score is 75.04 points, and teachers' scores are mostly distributed in the range of 70-75 points, and there are individuals with lower scores, reflecting that before the experiment, teachers' teaching ability as a whole is in the middle-upper level, but the individual differences are more obvious. After the experiment, the average value of teachers' teaching ability scores increased to 80.53 points, all teachers' teaching ability scores exceeded 78 points, and 9 out of 15 teachers' comprehensive scores increased by more than 5 points. This indicates that the proposed model effectively promotes the overall improvement of teaching ability by accurately identifying the shortcomings of teachers' ability and implementing differentiated interventions.

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