Classroom Teaching Decision-Making Optimization for Students' Personalized Learning Needs

https://doi.org/10.3991/ijet.v18i09.40233

Liyang Li(✉)
Department of Economics and Trade, Shijiazhuang University of Applied Technology, Shijiazhuang, China
2017010857@sjzpt.edu.cn

Abstract—Classroom teaching is the basic form of teaching in colleges and universities. Teachers need to constantly optimize classroom teaching decision-making to adapt to the ever-changing educational environment. In order to improve the quality of teaching, stimulate students' potential, and promote students' all-round development, it is necessary to fully consider the personalized needs of students in classroom teaching and provide more suitable teaching content and methods for them. To this end, this article takes the accounting major in higher vocational colleges as an example, and conducts a study on the optimization of classroom teaching decision-making for students' personalized learning needs. It introduces the psychological curve function based on expected performance and current performance to measure the satisfaction degree of students' personalized learning needs, and as an evaluation of whether students' personalized learning needs meet expectations, elaborates on the calculation method of expected performance and current performance of personalized learning. A multi-objective decision-making model for classroom teaching is constructed to achieve the three optimization objectives of maximizing the quality of classroom teaching, maximizing the attention of students' personalized learning needs, and maximizing students' dissatisfaction, and the solution method of the model is given. Experimental results verify the effectiveness of the proposed algorithm and the constructed model.

Keywords—students' personalized learning, learning needs, classroom teaching decision-making, multi-objective decision-making optimization

1 Introduction

With the development of educational technology and changes in social needs, the quality of student training has become increasingly prominent [1–5]. Classroom teaching is the basic form of teaching in colleges and universities. Teachers need to constantly optimize classroom teaching decision-making to adapt to the ever-changing educational environment [6–9]. Paying attention to and meeting students' personalized learning needs is the basic way to understand classroom teaching effects and is also an important source of driving teachers to improve teaching decisions [10–15].

Optimizing classroom teaching decision-making according to the personalized needs of students can help improve teaching quality. Teachers can formulate appropriate teaching programs and methods according to the interests, abilities and needs of each student to improve students' learning effects [16]. At the same time, personalized teaching decisions can better cultivate students' comprehensive qualities such as innovative ability, critical thinking, teamwork and interdisciplinary knowledge. This helps to cultivate talents with all-round development and adapting to the needs of society. The optimization of classroom teaching decision-making for students' personalized learning needs can promote educational innovation. In the process of exploring teaching methods and strategies adapted to the needs of students, it is possible to pioneer new educational models and practices.

Huang and Young [17] provides a classroom interaction system that can be used in conjunction with handheld devices. The system not only provides students with immediate responses to their learning status, but also supports teachers in their decision-making. In addition, the concept of Web 2.0 is applied in the system to allow students to share and exchange learning resources. Murtafiah et al. [18] explores the decision-making process of novice and experienced teachers when designing mathematics problems. Data collection for the decision-making process is based on teacher-designed problem observations and a framework that includes generating ideas, clarifying ideas, and evaluating the plausibility of ideas for creating math problems. The findings suggest that novice teachers are still less creative than experienced teachers when it comes to generating ideas. Phillips et al. [19] reports a pilot study in which the links between knowledge and decision-making in science, mathematics, and information technology teachers' lesson plans are quantified and represented using cognitive network analysis. The findings reveal a level of complexity that has been implied but so far not supported by empirical evidence. Olson et al. [20] determines the impact of two different teaching cases on multiple aspects of teachers' effective teaching decision-making. The teaching effect of 207 semesters is analyzed to determine the degree of decision-making differences on key issues. Compared with the group that completed the unit plan, teachers in both groups that optimized teaching decision-making are able to better consider how students learn when making decisions that include teaching activities and content.

Students have different interests, abilities, learning styles and background knowledge. In order to improve the quality of teaching, stimulate students' potential, and promote students' all-round development, it's necessary to fully consider the personalized needs of students in classroom teaching, and provide more suitable teaching content and methods. Existing research on teaching decision-making optimization lacks consideration of students' personalized learning needs. To this end, this article takes the accounting major in higher vocational colleges as an example, and conducts a study on the optimization of classroom teaching decision-making for students' personalized learning needs. In Chapter 2, the article introduces the psychological curve function based on expected performance and current performance to measure the satisfaction degree of students' personalized learning needs, and as an evaluation of whether students' personalized learning needs meet expectations, elaborates on the calculation method of expected performance and current performance of personalized learning. In Chapter 3, the article builds a multi-objective decision-making model for classroom teaching to achieve the three optimization objectives of maximizing classroom teaching quality, maximizing attention to personalized learning needs of students, and maximizing student dissatisfaction, and gives a solution method for the model. Experimental results verify the effectiveness of the proposed algorithm and the constructed model.

2 Construction of student satisfaction model

Student satisfaction is an evaluation of whether students' personalized learning needs meet expectations, and it is a representation of the degree of matching between teachers' classroom teaching decision-making and students' personalized needs. Student satisfaction is a variable dynamic target. This article introduces a psychological curve function based on expected performance and current performance to measure the satisfaction degree of students' personalized learning needs. Assuming that student satisfaction is represented by γ, the expected performance of students' personalized learning is represented by β, and the current performance of students' personalized learning is represented by α, the specific expression is given by the following formula:

$$\gamma = 1 - o^{-\left(\frac{\beta}{\alpha}\right)^2} \tag{1}$$

Based on the psychological curve function, this article puts forward the expected performance and current performance of teachers' classroom teaching decision-making attributes in three aspects: the individualization of teaching objectives, the adaptability of learning styles and the diversification of evaluation standards, and abstracts a model of students' satisfaction with the three attributes of candidate classroom teaching decision-making. It's assumed that the personalized learning expectation performance of the personalized degree *td* of teaching objectives is indicated by β_{td} and the attribute is indicated by β_δ. The personalized learning expectation performance of the adaptability of learning style and the diversification of evaluation criteria is represented by δ, respectively, the student's personalized learning current performance of the *i*-th candidate classroom teaching decision-making on individualization *td* is represented by $\alpha_{i,td}$, the student's personalized learning current performance of the *i*-th candidate classroom teaching decision on attributes δ the current performance of personalized learning is represented by $\alpha_{i,\delta}$, the satisfaction of the *i*-th candidate classroom teaching decision on satisfaction of personalized teaching objectives *td* is represented by $\gamma_{i,td}$, the satisfaction of the *i*-th candidate classroom teaching decision on attributes δ are represented by $\gamma_{i,\delta}$, then:

1. Personalized satisfaction with teaching objectives

$$\gamma_{i,ed} = \begin{cases} 1, & \beta_{td} >= \alpha_{i,td} \\ 1 - o^{-\left|\frac{\beta_{td}}{\alpha_{i,td}}\right|}, & \beta_{td} < \alpha_{i,td} \end{cases} \tag{2}$$

2. Adaptability of learning style and diversity satisfaction of evaluation criteria:

$$\gamma_{i,\delta} = \begin{cases} 1, & \beta_\delta >= \alpha_{i,\delta} \\ 1 - o^{-\left|\frac{\beta_\delta}{\alpha_{i,\delta}}\right|}, & \beta_\delta < \alpha_{i,\delta} \end{cases} \tag{3}$$

The performance involved in the above two formulas includes students' personalized learning expectation performance and current performance. The calculation process of the two performances is similar, and this article will explain the calculation process.

The adaptability attribute of learning style is composed of the diversity of learning methods *RR* and the richness of learning resources *B*, and the diversified attribute of evaluation criteria is composed of the diversity of evaluation methods *C*, the combination of process and results *Y*, self-evaluation and mutual evaluation *G*. In order to more accurately reflect the adaptability of learning styles and the diversification of evaluation criteria, this article uses different weights to reflect the importance of each parameter in each attribute.

Compared with most complex multi-attribute decision-making algorithms for calculating weights, fuzzy analytic hierarchy process is more suitable for describing uncertainties such as parameter fuzziness, and the weights obtained by this algorithm can more closely express students' personalized needs. Therefore, this article uses the fuzzy analytic hierarchy process to calculate the weight of learning method diversity and learning resource richness within the adaptability of learning style, and the weight of evaluation method diversity, process and result combination, self-evaluation, and mutual evaluation within the diversity of evaluation criteria.

Firstly, the target problem of whether students' personalized learning needs meet expectations is stratified, that's, it is divided into three layers: target layer, criterion layer and program layer. The target layer is the adaptability of learning styles and the diversified student performance of evaluation standards. The criterion layer is the decision factors that affect the adaptability of learning styles and the diversification of evaluation standards. The program layer is the normalized value of each parameter in each candidate classroom teaching decision. Figure 1 shows a schematic diagram of the hierarchical structure.

With the general calculation method of fuzzy judgment matrix, the five parameters of diversity of learning methods *RR*, richness of learning resources *B*, diversity of evaluation methods *D*, combination of process and results *Y*, self-evaluation and mutual evaluation *G* in the criterion layer are divided into two groups, respectively constructing matrices to characterize the importance of the adaptability of learning styles and the diversification of evaluation criteria in the target layer. Through the comparison and analysis among the parameters, quantitative scale values $s_{x,y}$ can be obtained. Table 1 shows the applicable comparison scale. It's essential to further obtain the fuzzy judgment matrix $S = s_{x,y}*(d*d)$, and substitute the two attributes of learning style adaptability and evaluation standard diversification to obtain the corresponding fuzzy complementary judgment matrices S_{rt} and S_{rp}. This article obtains S_{rt} and S_{rp} based on the scale method, namely:

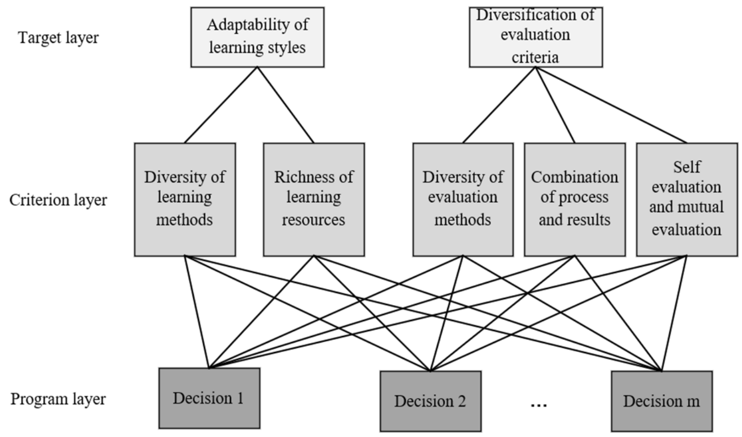

Fig. 1. Schematic diagram of hierarchical structure

Table 1. Comparison metrics

Scale Value	Definition	Description
0.9	Extremely important	The former is extremely important compared to the latter.
0.8	Very important	The former is very important compared to the latter.
0.7	More important	The former is more important than the latter.
0.6	Slightly important	The former is slightly important compared to the latter.
0.5	As important as	The former is as important as the latter.
0.1, 0.2, 0.3, 0.4, 0.5	Inverse comparison	Inverse comparison of the above comparisons

$$S_{rt} = \begin{array}{ccc} & R & B \\ R & 0.4 & 0.5 \\ B & 0.5 & 0.6 \end{array} \tag{4}$$

$$S_{rp} = \begin{array}{cccc} & C & Y & G \\ C & 0.5 & 0.4 & 0.7 \\ C & 0.6 & 0.5 & 0.7 \\ G & 0.3 & 0.3 & 0.5 \end{array} \tag{5}$$

Calculate the weight of each parameter based on the general formula for solving the weight of the fuzzy complementary judgment matrix, let $\Sigma^{m}_{x=1} q_x = 1$, $q_x \geq 0$, $x = 1, 2, ..., d$, the number of matrix rows is represented by d, the x-th row and the y-th column are represented by x and y, then:

$$q_x = \frac{\sum_{b=1}^{m} s_{x,y} + \frac{m}{2} - 1}{d\left(d-1\right)}, x = 1, 2, ..., d \tag{6}$$

Combining the above three formulas, the adaptability of learning style and the diversified weight vector of evaluation criteria can be obtained:

$$\begin{array}{cc} & R \quad B \\ q_{rt} = & 0.55 \quad 0.45 \end{array} \tag{7}$$

$$\begin{array}{cc} & C \quad\quad Y \quad\quad G \\ q_{rp} = & 0.412 \quad 0.371 \quad 0.217 \end{array} \tag{8}$$

It's assumed that the weight vector of the adaptability *rt* of the learning style is represented by $q_{rt,}$ and the weight vector of the diversification *rp* of the evaluation standard is represented by q_{rp}. Therefore, the weights of learning method diversity *R* and learning resource richness *B* in *rt* are 0.55 and 0.45 respectively. In *rp*, the weights of evaluation method diversity degree C, process and result combination *Y*, self-evaluation and mutual evaluation degree *G are* 0.412, 0.371 and 0.217 respectively. Through the consistency check, it can be seen that the adaptability of the learning style and the diversified fuzzy judgment matrix of the evaluation standard are consistent, and the weight value results are completely reasonable.

The normalized value of price is defined as the composite value of the personalized attributes of the teaching objective. It's assumed that the personalized attribute value of the teaching goal of classroom teaching decision *i* is denoted by $\alpha_{i,td}$ and the price is denoted by *D*. Given the normalized values and weights of the diversity of evaluation methods, the combination of process and results, self-evaluation and mutual evaluation, the diversity of learning methods, and the richness of learning resources, the comprehensive value of the adaptive attribute of learning style and the diversified attribute of evaluation criteria is the sum of the weight and the normalized value SQ of the corresponding parameters of the two attributes. Assuming that the comprehensive values of personalization of teaching objectives *td*, adaptability of learning styles *rt*, and diversification of evaluation criteria *rp* for the *i*-th classroom teaching decision are represented by $\alpha_{i,td}$, $\alpha_{i,rt}$ and $\alpha_{i,rp}$, then:

$$\alpha_{i,td} = SQ_{i,D} \tag{9}$$

$$\alpha_{i,rt} = q_R \times SQ_{i,R} + q_B \times SQ_{i,B} \tag{10}$$

$$\alpha_{i,rp} = q_C \times SQ_{i,C} + q_Y \times SQ_{i,Y} + q_G \times SQ_{i,G} \tag{11}$$

Substitute the six parameters of the current candidate classroom teaching decision-making, and obtain the comprehensive value of the individualization of the teaching objectives, the adaptability of the learning style, and the diversified attributes of the evaluation criteria of all the current candidate classroom teaching decisions, which this article defines it as the current performance of students' personalized learning, including the current performance of students' personalized learning $\alpha_{i,td}$ in the case of personalized teaching objectives, the current performance of students' personalized learning in the case of adaptive learning styles $\alpha_{i,rt}$ and the current performance of students' personalized learning in the case of diversified evaluation standards $\alpha_{i,rp}$.

n group of parameter data and the results of teachers making classroom teaching decisions are obtained from historical data when students are faced with *n* overlapping classroom teaching decisions. When the *n* group of data is substituted into the above formula, it can calculate the personalization of teaching objectives, the adaptability of learning styles, and the diversification of evaluation standards when making classroom teaching decisions for n groups of students with personalized learning needs, that's, the comprehensive value set of the three attributes $\Psi_w=\{\alpha_{1,w},\alpha_{2,w},...,\alpha_{m,w}\}$. Among them, *w* is the three attributes of personalization of teaching objectives, adaptability of learning styles, and diversification of evaluation standards. Considering that there will be a small part of data distortion, this article averages the comprehensive values of each attribute obtained from *f* times overlapping classroom teaching decision-making situations. It's assumed that the comprehensive values of personalization of teaching objectives, adaptability of learning styles, and diversification of evaluation standards in the *i*-th overlapping situation are represented by $\beta_{i,w}$, respectively, and the average value of the comprehensive values of students' demand for classroom teaching decision-making attributes under the historical situation *f* overlapping is represented by β_w, which is defined herein as expected performance of personalized learning.

$$\beta_w = \frac{1}{f}\sum_{i=1}^{f}\alpha_{i,w} \tag{12}$$

Substituting the value of the set Ψ_w into the above formula, it's possible to obtain the expected performance β_{td} of students' personalized learning in the case of personalized teaching objectives, the expected performance β_{rt} of personalized learning in the case of adaptive learning style and the expected performance β_{rp} in the case of diversified evaluation standards.

3 Classroom teaching decision-making optimization

Classroom teaching decision-making for students' personalized learning needs to comprehensively consider improving teaching quality, cultivating students' independent learning ability, discovering students' potential, enhancing students' participation, paying attention to students' emotional development, promoting cooperation and communication among students, and adapting to multiple factors such as diversified evaluation standards, carry out overall classroom teaching decision-making planning, make scientific use of available teaching resources, and rationally organize and arrange teaching content to ensure that the classroom teaching effect reaches the expected level. Therefore, classroom teaching decision-making for students' personalized learning needs focuses on whether teachers can pay attention to students' personalized needs, reflects respect and satisfaction for students' differences in teaching decisions, and ensures the teaching effect level of each link of the classroom within an acceptable range to the greatest extent.

The multi-objective decision-making model of classroom teaching herein mainly realizes three optimization objectives of maximizing the quality of classroom teaching, maximizing the attention of students' personalized learning needs, and maximizing students' dissatisfaction. Based on the determined optimization goal of classroom teaching decision-making, three objective functions are set for the classroom teaching decision-making model, namely objective function G_1: Maximize the overall quality of classroom teaching within the duration of classroom teaching; objective function G_2: Maximize attention to students' personalized learning needs within the duration of classroom teaching; G_3: Minimize student dissatisfaction within the duration of classroom teaching. In order to facilitate quantitative analysis, this article divides the duration of classroom teaching. Figure 2 shows the process of dividing the duration of classroom teaching.

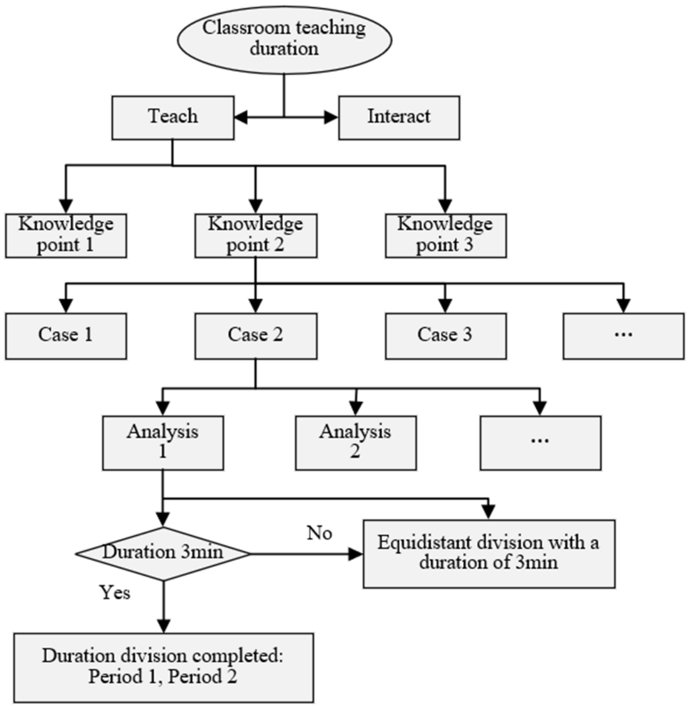

Fig. 2. Classroom teaching duration division process

It's assumed that the index code of classroom teaching quality is represented by i, j, the number of classroom teaching link is represented by l, the degree of personalized learning needs of students is represented by K_l, the weight of the importance of teaching link l is represented by θ_l, and the teaching quality of the classroom in the quality status i of the teaching link l is represented by O_{li} after the optimization of the corresponding teaching decision, the duration of classroom teaching is represented by P, the p-th period within the duration of classroom teaching is represented by p, the proportion of the duration of teaching link at the end of the p-th period in quality state

i to the duration of classroom teaching is represented by S_{ip}, the teaching link l at the end of the p-th period in the quality state i is implemented to optimize the proportion of teaching decisions to the duration of classroom teaching is represented by a_{lip} and student dissatisfaction in the teaching link in the quality state i is indicated by D_i. The specific objective function is given by the following formula:

$$MaximizeG_1 = \sum_{k=1}^{n}\sum_{p=1}^{P}\sum_{i=1}^{10}\theta_l S_{i(p-1)} a_{lip} O_{li} K_l \tag{13}$$

$$MaximizeG_2 = \sum_{l=1}^{n}\sum_{t=1}^{P}\left(S_{1p} + S_{2p}\right)K_l \tag{14}$$

$$MinimizeG_3 = \sum_{l=1}^{n}\sum_{p=1}^{P}\sum_{i=1}^{10} S_{i(p-1)} a_{lip} D_i K_l \tag{15}$$

Assuming that after the teaching environment with the teaching quality state j implements the optimal teaching decision, the transition probability from state j to state i is represented by P_{lji}, the dissatisfaction of students in the entire classroom teaching duration is represented by Y, and the fluctuation coefficient of student dissatisfaction is represented by x%. The following formula gives the method of calculating the proportion of the duration of teaching link in each teaching quality status at the end of each period within the duration of classroom teaching to the duration of classroom teaching.

$$S_{ip} = \sum_{l=1}^{n}\left[\left(1-a_{lip}\right)S_{i(p-1)}T_{lii} + \sum_{j=1}^{10} a_{ljp} S_{j(p-1)} P_{lji}\right] \quad i = 1, \forall p \tag{16}$$

$$S_{it} = \sum_{l=1}^{n}\left[\left(1-s_{lip}\right)S_{i(p-1)}T_{lii} + \left(1-a_{l(i-1)p}\right)S_{(i-1)(p-1)}T_{l(i-1)i} + \sum_{j=1}^{10} a_{ljp} S_{j(t-1)} P_{lji}\right] i \neq 1, \forall p \tag{17}$$

The constraints of the model are given by the following formula. The following formula constrains the dissatisfaction of students within the duration of classroom teaching.

$$\sum_{l=1}^{n}\sum_{i=1}^{10}\sum_{p=1}^{10} a_{lip} S_{i(p-1)} D_i K_l \leq Y \qquad \forall i, p \tag{18}$$

The following formula ensures that the fluctuation of student dissatisfaction within the duration of classroom teaching remains relatively stable, so that the difference of student dissatisfaction in adjacent teaching periods will not be too large.

$$\left(1-x\%\right)\frac{Y}{P}\le\sum_{l=1}^{n}\sum_{i=1}^{10}a_{lip}S_{i(p-1)}D_iK_l\le\left(1+x\%\right)\frac{Y}{P}\quad\forall p=1,2,...,10 \tag{19}$$

The following formula ensures that the proportion of classroom teaching quality in each teaching period is 100%.

$$\sum_{i=1}^{10}S_{ip}=1\quad\forall p=1,2,...,10 \tag{20}$$

For the above optimization model, this article realizes the calculation of the optimal solution of the model by minimizing the weighted sum of deviations between the ideal solution of the model and the maximum and minimum values of the objective functions of G_1, G_2 and G_3. This article first determines the weights of G_1, G_2 and G_3, and then constructs the following comprehensive objective function formula:

$$MinimizeC=\sum_{i=1}^{3}\frac{\theta_i\left(c_i^-+c_i^+\right)}{G_{i-\max}-G_{i-\min}} \tag{21}$$

The NSGA-II algorithm is used to solve the maximum and minimum values of G_1, G_2 and G_3. Figure 3 shows the algorithm flow. Since the calculation results of G_1, G_2 and G_3 have different orders of magnitude, they need to be standardized. Assuming that the weight of the i-th objective determined according to the AHP is represented by θ_i, the minimum and minimum values of the i-th objective function are represented by G_{i-min} and G_{i-max} and the negative deviation variable and positive deviation variable are represented by c_i^- and c_i^+, the final comprehensive objective function C takes the form of a weighted function and is given by the following formula:

$$C_i\left(A\right)+c_i^--c_i^+=G_{i-\max} \tag{22}$$

$$C_i\left(A\right)+c_i^--c_i^+=G_{i-\max} \tag{23}$$

The optimal classroom teaching decision-making programs oriented to students' personalized learning needs can be obtained by solving the above formula. There are differences in the optimal classroom teaching decision-making programs calculated by different objective function weights.

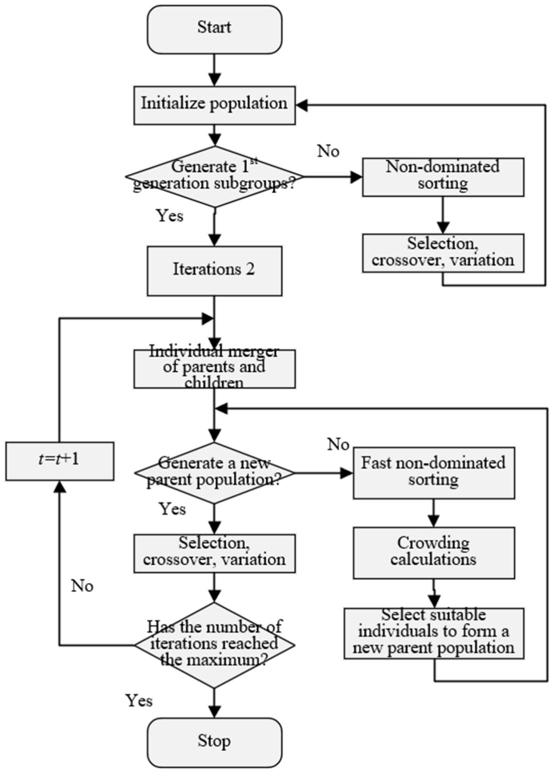

Fig. 3. *NSGA-II* algorithm flowchart

4 Experimental results and analysis

Figure 4 shows that average student satisfaction varies over the number of students. It can be seen from the figure that there are certain differences in the change laws of the average student satisfaction curves of *CART* regression algorithm, *KNN* regression algorithm and the algorithm of this article. Although the three algorithms fluctuate greatly when the number of students is less than 30, the student satisfaction curve of the algorithm in this article is higher in the figure than the other two algorithms. When the number of students is less than 10, the three attributes of personalization of teaching objectives, adaptability of learning styles and diversification of evaluation standards have fewer historical sample data, which leads to some uncertainty in the calculation of students' current and expected performance in personalized learning, which is the main reason for the fluctuation of student satisfaction values. *CART* regression algorithm and *KNN* regression algorithm are more about the quality of classroom teaching, so the difference in output results is small.

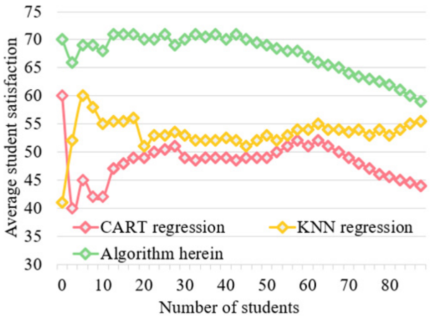

Fig. 4. Changes in average student satisfaction over the number of students

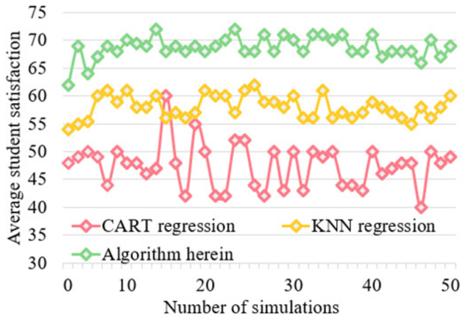

Fig. 5. Change of average student satisfaction over the number of simulations

Figure 5 shows the average student satisfaction over the number of simulations. It can be seen from the figure that when the number of students is constant, the three algorithms are simulated 50 times, and the average satisfaction of each student in the algorithm in this chapter is more than 80%, but only 70% and 60% in the other two algorithms. In other words, among the three algorithms, the algorithm in this article has the highest average student satisfaction. The main reason is that the algorithm in this article not only guarantees the quality of classroom teaching, but also meets the personalized needs of students and effectively improves student satisfaction. The experimental results in Figures 4 and 5 verify that the algorithm in this article can better meet the personalized learning needs of students.

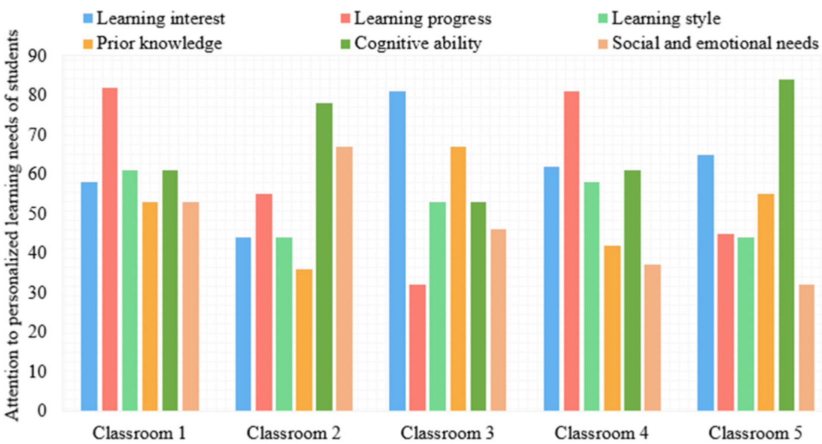

Fig. 6. Attention paid to students' personalized learning needs in different classes of accounting majors

This article involves the attention paid to students' personalized learning needs in different classes of accounting majors, as shown in Figure 6. It can be seen from the figure that the classroom teaching decision-making studied in this article focuses on students' personalized learning needs based on learning interest, learning progress, and learning style, while considering prior knowledge, cognitive ability, social and emotional needs, etc. For theoretical classes that focus on lectures, in terms of students' personalized learning needs, teachers pay more attention to students' learning interests, prior knowledge, and cognitive abilities, such as Classroom 2, Classroom 3, and Classroom 5 in the figure. For interactive practical classrooms, teachers pay more attention to students' learning progress, learning style, and social and emotional needs in students' personalized learning needs, such as Classroom 1, Classroom 2, and Classroom 4 in the figure.

Based on the actual teaching decision-making experience in accounting major classrooms, it constructs an optimization model for teaching decision-making. There are 7 decision-making indicators in the model, including the diversity of learning methods, the personalization of teaching objectives, the richness of learning resources, the adaptability of learning styles, the attention to students' personalized learning needs, and the diversification of evaluation standards. The decision-making indicators are combined with reference to the indicator grading standards in Table 2. Classroom teaching content is used as the final reference condition of the teaching decision-making program to evaluate the applicability of the teaching decision-making program. Through the teaching decision-making optimization model and the teaching decision-making program table given in Table 2, it obtains the alternative teaching decision-making optimization program.

Table 2. Classroom teaching decision-making optimization program table

Class Nature	Decision Optimization Program	Diversity of Learning Methods	Personalization of Teaching Objectives	Richness of Learning Resources
Lecture	1	>=90	<=5	>100
	2	>=90	<=5	>100
	3	>=90	<8	>100
	4	80–90	5–15	<60
	5	80–90	5–10	<60
Interaction	6	<=80	>=10	<60
	7	<=80	>=10	<60
	8	<=80	>=15	<30
	9	<=80	>=15	<30
	10	<=80	>=15	<30

Class Nature	Adaptability of Learning Styles	Attention to Personalized Learning Needs of Students	Diversity of Evaluation Criteria
Lecture	<=2.3	>40	<5
	<=2.3	>40	<5
	<=2.3	<=40	<5
	>2.3	<=40	>=5
	>2.3	<=40	>=5
Interaction	>2.3	<=40	>=5
	>2.3	<=40	>=5
	>2.3	<=40	>=5
	>2.3	<=40	>=5
	>2.3	<=40	>=5

This article calculates and analyzes the multi-objective optimization results of classroom teaching decision-making based on the genetic algorithm *geatpy* library provided by *python*. The initial population size is set to 100. After 100 iterations, the model generates several classroom teaching decision-making optimization programs. Figure 7 shows the 50 Pareto optimal solutions selected from them. In this article, θ_1=0.4, θ_1=0.3 and θ_1=0.3 are selected in the simulation example of the accounting classroom, and the total score of program 32 is the highest. Therefore, program 32 is used to optimize the teaching decision in the classroom.

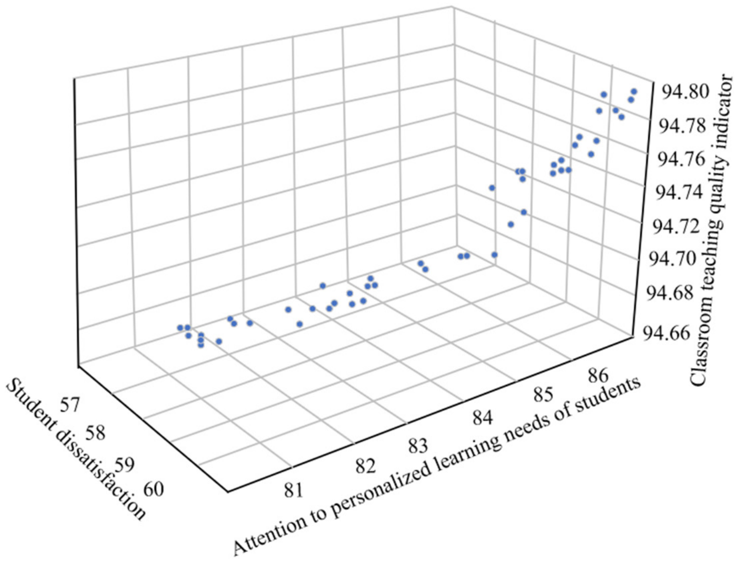

Fig. 7. Multi-objective optimization results of classroom teaching decision-making

5 Conclusion

This article takes the accounting major in higher vocational colleges as an example, and conducts a study on the optimization of classroom teaching decision-making for students' personalized learning needs. It introduces the psychological curve function based on expected performance and current performance to measure the satisfaction degree of students' personalized learning needs, and as an evaluation of whether students' personalized learning needs meet expectations, elaborates on the calculation method of expected performance and current performance of personalized learning. A multi-objective decision-making model for classroom teaching is constructed to achieve the three optimization objectives of maximizing the quality of classroom teaching, maximizing the attention of students' personalized learning needs, and maximizing students' dissatisfaction, and the solution method of the model is given. Combined with the experiment, it analyzes the change of average student satisfaction over the number of students and the change of average student satisfaction over the number of simulations, which verifies that the algorithm in this article can better meet the personalized learning needs of students. It involves the attention paid to students' personalized learning needs in different classes of accounting majors, and gives the corresponding analysis results. Finally, it develops the classroom teaching decision-making optimization program table, and visualizes 50 Pareto optimal solutions, which verifies the effectiveness of the constructed model.

6 References

[1] Wang, L., Li, H., Zhang, J., Yang, J. (2022). Grey relational analysis method for probabilistic double hierarchy linguistic multiple attribute group decision making and its application to college tennis classroom teaching effect evaluation. Mathematical Problems in Engineering, 2022: 7419496. https://doi.org/10.1155/2022/7419496

[2] Marino, S. (2022). Developing a sustainable developing a sustainable development goals research hub among MERCOSUR's universities: A case study. Opportunities and Challenges in Sustainability, 1(1): 2–12. https://doi.org/10.56578/ocs010102

[3] Wang, X., Li, Z., Dong, L., Li, W. (2022). The flipped classroom model of Japanese teaching based on intelligent decision-making system. Scientific Programming, 2022: 2792428. https://doi.org/10.1155/2022/2792428

[4] Batrouny, N.A., Miel, K., Wendell, K.B. (2019). Board 110: Work in progress: Elementary students' disciplinary talk in a classroom with an explicit engineering decision-making scaffold. In 2019 ASEE Annual Conference & Exposition. Tampa, Florida. https://doi.org/10.18260/1-2--32188

[5] Bie, M., Song, K. (2018). Applications of hesitant fuzzy multi-attribute decision making in the teaching effectiveness evaluation of flipped classroom model. IOP Conference Series: Materials Science and Engineering, 394: 052007. https://doi.org/10.1088/1757-899X/394/5/052007

[6] Pardo, A.M.S. (2018). Computational thinking between philosophy and STEM-Programming decision making applied to the behavior of "moral machines" in ethical values classroom. IEEE Revista Iberoamericana de Tecnologías del Aprendizaje, 13(1): 20–29. https://doi.org/10.1109/RITA.2018.2809940

[7] Seoane-Pardo, A.M. (2016). Computational thinking beyond STEM: An introduction to "moral machines" and programming decision making in ethics classroom. In Proceedings of the Fourth International Conference on Technological Ecosystems for Enhancing Multiculturality, Salamanca, Spain, pp. 37–44. https://doi.org/10.1145/3012430.3012494

[8] Ogata, H., Yano, Y. (2008). Supporting a decision making for task assignments in language learning outside classroom with handhelds. In Proceedings of the 16th International Conference on Computers in Education, Taiwan, China, pp. 713–720. https://doi.org/10.1109/ICALT.2008.80

[9] Gokturk, S., Mueller, R.O. (2010). Multidimensionality of teacher participation in school decision making. Journal of Applied Sciences, 10(14): 1421–1427. https://doi.org/10.3923/jas.2010.1421.1427

[10] Ashar, M., Kamdi, W., Kurniawan, D.T. (2021). Professional skills development through the network learning community using an online learning platform. International Journal of Interactive Mobile Technologies, 15(12): 202–210. https://doi.org/10.3991/ijim.v15i12.21587

[11] Wang, K.L., Liu, W.Y. (2015). Model of teachers' personalized decision making on activities and resources in web-based training. In ICWL 2013 Workshops: USL 2013, IWSLL 2013, KMEL 2013, IWCWL 2013, WIL 2013, and IWEEC 2013, Kenting, Taiwan, pp. 52–59. https://doi.org/10.1007/978-3-662-46315-4_6

[12] Wang, F., Han, M., Wei, P. (2022). A dynamic learning interest model for a personalized learning requirement analysis of college students. International Journal of Emerging Technologies in Learning, 17(23): 160–175. https://doi.org/10.3991/ijet.v17i23.35937
[13] Vatrapu, R., Teplovs, C., Fujita, N., Bull, S. (2011). Towards visual analytics for teachers' dynamic diagnostic pedagogical decision-making. In Proceedings of the 1st International Conference on Learning Analytics and Knowledge, Banff Alberta, Canada, pp. 93–98. https://doi.org/10.1145/2090116.2090129
[14] Zhang, L., Zeng, X., Lv, P. (2022). Higher education-oriented recommendation algorithm for personalized learning resource. International Journal of Emerging Technologies in Learning, 17(16): 4–20. https://doi.org/10.3991/ijet.v17i16.33179
[15] Simon, S., Ditrichs, R., Grier, J. B. (1995). The simulated class as a method for studying teacher decision making. Computers in Human Behavior, 11(2): 163–180. https://doi.org/10.1016/0747-5632(94)00020-I
[16] Oisboid, D.M., Ettinger, L., Abedi, J., Shavelson, R.J. (1989). Capturing teachers' decision-making policies using a microcomputer simulation. Computers & Education, 13(2): 147–155. https://doi.org/10.1016/0360-1315(89)90007-9
[17] Huang, C.W., Young, S.S. (2011). Design of an in-classroom interaction system supporting instructor's decision making. In 2011 International Conference on Electrical and Control Engineering, Yichang, China, pp. 6512–6514. https://doi.org/10.1109/ICECENG.2011.6056968
[18] Murtafiah, W., Sa'dija, C., Chandra, T.D., Zayyadi, M. (2020). Novice and experienced mathematics teachers' decision making process in designing math problem. Journal of Physics: Conference Series, 1464: 012030. https://doi.org/10.1088/1742-6596/1464/1/012030
[19] Phillips, M., Kovanović, V., Mitchell, I., Gašević, D. (2019). The influence of discipline on teachers' knowledge and decision making. In Advances in Quantitative Ethnography: First International Conference, ICQE 2019, Madison, WI, USA, pp. 177–188. https://doi.org/10.1007/978-3-030-33232-7_15
[20] Olson, J.K., Bruxvoort, C.N., Vande Haar, A.J. (2016). The impact of video case content on preservice elementary teachers' decision-making and conceptions of effective science teaching. Journal of Research in Science Teaching, 53(10): 1500–1523. https://doi.org/10.1002/tea.21335

7 Author

Liyang Li, Female, graduated from Lanzhou University of Finance and Economics with a master's degree in accounting, and she is a lecturer in Shijiazhuang University of Applied Technology. Her main research interests are financial accounting and higher vocational education. She has published nine academic papers in recent three years and participate in many skill competitions and win awards.

Article submitted 2023-02-07. Resubmitted 2023-04-05. Final acceptance 2023-04-12. Final version published as submitted by the authors.