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The effect of teaching management strategies on craftsmanship enhancement based on multi-objective optimization

Fangfang Lian[1,*], *Peng Zhang*[2], *Lei Xie*[1], *Jingxuan Zhu*[3] *and Ling Ge*[4]

[1] Institute of Ecology & Health, Hangzhou Polytechnic University, Hangzhou, Zhejiang, 310018, China
[2] Hangzhou Zhongmai Enterprise Management Consulting Co., Ltd., Hangzhou, Zhejiang, 310023, China
[3] Hangzhou Ecological Environment Bureau, Hangzhou, Zhejiang, 310023, China
[4] Zhejiang Fengniao Certification Service Co., Ltd., Hangzhou, Zhejiang, 310012, China

SUMMARY: *In the context of promoting "craftsmanship", how to improve students' craftsmanship through scientific teaching management strategies has become an important issue in education. In this paper, a multi-objective optimization model of teaching management is constructed with the objectives of minimizing the management cost, maximizing the index of improving craftsmanship and maximizing the satisfaction of teaching. In order to solve the model, the classical NSGA-II algorithm is improved by introducing the matrix-encoded multi-crossover operator, the sub-elitist initialization population strategy, and the improved Pareto dominance relation, which enhances the convergence performance of the algorithm and the uniformity of the distribution of the solution set. Simulation experiments are conducted through the standard test function DTLZ series, and the improved NSGA-II algorithm outperforms the comparative models in DTLZ2, DTLZ4, and DTLZ7 test problems, indicating that it has a better multi-objective solving capability. An empirical study on the effect of craftsmanship enhancement was conducted based on 150 student samples, and the implementation of teaching management strategies based on multi-objective optimization can significantly enhance students' comprehensive craftsmanship (Sig=0.001). This study provides a multi-objective optimization method for educational management department's teaching management strategy development for reference, which has important value and practical significance.*

KEYWORDS: *NSGA-II algorithm; multi-objective optimization model; initialization population strategy; Pareto dominance relationship; craftsmanship; teaching management strategy*

1 Introduction

Teaching management is the central work of the school, and grasping teaching routine management is the fundamental guarantee for improving the quality of teaching in schools and the basic premise for ensuring the steady development of a school [1]. In the Opinions on Deepening Education and Teaching Reform and Comprehensively Improving the Quality of Compulsory Education issued in 2019, it is mentioned that teaching management should be strengthened, and it is clearly required that schools should improve teaching management protocols. Whether it is the state's emphasis on sound teaching management protocols or the

*2010010002@hzvtc.edu.cn
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local government's and education department's emphasis on sound school rules and regulations, it reflects the importance of the routine management of school teaching. Teaching management can first of all make the school's operation mechanism standardized, to avoid the unclear responsibilities of various departments, the phenomenon of “messy war” or “kicking the ball” [2]. Secondly, it can standardize teachers' teaching behaviors such as class preparation, class attendance, homework correction, tutoring, teaching and research activities, prompting each teacher to do a good job in accordance with the standards of teaching routines, improving teachers' educational and teaching ability, and promoting teachers' professional development [3, 4]. Finally, it will also play a role in the development of students, for example, through the standardized curriculum can promote the overall development of students, through the monitoring of the classroom can ensure the learning efficiency of students in the classroom, through the supervision of tutoring can enhance the personalized development of students and so on [5].

In the school's talent cultivation goals, craftsmanship is the basic principle to follow [6]. The teaching management work of the school mainly includes the following aspects [7, 8]: first, the supervision and management for the realization of teaching objectives, second, the management for the development of teaching plans, third, the management for the construction of professional courses, and fourth, the management for the construction of learning and teaching styles. In this series of management work, the integration of craftsmanship focuses on the above aspects of work as the basis for the development of normative, feasible, comprehensive and standardized features of the work of the implementation of standards, and strive to make the school teaching management process of all aspects of the operation and management of the work of the process have to match the specific content of the work of the implementation of the process [9, 10]. Craftsmanship can guide the school teaching management to standardization, standardization direction, but the current research on the impact of teaching management strategies on the enhancement of craftsmanship is relatively scarce, so it is imperative to study the impact of optimization of teaching management strategies on the enhancement of craftsmanship.

In the rapid development of intelligent technology and algorithms, the field of teaching management in schools is ushering in new opportunities and challenges. Literature [11] developed a new teaching management system using an improved association rule algorithm setup, which was used by Apriori optimization algorithm to mine the data related to teaching management and synthesize the frequent itemsets, and the method used significantly enhances the performance of information mining, and at the same time improves the efficiency and quality of the work of the educational management department. Literature [12] based on the improvement of dynamic programming algorithm for the optimization of teaching management in colleges and universities, the algorithm realizes the different types of teaching management activities division as well as the integration of things, in the experimental process shows good stability, in the case of complex, multi-volume data can still maintain a high computational efficiency. Literature [13] gives full play to the advantages of modern advanced technology in data processing, using data mining technology to analyze the learning behavior and performance of students, and then using cloud computing technology to build an educational information platform, realizing efficient and safe information storage, and finally introducing intelligent decision-making tools to improve the efficient teaching management mode. Literature [14] designed a distributed control system-driven teaching management informatization framework, and the results of the feasibility comprehensive evaluation showed that the informatization teaching level of teachers supported by the informatization framework was improved to varying degrees, with a score of 3.59 for teaching practice ability, and a score of 3.13 for informatization professional practice ability. Literature [15] proposes an online cloud teaching management strategy based on the development needs of university informatization, which meets the basic functional requirements of online learning management and has better performance of computing resources, reducing teaching costs while improving teaching management efficiency. Literature [16] collected a series of problems and optimization suggestions from managers about teaching management through on-site investigation, and optimized teaching management by integrating innovative teaching management ideas, reforming teaching management structure, integrating advanced technology tools and strengthening teaching management team. Literature [17] designed a sports teaching management system based on multi-intelligence body, and the operational efficiency of this optimization system is greatly improved compared with the traditional system, and it has obvious advantages in personalized teaching management, sharing and collaboration of teaching resources, etc., which is an important direction for the optimization of teaching informatization.

In addition, literature [18] for the traditional teaching management mode of resource allocation inefficiency and other problems, try to apply artificial intelligence digital twin technology to achieve multi-objective optimization of teaching management, through the analysis can be seen, the method used not only can predict the academic risk problems, but also improve the efficiency of teaching management and promote the personalized development of students. Literature [19] used particle swarm optimization algorithm to optimize the teaching management data system, the status of teaching management data system in the campus information construction is obvious, is responsible for the students' learning situation, teachers' teaching situation and the use of teaching resources in the core part of the optimized system to help the school to better manage the students. Literature [20] embedded the particle swarm optimization algorithm into the teaching management system to optimize the allocation of teaching resources and improve the utilization of resources, and the results of the study were satisfactory, and the proposed strategy greatly regulated the balance between the number of computers and the number of teachers, and successfully avoided the problem of resource waste. Literature [21], in order to optimize the teaching management evaluation system in colleges and universities, combines the particle swarm optimization algorithm with the back propagation neural network algorithm and establishes the teaching management evaluation index system, the teaching management evaluation system based on the optimization algorithm fully embodies the effectiveness and intelligence in the test, and the evaluation prediction and the real evaluation have a better degree of fit. Literature [22] uses the improved genetic algorithm to optimize the structure of the teaching management system of colleges and universities with further improvement in applicability and accuracy, and the improved algorithm is less affected by the crossover probability and has stronger stability, and the algorithm-driven teaching management system is expected to realize the practical needs of teaching management such as reasonable arrangement of teaching tasks.

Craftsmanship cultivation in the education sector is mostly researched from the aspects of industry-education integration and school-enterprise cooperation, which is because craftsmanship itself is a kind of professional spirit. Literature [23] points out that craftsmanship embodies employees' values and outlook on life from the three levels of morality, quality, and competence, and for this reason, the cultivation of craftsmanship in schools has been explored in depth, and reference suggestions for the cultivation of students' craftsmanship have been put forward in the employment and entrepreneurship education in schools. Literature [24] discusses the important position of manufacturing industry in maintaining national comprehensive national strength and international competitiveness, and points out that craftsmanship is the spiritual guarantee for promoting the quality and efficiency of manufacturing production and industrial upgrading, etc. In this regard, it discusses the effective ways to cultivate students' craftsmanship from the three dimensions of the government, enterprises and colleges and universities. Literature [25] in the context of the integration of industry and education, through the implementation of strategies such as strengthening the construction of the faculty, optimizing the curriculum, innovative teaching methods, and improving the students' professional practice ability, it is of great significance for the cultivation of high-quality, high-level artisanal talents.

In addition, the literature [26] puts forward the path of cultivating computer talents with artisanal spirit by taking the higher vocational computer professional course as the research object, emphasizing that practical teaching is the key link for the realization of the path, and secondly, through the cooperation between schools and enterprises, strengthening student management and so on, which is conducive to the cultivation of students' artisanal spirit. Literature [27] integrates the traditional cultural heritage goal in the cultivation of craftsmanship in vocational education, i.e., cultivating students' professional skills on the basis of traditional Chinese traditional culture, and this innovative approach realizes the cultivation of high-quality talents who focus on research and strive for excellence. Literature [28] in order to enhance the students' craftsmanship, through optimizing the curriculum and professional construction while combining with the industry-teaching fusion teaching strategy, the craftsmanship penetrates into all corners of the students' teaching, and after a period of time of teaching practice, the students' quality of education, comprehensive quality, and professional ability have been developed in a high-quality way. Literature [29] designed a multi-dimensional curriculum module in the teaching of civil engineering structural inspection, combined with practical case studies and immersive training experience, to ensure that the students' professional ability to improve at the same time to strengthen the transformation of students' spirit of craftsmanship, rigorous, honest and responsible attitude to the implementation of the organic integration of knowledge and skills.

At present, there is no relevant literature to conduct scientific quantitative research by establishing a robust optimization model for the dynamic change characteristics of craftsmanship talent demand. This paper establishes a multi-objective robust optimization model for the formulation of teaching management strategies to address the above problems. On the basis of analyzing the problem of multi-objective optimization of teaching management policy for the enhancement of craftsmanship, a model solving algorithm based on dominance intensity, matrix coding and random generation of elite initial population is proposed. The algorithm enhances the selection pressure by individual comparison through dominance intensity. It also combines the multiple crossover operator to maintain the population diversity. Simulation experiments and case-based empirical experiments are designed to validate the performance and application effect of this paper's algorithm.

2 A multi-objective optimization model of teaching management for craftsmanship enhancement

2.1 Definition of variables

In order to construct the optimization model of teaching management, the following decision variables and parameters are defined:

r_i: denotes the number of trainees cultivated by the institution in the i th year, which is used to supplement the demand for artisanal talents in the $i+4$ th year (the cultivation cycle is 4 years, and let the Gh th year be the planning year, the planning period is 5 years, and the years of demand for talents are from the $Gh+5$ th year to the $Gh+9$ th year, then

$i = Gh+1, \cdots, Gh+5$.

t_i: indicates the number of trainees cultivated through teaching management in the i th year, which is used to supplement the demand for artisanal talents in the $i+1$ th year (the cultivation cycle is 1 year, $i = Gh+4, \cdots, Gh+8$).

μ_{hk}, σ_{hk}: denote the mean and standard deviation of the quality of talent cultivation of cultivation mode U_h on the competence indicator A_k, respectively, where $h = r, t$; $k = 1, 2, 3, 4$.

v_{hk}: denotes the percentage of the number of people trained by the training model U_h at the medium-high level on the competency indicator A_k, where $h = r, t$; $k = 1, 2, 3, 4$.

ω_{ik}: indicates the degree of importance of the competency indicator A_k in the competency demand structure in the i th year.

2.2 Determination of optimization objectives

From the foregoing discourse in the previous section, it is clear that there exist notable disparities regarding the quality attributes of artisanal skills between two different modes of cultivation. In light of keeping the scale of cultivation constant, any disparity in the distribution of people within these modes of cultivation will definitely impact the level of artisanal skills. In the context of a stable aggregate demand for cultivation, optimizing the ratio of cultivation between these two modes of cultivation seeks to accomplish three goals: (1) reducing management costs, (2) maximizing the index of craftsmanship development, and (3) attaining a high level of pedagogic satisfaction.

2.3 Analysis of constraints

Constraint 1: The overall number of artisanal talents in demand in the coming years, calculated on the basis of the relevant policies for the technical talents to be withdrawn from active service in the next few years and taking into account the overall planning of the number of talents, will remain relatively stable provided that there is no change in the establishment system and the policy environment.

$$\begin{gathered}\sum_{i=Gh+1}^{n} \left| r_i + t_{(i+3)} \right| = \sum_{i=Gh+1}^{n} X_{i+4} \\ \left(n \in \left[Gh+1, Gh+5 \right]; \| \text{Round up to the next integer} \right)\end{gathered} \tag{1}$$

X_i is the total demand of talents in the i th year.

Constraint 2: In order to ensure that the artisanal talent team has the ability to accomplish various tasks, the average level of the artisanal talent team in each ability indicator should not be lower than a certain qualified value, which is set at 0.6 in this paper.

$$\frac{\sum_{i=Gh+1}^{Gh+5} \omega_{ik} \times \left[\mu_{rk} \times r_i + \mu_{tk} \times t_{i+3} \right]}{\sum_{i=Gh+1}^{Gh+5} \left[r_i + t_{i+3} \right]} \geq 0.6 \left(\forall k \right) \tag{2}$$

Constraint 3: The enrollment cannot be less than zero.

$r_i \geq 0$, $t_i \geq 0$ and r_i, t_i are integers.

2.4 Model analysis

Consider the constraint 1: $\sum_{i=Gh+1}^{n}\left[r_i + t_{i+3}\right] = \sum_{i=Gh+1}^{n} X_{i+4}$, which means that the sum of the number of trainers during the planning period is constant, so the objective can be transformed as:

$$P_1 : \max = \sum_{i=Gh+1}^{Gh+5}\left[r_i \times f_{ir} + t_{i+3} \times f_{it}\right] \tag{3}$$

$$P_2 : \max = \sum_{i=Gh+1}^{Gh+5}\left[r_i \times f'_{ir} + t_{i+3} \times f'_{it}\right] \tag{4}$$

where $f_{ih} = \sum_{k=1}^{4}\omega_{ik} \times \mu_{hk}$, $f'_{ih} = \sum_{k=1}^{4}\omega_{ik} \times v_{hk}$, $h = r, t, i = Gh+1, \cdots, Gh+5$. Analyzing the above objectives and constraints, this model is a bi-objective integer programming problem. Therefore, when weighing P_1 and P_2, it is necessary to construct the discriminant for each year first:

$$\left\{\left\{h \middle| \max(f_{ih})\right\} = \left\{h \middle| \max(f'_{ih})\right\}\right\} \ and \ \left\{\left\{h \middle| \min(f_{ih})\right\} = \left\{h \middle| \min(f'_{ih})\right\}\right\} \tag{5}$$

If the value of the equation (5) in each year is TRUE, then the two objectives are homothetic, and the optimal solution must be obtained at the endpoints of the domain of definition of the variables; otherwise, the two objectives are anisotropic, and the feasible solution will need to be obtained through multi-objective planning.

The following mainly discusses the planning solution process under the heterogeneous objective:

(1) Disregard P_2 and solve P_1 to obtain P_1^*, whose integrated mean is denoted as t_a^*;

$$t_a^* = \left(\sum_{i=Gh+1}^{Gh+5}\left[r_i \times f_{ir} + t_{i+3} \times f_{it}\right] \middle| \max P_1\right) \tag{6}$$

(2) Disregard P_1 and solve for P_2 to obtain P_2^*, whose composite mean is noted as t_b^*;

$$t_b^* = \left(\sum_{i=Gh+1}^{Gh+5}\left[r_i \times f_{ir} + t_{i+3} \times f_{it}\right] \middle| \max P_2\right) \tag{7}$$

(3) Add P_1 to the constraints and model the planning as follows:

Objective function:

$$Max = \sum_{i=Gh+1}^{Gh+5}\left[r_i \times f'_{ir} + t_{i+3} \times f'_{it}\right] \tag{8}$$

Binding:

$$\sum_{i=Gh+1}^{n} \left| r_i + t_{(i+3)} \right| = \sum_{i=Gh+1}^{n} X_{i+4} \left(n \in \left[Gh+1, Gh+5 \right] \right) \tag{9}$$

$$\sum_{i=Gh+1}^{Gh+5} \left[r_i \times f_{ir} + t_{i+3} \times f_{it} \right] \geq t \tag{10}$$

where the parameter t denotes a series of values with $\frac{\left|t_a^* - t_b^*\right|}{n}$ as the step, t_a^* or t_b^* as the starting point, and t_a^* or t_b^* as the ending point, and corresponding to a t-value there is a set of feasible solutions.

$$\frac{\sum_{i=Gh+1}^{Gh+5} \omega_{ik} \times \left[\mu_{rk} \times r_i + \mu_{tk} \times t_{i+3} \right]}{\sum_{i=Gh+1}^{Gh+5} \left[r_i + t_{i+3} \right]} \geq 0.5 \tag{11}$$

(4) $r_i \geq 0$, $t_i \geq 0$ and r_i, t_i are integers.

3 Multi-objective optimization model solving based on improved NSGA-II algorithm

The improved NSGA-II algorithm based on dominance intensity inherits the fast non-dominated sorting algorithm of the classical NSGA-II's algorithm. The differences between the two are: the former uses dominance intensity to compare the superior and inferior performance of individuals in the nondominated set, while the latter compares them through crowding; when the dominance intensity is the same, the former evaluates the individuals through the new type of crowding distance; the former adopts the adaptive elite retention strategy, while the latter uses the conventional elite retention strategy, and in this paper, based on the actuality of efficiently solving the multi-objective optimization model of teaching and learning management oriented to the enhancement of the artisanal spirit, the paper The conventional elite retention strategy is adopted and the better elite population is generated at the time of population initialization to accelerate the optimization process so as to satisfy the accelerated convergence and improve the quality of the solution set.

3.1 Dominance strength calculations and inter-individual comparisons

The dominance intensity ε is calculated as shown in equation (12), and it is clear that the smaller the dominance intensity of an individual, the closer it is to the target value, and thus the better the individual is. The dominance intensity can effectively identify and remove pseudo non-dominated solutions.

$$\begin{cases} \varepsilon = \varepsilon_{st} + \varepsilon_s + \varepsilon_{std} \\ \varepsilon_{st} = \dfrac{f_{st}^{\max} - f_{st}}{f_{st}^{\max}} \\ \varepsilon_s = \dfrac{f_s^{\max} - f_s}{f_s^{\max}} \\ \varepsilon_{std} = -\dfrac{f_{std}}{n} \end{cases} \tag{12}$$

The computation of the novel crowding distance i_D considering variance is the same as that provided in the literature. The improved NSGA-II algorithm has three attributes for each individual after fast nondominated ranking, dominance intensity calculation and congestion distance calculation: nondominated rating i.e. Rank, dominance intensity ε and congestion distance i_D. For any two individuals i and individual j, there can be a prioritization relationship as shown in equation (13):

$$\text{Subject } i \text{ is superior to subject } j \Leftrightarrow \begin{cases} Rank_i < Rank_j \\ Rank_i = Rank_j \wedge \varepsilon_i < \varepsilon_j \\ Rank_i = Rank_j \wedge \varepsilon_i = \varepsilon_j \wedge i_D^i > i_D^j \end{cases} \tag{13}$$

3.2 Improved Pareto dominance relationships

Suppose that X_1 and X_2 are two solutions to a multi-objective optimization problem, and X_1 is said to dominate X_2, denoted as $X_1 \succ X_2$, when and only when Eq. (14) holds, where X_1 is nondominated and X_2 is dominated.

$$\begin{cases} \forall\, i \in \{1, 2, \cdots, m\},\ f_i(X_2) \geq f_i(X_2) \\ \exists\, j \in \{1, 2, \cdots, m\},\ f_j(X_2) > f_j(X_2) \end{cases} \tag{14}$$

Since the solution problem in this paper should satisfy the maximization of the objective functions f_{s1}, f_{s2}, and f_{s3}, the Pareto dominance rule is modified in order to obtain the maximum possible value on all objective functions.

3.3 Initial population sub-elitism

When NSGA-II algorithm solves the multi-objective problem of teaching management, it requires thousands of iterations to converge for larger problems, and it is easy to be trapped in local optimization. Therefore, the initial population sub-elitization strategy is adopted: that is, all individuals of the initial population obtain the maximum value on the objective function f_{st}, f_s. The steps of initial population subelitization are as follows: (1) Generate a copy of matrix A into initial chromosome matrix C; (2) Determine the set of students with class placement intentions from matrix A, while obtaining the number of teachers in each class from matrix B; (3) Generate $\lfloor tnum_k / g \rfloor$ groupings of randomly selected teachers on each class, noting teachers in unassigned groups; (4) Based on the number of unassigned teachers in each class in descending order, the remaining teachers are combined to form groups according to a “rounding up" method that maximizes class and teacher ratings; (5) Assign students who have filled out a teacher to the grouping of the teacher they have filled out; (6) Calculate the number of students in each group, assign each student who has not filled in a teacher to a group whose number of students is less than the standard number of students, and update the number of students in each group.

In the above steps, the key lies in the "rounding" method in step (4). After step (3), the descending sequence of the number of teachers in the unassigned group for each class is $N=\{4,4,3,3,1\}$, and it is clear that one teacher randomly selected from $N[1]$ and $N[5]$, $N[2]$ and $N[4]$, and the remaining two teachers from $N[3]$ and $N[4]$ can be rounded up to exactly 5 teachers in each group, which can be combined into a grouping that maximizes the ratings of the teachers and the classes.

3.4 Multi-crossing operators

Another key technique of the GGA algorithm is the construction of efficient crossover and variational operators that can quickly converge to the optimum. The graduate admission interview grouping problem encodes the chromosomes in a matrix fashion, while grouping is involved in the matrix, so four crossover operators are proposed: row crossover, column crossover, division-in-group crossover and group crossover. These crossover operators are randomly executed with the same probability (25%) during the execution of the genetic algorithm.

(1) Row crossover. First, randomly select a row r to crossover, set the two chromosomes involved in the crossover as $C1$ and $C2$, find the group to which row r of $C1$ and $C2$ belongs (set to $g1$ and $g2$), then replace all rows in group $g1$ of $C1$ with row r of $C2$, and similarly replace all rows in group $g2$ of $C2$ with row r of $C1$, and then update the relevant attributes of the chromosomes (e.g., f_{st}, f_s, f_{std}, etc.) after performing conflict detection.

(2) Column crossover. The process of column crossover is similar to that of row crossover, which also needs to be adjusted after crossover and will not be repeated here.

(3) Division-in-group crossover. To perform a teacher-in-group crossover, 1 different teacher (the group number cannot be the same either) is randomly selected for crossover in the chromosomes involved in the crossover, respectively.

(4) Group crossover. For two chromosomes, randomly find a group with the group number g_n to exchange. When exchanging, first save which students are in each group, then exchange the teachers in these 2 groups, and finally make adjustments for duplicate teachers.

3.5 Variational operators

Variation by columns and variation by groups randomly select the variation operator in an equal probability method. For variation by column, 2 different columns are randomly selected for exchange. For variation by group, two different groups are randomly selected, and then a teacher is randomly selected in each of the two groups for exchange.

4 Experimental simulation results of the improved NSGA-II algorithm

4.1 Evaluation indicators and parameterization

4.1.1 Evaluation indicators

In this chapter, the performance of the improved NSGA-II algorithm is verified, and the two-objective test function of the ZDT series and the three-objective test function of the DTLZ series are selected for simulation experiments. A set of uniformly distributed real solutions of the test functions in the objective space is the experimental data used to evaluate the improved NSGA-II algorithm, and the ZDT test functions are as follows:

The set of DTLZ test functions is as follows:

(1) DTLZ1

$$\begin{cases} \min\ f_1(x) = \frac{1}{2} x_1 x_2 \left(1 + g(x)\right) \\ \min\ f_2(x) = \frac{1}{2} x_1 (1 - x_2)\left(1 + g(x)\right) \\ \min\ f_3(x) = \frac{1}{2}(1 - x_1)\left(1 + g(x)\right) \\ g(x) = 100\left(10 + \sum_{i=3}^{m}\left((x_i - 0.5)^2 - \cos\left(20\pi(x_i - 0.5)\right)\right)\right) \\ s.t.\ 0 \le x_i \le 1, i = 1, 2, \cdots, 12 \end{cases} \tag{15}$$

(2) DTLZ2

$$\begin{cases} \min\ f_1(x) = \cos\left(\frac{\pi}{2} x_1\right)\cos\left(\frac{\pi}{2} x_2\right)\left(1 + g(x)\right) \\ \min\ f_2(x) = \cos\left(\frac{\pi}{2} x_1\right)\sin\left(\frac{\pi}{2} x_2\right)\left(1 + g(x)\right) \\ \min\ f_3(x) = \sin\left(\frac{\pi}{2} x_1\right)\left(1 + g(x)\right) \\ g(x) = \sum_{i=3}^{m}(x_i - 0.5)^2 \\ s.t.\ 0 \le x_i \le 1, i = 1, 2, \cdots, 12 \end{cases} \tag{16}$$

(3) DTLZ3

$$\begin{cases} \min\ f_1(x) = (1+g(x))\cos\left(\frac{\pi}{2}x_1\right)\cos\left(\frac{\pi}{2}x_2\right) \\ \min\ f_2(x) = (1+g(x))\cos\left(\frac{\pi}{2}x_1\right)\sin\left(\frac{\pi}{2}x_2\right) \\ \min\ f_3(x) = (1+g(x))\sin\left(\frac{\pi}{2}x_1\right) \\ g(x) = 100\left(10+\sum_{i=3}^{m}\left((x_i-0.5)^2-\cos(20\pi(x_i-0.5))\right)\right) \\ s.t.\ 0 \le x_i \le 1,\ i=1,2,\cdots,12 \end{cases} \tag{17}$$

(4) DTLZ4

$$\begin{cases} \min\ f_1(x) = (1+g(x))\cos\left(\frac{\pi}{2}x_1^{\alpha}\right)\cos\left(\frac{\pi}{2}x_2^{\alpha}\right) \\ \min\ f_2(x) = (1+g(x))\cos\left(\frac{\pi}{2}x_1^{\alpha}\right)\sin\left(\frac{\pi}{2}x_2^{\alpha}\right) \\ \min\ f_3(x) = (1+g(x))\sin\left(\frac{\pi}{2}x_1^{\alpha}\right) \\ g(x) = \sum_{i=3}^{m}(x_i-0.5)^2 \\ s.t.\ 0 \le x_i \le 1,\ i=1,2,\cdots,12 \end{cases} \tag{18}$$

(5) DTLZ7

$$\begin{cases} \min\ f_1(x) = x_1 \\ \min\ f_2(x) = x_2 \\ \min\ f_3(x) = (1+g(x))h(f_1, f_2, g(x)) \\ g(x) = 1+\frac{9}{22}\sum_{i=3}^{m}(x_i) \\ h(f_1, f_2, g(x)) = 3-\sum_{i=1}^{2}\left(\frac{f_i}{1+g}(1+\sin(3\pi f_i))\right) \\ s.t.\ 0 \le x_i \le 1,\ i=1,2,\cdots,12, \end{cases} \tag{19}$$

The performance of the proposed multi-objective algorithm is investigated based on two criteria:

1. Convergence: This criterion will be measured by the closeness between the generated solution by the algorithm and the real solution.

2. Distributability: The uniformity of the solution distribution generated by the algorithm will be considered to measure its distributability.

For assessing the performance of the improved NSGA-II algorithm, this paper adopts a single measure for comparing the proposed algorithm with other competing algorithms.

Generation Distance (GD): is used to estimate the degree of convergence between the nondominated solution obtained by the algorithm and the true nondominated solution.GD is defined as in the following equation:

$$GD = \sqrt{\sum_{i=1}^{n} d_i^2 \Big/ n} \tag{20}$$

qhere d_i denotes the minimum Euclidean distance from each individual to the frontier surface, and n denotes the number of nondominated solutions obtained by the algorithm.GD mainly reacts to the convergence of the algorithm, and the smaller the value of GD indicates the better the convergence.

Spacing metric (SP): evaluates the distributability of the solution in the target space by calculating the change in the distance between each individual in the resulting solution and the neighboring individuals.SP is defined by the following formula:

$$SP = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\bar{d} - d_i\right)^2} \tag{21}$$

$$d_i = \min_k \left(\sum_{j=1}^{m} \left| f_j\left(X_i\right) - f_j\left(X_k\right) \right| \right), i, k = 1, 2, \cdots, n \tag{22}$$

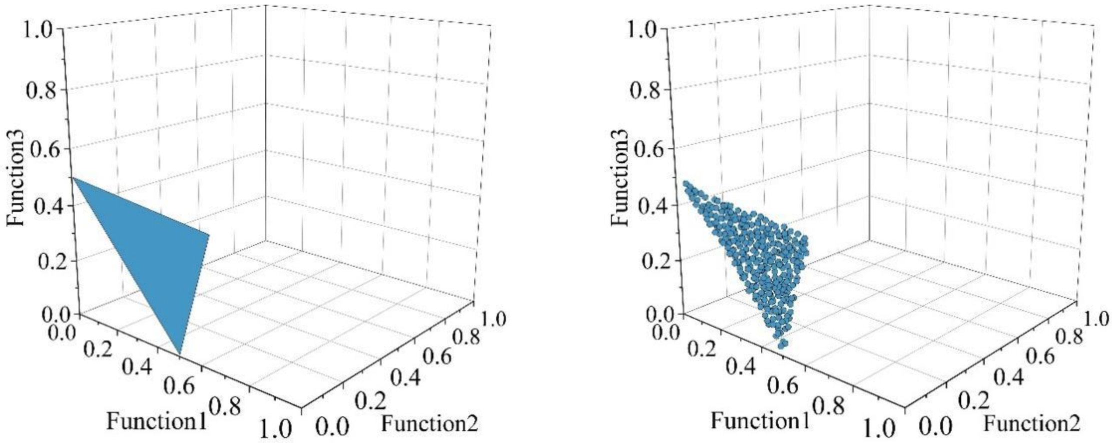
4.1.2 Parameter setting

Let the population size N=400, EA max 400, Maximum number of iterations: DTLZ series test function: 4000, Number of grids per dimension a=12.

4.2 Analysis of the results of the comparison experiment

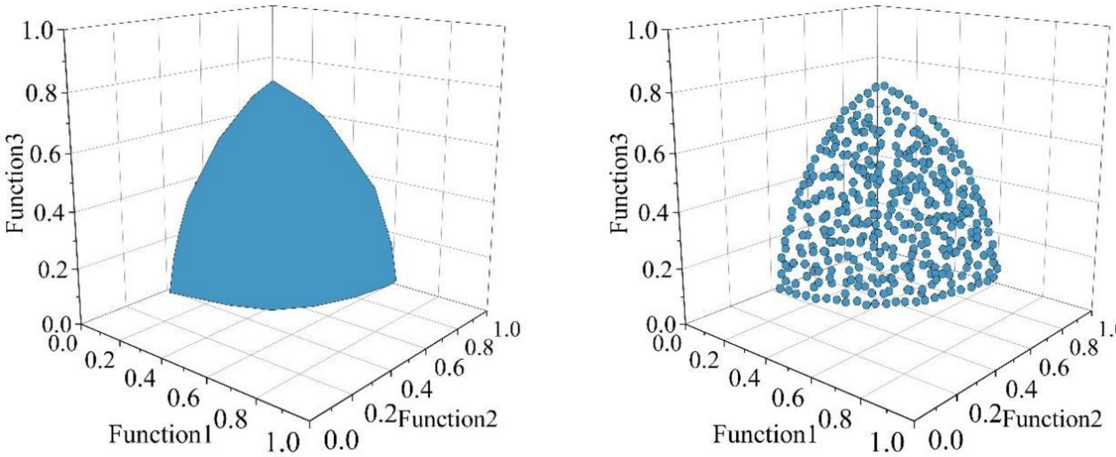
4.2.1 Comparison of this paper's algorithm with the theoretical optimum

In this section, the test functions in Section 4.1.1 are used for the experiments. Figures 1 to 5 show the comparison between the optimal frontier surfaces derived from the improved NSGA-II algorithm regarding DTLZ1, DTLZ2, DTLZ3, DTLZ4, DTLZ7 and the real Pareto optimal frontier surfaces in Figures (a) and (b), respectively. In the optimization problem with three objectives, the non-dominated solution obtained by the improved NSGA-II algorithm does not show the phenomenon of small region aggregation, and the shape of the required frontier surface remains basically consistent with the shape of the real frontier surface, which can be better close to the real optimal frontier surface. Therefore, the improved NSGA-II algorithm can effectively approximate the theoretical optimal frontier of the multi-objective optimization problem, and the pyramid structure and diversity strategy make it have uniform distribution.



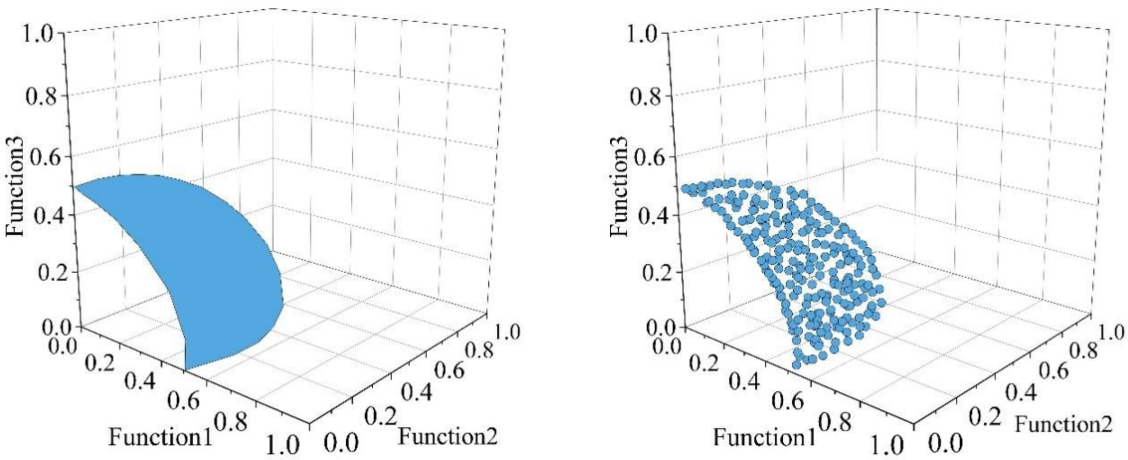
(a)Improved NSGA-II (b)Real

Figure 1: DTLZ1



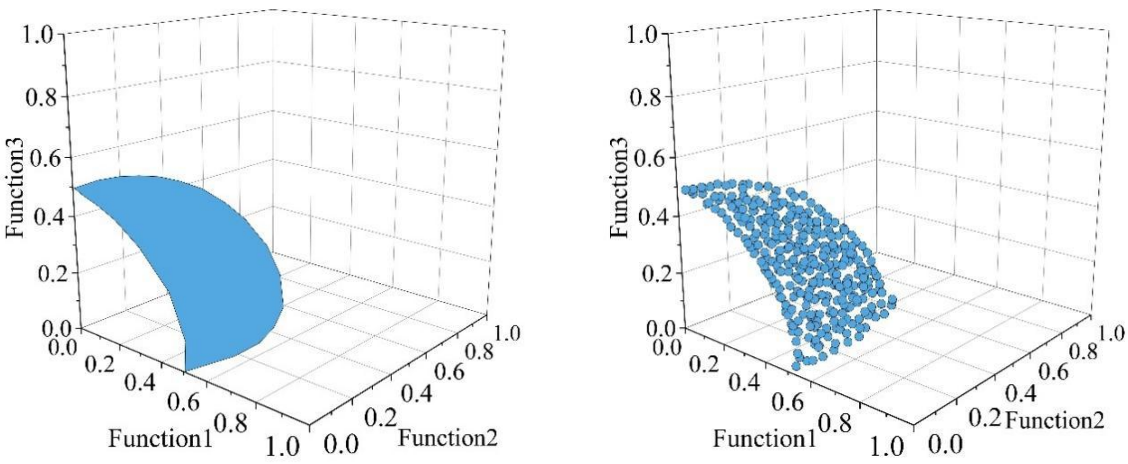
(a)Improved NSGA-II (b)Real

Figure 2: DTLZ2



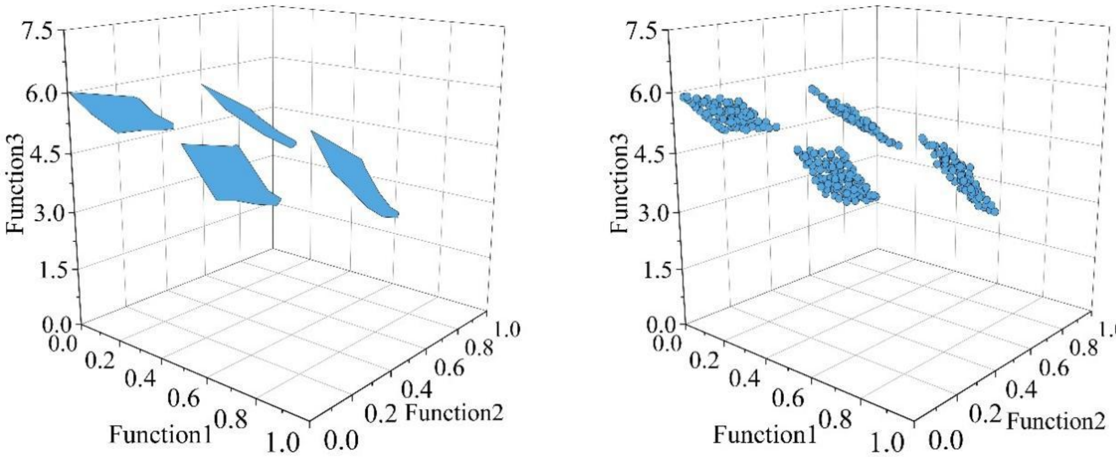
(a)Improved NSGA-II (b)Real

Figure 3: DTLZ3



(a)Improved NSGA-II (b)Real

Figure 4: DTLZ4



(a)Improved NSGA-II (b)Real

Figure 5: DTLZ7

4.2.2 Comparison of this paper's algorithm with similar algorithms

For simulation in this section, the dimensions of the test function will be taken as 4.1.1 to analyze the performance of the suggested improvement in the NSGA-II method. In order to test the performance of the proposed algorithm compared to similar types of algorithms, the comparative analysis is done as follows, and its results are shown in Table 1 below. Performance analysis results of the improved NSGA-II algorithm are represented as averages of generational distance (GD) and spread (SP) over 30 independent executions. For comparison, classical improved NSGA-II, SPEA2, OMOPSO (improved multi-objective PSO algorithm), and MOABC/D algorithms are used.

In problems DTLZ1, DTLZ4, and DTLZ7, the best GD mean and variance are attained by the enhanced NSGA-II algorithm. The lowest GD mean is an indicator that there is a reduction in the average distance between the nondominated solution set and the true Pareto front, showing that there has been improvement in terms of the convergence of the algorithm. Similarly, a low GD variance is an indicator that the enhanced NSGA-II gives similar experiment results as well as consistent convergence behavior in different runs. In the cases of DTLZ1 and DTLZ3, the enhanced NSGA-II obtains the highest mean and variance of GD compared to NSGA-II, SPEA2, and MOABC/D algorithms but lower than OMOPSO, implying that the convergence ability of the enhanced algorithm is surpassed by the latter in the two problems. In the five test problems, the enhancement approach for NSGA-II gives the best GD mean and variance in three problems (DTLZ2, DTLZ4, DTLZ7) and the best GD mean and variance in DTLZ2 (3.63E-6 and 5.95E-7, respectively).

Table 1: The mean and standard deviation of the GD index

Test problem		Improved NSGA-II	Mo-PS	SPEA2	OMOPSO	MOABC/D
DTLZ1	Average	2.04E-5	1.42021	0.03683	1.28E-6	0.00751
	Stdve	1.14E-6	0.52204	0.00612	4.74E-7	6.22E-5
DTLZ2	Average	3.63E-6	0.00672	0.00424	5.62E-6	0.00195
	Stdve	5.95E-7	0.00105	0.00212	1.31E-6	2.32E-4
DTLZ3	Average	1.54E-5	0.01131	0.0495	4.54E-6	0.00196
	Stdve	3.66E-6	0.00252	0.00212	1.46E-6	3.13E-4
DTLZ4	Average	4.55E-5	0.05633	0.08323	6.22E-5	0.00192
	Stdve	6.91E-6	2.42E-4	0.04371	1.85E-5	1.86E-4
DTLZ7	Average	3.74E-4	0.00293	0.00361	3.86E-4	4.52E-4
	Stdve	2.22E-6	1.42E-4	5.44E-4	1.53E-5	4.43E-6

Table 2 shows the SP mean and standard deviation obtained by the improved NSGA-II algorithm and the four compared algorithms. In problems DTLZ1, DTLZ2, DTLZ4 and DTZL7, the SP mean and variance of this paper's algorithm are the smallest, indicating that the nondominated solutions are more uniformly distributed in the solution space, and the distributability is more stable in several independent experiments. In problem DTLZ3, the SP mean and variance of MOABC/D are smaller than the improved NSGA-II. For problem DTLZ3, the combination of GD mean and SP mean shows that although the convergence of this paper's algorithm is worse than OMOPSO, the uniformity is better than it. As a whole, 4 out of 5 optimization problems have optimal SP mean values obtained by the improved NSGA-II algorithm, indicating that the improved NSGA-II algorithm ensures that the nondominated solutions have a uniform distribution. Combining the above data, it can be seen that: for the multi-objective test problem, the improved NSGA-II algorithm reflects better results in both convergence index and distribution index, therefore, the improved NSGA-II algorithm in this paper has good solution performance in the multi-objective optimization problem.

Table 2: The average and standard deviation of the SP index

Test problem		Improved NSGA-II	Mo-PS	SPEA2	OMOPSO	MOABC/D
DTLZ1	Average	1.67E-4	0.10331	0.06351	6.86E-4	2.41E-4
	Stdve	3.57E-5	0.04851	0.04852	1.01E-4	5.32E-4
DTLZ2	Average	6.46E-4	0.03762	0.01583	0.03362	0.00133
	Stdve	1.48E-4	0.00262	0.00205	1.71E-4	0.00266
DTLZ3	Average	0.00244	0.03585	0.04542	0.00263	3.51E-4
	Stdve	6.63E-5	0.00254	0.00345	5.62E-5	2.12E-5
DTLZ4	Average	2.14E-4	0.06452	0.11412	2.32E-4	2.73E-4
	Stdve	3.38E-5	0.01921	0.02563	1.25E-4	4.24E-5
DTLZ7	Average	3.24E-5	7.53E-4	0.00235	3.94E-4	4.55E-5
	Stdve	2.57E-7	4.77E-5	1.265E-4	1.65E-5	1.43E-6

4.3 Analysis of multi-objective optimization results

The application of the improved NSGA-II optimization algorithm proposed in this paper can find an instructional management policy solution, i.e., the set of Pareto optimization solutions, that satisfies multiple optimization objectives of minimizing instructional management costs, maximizing the effectiveness of students' craftsmanship development, and maximizing instructional satisfaction. Figure 6 shows the Pareto optimization frontiers composed of Pareto optimization solutions for this case. Figure 7 shows the convergence of objective functions 1 and 2.

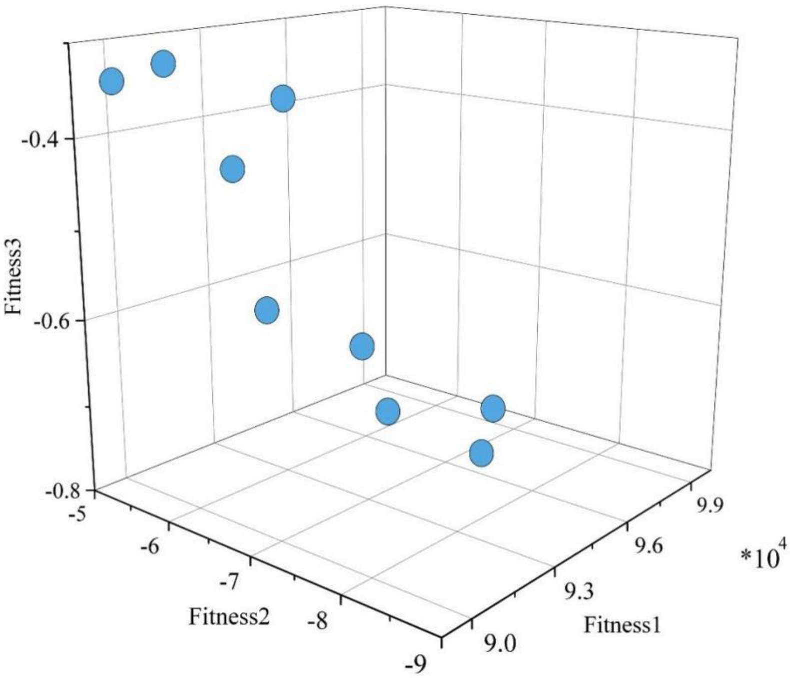


Figure 6: Pareto optimization frontier

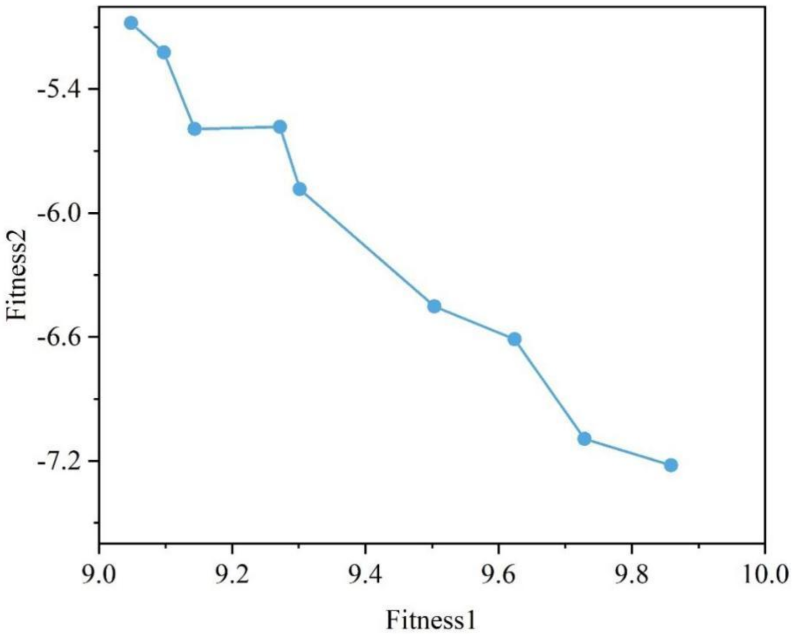


Figure 7: The convergence of the target function 1 and 2

As there are many objective functions involved and interrelated to each other, the use of a multi-objective optimization technique results in Pareto optimal solutions. There are several

Pareto optimal solutions; however, each Pareto optimal solution ensures the maximization of one or two objective functions, but not all three objective functions at once. Thus, nine Pareto optimal solutions arise, as shown in Table 3 below.

Table 3: Pareto optimal solution

Policy combination number	Practice class	Teacher training input	Diversity of evaluation	Administrative cost (10,000 yuan per year)	Artisan's mental improvement index	Teaching satisfaction
1-4-2-5	40%	10%	70%	3251	8.50	80%
1-3-2-5	35%	15%	40%	3630	8.59	90%
1-4-2-6	38%	25%	50%	3788	8.67	90%
1-5-4-3	42%	16%	60%	3654	8.78	95%
1-4-2-3	36%	30%	80%	3891	9.20	89%
1-4-3-5	38%	15%	40%	4250	9.35	92%
1-2-3-5	45%	25%	50%	4155	9.24	94%
1-2-4-5	33%	30%	60%	4562	9.05	86%
1-3-4-5	28%	16%	70%	4815	9.56	91%

Figure 8 shows the results of the ascending order of the value of the objective function 1 of the 9 solutions, in which the histogram of the value of the objective function 2 and the right axis indicates that, the 9 solutions will be the value of the objective function 1, respectively, each divided by 10,000, the value of the objective function 1 and 3 corresponds to the value of the left axis. Observe the trend of change, known objective function 1 the smaller the better, objective function 2 and 3 the larger the better, the analysis shows that there is an obvious trade-off between management costs, craftsmanship improvement index and teaching satisfaction, management costs often help with the reduction of craftsmanship to improve the index or teaching satisfaction with the corresponding changes, indicating that in the actual management of the need for trade-offs and choices according to the specific objectives.

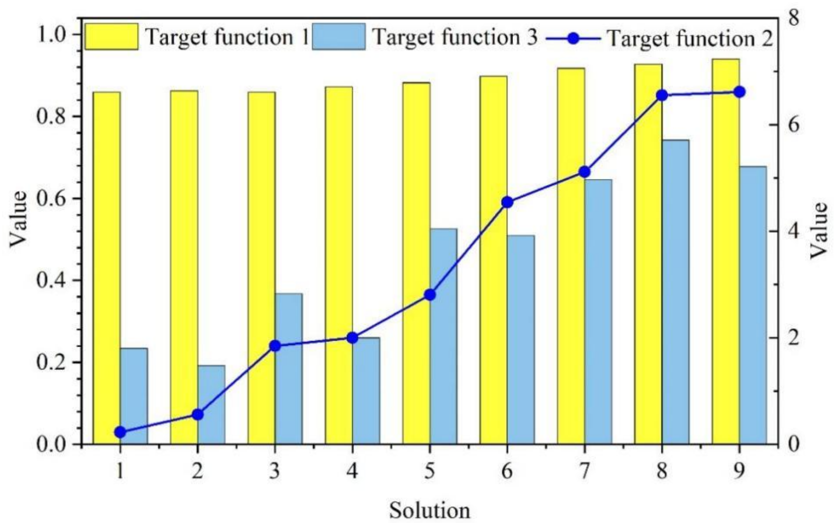


Figure 8: The result of the ascending order of the target function 1 of 9 solutions

5 Empirical analysis of students' craftsmanship assessment and enhancement effect

5.1 Basic information about the sample

Based on the existing student population of 175 students from March 2020 to June 15, 2020 in the Craftsmanship Forging Program teaching experiment, a total of 150 student self-assessment data were obtained by comparing the survey data before and after the implementation of the instructional management policy based on multi-objective optimization and eliminating the missing and invalid data.

5.2 Measurement of students' craftsmanship dimensions

In order to assess the impact of the learning platform intervention on the students' competencies associated with artisanship, this research measured the levels of students' artisanship competencies before and after the implementation of the policy. In order to measure the effect size, a paired samples t-test was used in SPSS 24.0. The pre-test and post-test measurements, as well as the results from the paired samples t-test, are illustrated in Tables 4 and 5 below. It should be noted that the mean pre-test measurement of the students' competence related to artisanship was 3.581, whereas the mean post-test measurement was 3.795. Finally, the results of the paired samples t-test indicate that the significance value (Sig.) was equal to 0.001, which is lower than 0.05.

Further analysis revealed that the pre-test average of students' on-site operation ability was 3.581 and the post-test average was 3.785. Besides, the paired sample t-test analysis indicated that Sig = 0.064 > 0.05, meaning there is no statistically significant difference between pre-test and post-test evaluation of students' on-site operation ability at the 5% significance level. In this case, the effect of enhancing on-site operation ability by implementing optimal teaching management policies is not statistically significant. Again, the average value of students' professional and technical ability in the pre-test was 3.595 while the average in the post-test was 3.748. Moreover, Sig = 0.086 > 0.05, meaning there is no significant difference between pre-test and post-test evaluations of professional and technical competence of the learners at the 5% significance level.

The mean value of the pre-test of students' classroom management ability is 3.878, and the mean value of the post-test is 3.973, and the paired-sample t-test of the two shows that Sig=0.211 is greater than 0.05, which means that there is no difference between the pre-test and the post-test of the students' classroom management ability in the case of the 5% level of the positivity, i.e., it is not significant to improve the classroom management ability through the implementation of the optimized teaching and learning management policy. The mean value of students' self-development ability is 3.282 in the pre-test and 3.671 in the post-test, and the paired samples t-test result shows that Sig=0.000 is less than 0.05, which means that there is a difference between the pre-test and post-test of students' self-development ability at the 5% level of the positivity, that is to say, their self-development ability can be improved through the implementation of the optimized teaching and learning management policy.

Table 4: Analysis of the spirit dimension of artisans

Pairing	N	Mean	Standard deviation	Standard error of mean
Field operational ability	150	3.581	1.034	0.083
Field operation ability	150	3.785	0.983	0.077
Technical ability pretest	150	3.595	0.904	0.072
Technical ability after test	150	3.748	0.887	0.072
Team management ability	150	3.878	0.711	0.057
Team management ability	150	3.973	0.722	0.058
Pre-ability measurement	150	3.282	1.138	0.092
Self-development ability	150	3.671	0.984	0.079
Before the craftsman's spirit	150	3.581	0.636	0.051
The artisan is measured	150	3.795	0.502	0.042

Table 5: Matching sample t test results

Pairing	Mean	Standard deviation	Standard error of mean	t	df	Sig.2
The field operation ability is measured before the field operation ability	−0.204	1.362	0.112	−1.858	149	0.064
The technical ability of the professional technical ability is measured after the technical ability	−0.151	1.086	0.085	−1.744	149	0.086
The team management ability is measured by the team management ability	−0.093	0.908	0.072	−1.251	149	0.211
Self-development ability to test the ability of self-development	−0.392	1.321	0.104	−3.683	149	0.000
The craftsman's spirit is measured by the artisan spirit	−0.212	0.739	0.059	−3.517	149	0.001

5.3 Interactive effects of student heterogeneity on craftsmanship

Some studies have shown that students' heterogeneous characteristics may have an effect on their learning ability, among other things. Therefore, in order to analyze whether students' age and years of working experience affect the effectiveness of students' participation in training on instructional management strategies for multi-objective optimization. In this paper, Two-way ANOVA was used to analyze the results as shown in Table 6. The results of Wilks' Lambda test for age showed that sig=0.000; the results of Wilks' Lambda test for years of working experience showed that sig=0.000; and the results of Wilks' Lambda test for the interaction term of age and years of working experience showed that the F-value was sig=0.000; which indicates that the sample data obeyed a normal distribution. A two-way ANOVA revealed that there is a difference between different ages on students' field operation ability, professional and technical ability, and craftsmanship; there is a difference between different years of work on students' field operation ability, self-development ability, and craftsmanship; there is an interaction between the interaction terms of different ages and years of work on students' field operation ability professional and technical ability and craftsmanship, and there is no interaction on students' class management competence and self-development competence did not interact.

Table 6: Tests of inter subjective effects

Source	Dependent variable	Type III sum	Mean square	F	Sig.	Partial Eta square
Calibration model	Field operation capacity	67.397	4.491	7.850	0.000	0.469
	Technical ability	36.850	2.455	4.064	0.000	0.309
	Team management ability	22.795	1.519	3.682	0.000	0.282
	Self-development ability	36.056	2.402	2.970	0.000	0.246
	Craftsman spirit	30.031	2.007	33.358	0.000	0.784
Intercept	Field operation capacity	690.026	690.02	1205.505	0.000	0.896
	Technical ability	727.342	727.345	1203.212	0.000	0.898
	Team management ability	859.008	859.014	2085.218	0.000	0.944
	Self-development ability	699.668	699.666	866.519	0.000	0.848
	Craftsman spirit	743.000	743.002	1238.209	0.000	0.989
Age	Field operation capacity	11.775	3.924	6.860	0.000	0.138
	Technical ability	8.877	2.963	4.901	0.003	0.099
	Team management ability	2.442	0.805	1.976	0.122	0.047
	Self-development ability	0.849	0.284	0.349	0.791	0.009
	Craftsman spirit	3.245	1.080	18.024	0.000	0.286
Working life	Field operation capacity	8.312	2.088	3.627	0.007	0.093
	Technical ability	2.477	0.620	1.018	0.396	0.026
	Team management ability	2.870	0.716	1.744	0.145	0.044
	Self-development ability	9.045	2.254	2.785	0.027	0.071
	Craftsman spirit	4.150	1.039	17.287	0.000	0.343
Age * Working life	Field operation capacity	17.586	2.195	3.849	0.000	0.184
	Technical ability	12.471	1.557	2.580	0.012	0.136
	Team management ability	3.324	0.413	1.007	0.434	0.056
	Self-development ability	5.661	0.706	0.874	0.541	0.046
	Craftsman spirit	3.290	0.407	6.850	0.000	0.294
Error	Field operation capacity	77.819	0.578			
	Technical ability	82.213	0.603			
	Team management ability	56.076	0.412			
	Self-development ability	110.223	0.803			
	Craftsman spirit	8.160	0.061			

6 Conclusion

In this paper, we constructed an optimization model with management cost, craftsmanship improvement index and teaching satisfaction as the optimization objectives, and solved the optimization model based on the improved NSGA-II algorithm.

Among the three-objective test functions, the convergence of this paper's improved NSGA-II algorithm is slightly worse than the OMOPSO algorithm on the DTLZ1 and DTLZ3 test functions, but this paper's algorithm obtains a better performance in the three test problems, DTLZ2, DTLZ4, and DTLZ7, and the GD mean and variance are the smallest in the DTLZ2 objective test function, which are 3.63E-6 and 5.95E-7. Overall, the improved NSGA-II algorithm is competitive with other state-of-the-art algorithms.

The final set of Pareto-optimal solutions obtained indicates that there is no single strategy that can simultaneously optimize the three objectives of management cost, craftsmanship enhancement index, and teaching satisfaction, and that there is an inherent trade-off between the three objectives, which the decision maker needs to choose according to the actual situation as well as the actual preferences.

The implementation of teaching management strategies based on multi-objective optimization can improve students' comprehensive quality of craftsmanship as a whole, with the most significant improvement in self-development ability, with the mean of the post-test increasing by 0.389 compared to the mean of the pre-test. There is a significant interaction effect between students' age and years of working experience on the enhancement of their own craftsmanship, suggesting that the development of teaching management strategies needs to take into account the group differences within the students, and implement differentiated and precise teaching management strategies.

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About the Author

Fangfang Lian was born in Lishui, Zhejiang, P.R. China, in 1982. She received the Master degree from Zhejiang Gongshang University, she works in Institute of Ecology & Health, Hangzhou Polytechnic University. Her research interests include educational management, innovation and entrepreneurship.

Peng Zhang was born in Dezhou, Shandong, P.R. China, in 1978. He received the bachelor‘s degree from China Jiliang University, P.R. China. Now, he works in Hangzhou Zhongmai Enterprise Management Consulting Co., Ltd. His research interests include control theory and application, applied mathematics.

Lei Xie was born in Jiaxing, Zhejiang, P.R. China, in 1984. She received the Master degree from Zhejiang University of Technology, she works in Institute of Ecology & Health, Hangzhou Polytechnic University. Her research interests include environmental pollution control, new material research and development.

Jingxuan Zhu was born in Lishui, Zhejiang, P.R. China, in 1983. She received the Master degree from Zhejiang University, she works in Hangzhou Ecological Environment Bureau. Her research interests include environmental protection law.

Ling Ge was born in Zhumadian, Henan, P.R. China, in 1981. She received the bachelor‘s degree from Fudan University, she works in Zhejiang Fengniao Certification Service Co., Ltd. Her research interests include food safety and law.

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