J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 5763--5783

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

Combinatorial Press

Research on Teaching Reform Supported by Multi-Objective Optimization Algorithm for the Process of Civicization of Yoga Courses in Universities

Kun Jiang[1,✉], Congcong Ma[1], Yong Li[1]

[1] *Sports Department, Shaanxi Fashion Engineering University, Xianyang, Shaanxi, 712046, China*

ABSTRACT

This paper establishes a multi-objective optimization model for the process of yoga course ideology and politics in colleges and universities through the group paper technology, and adopts an improved genetic algorithm to solve the model. Integrating the online and offline hybrid teaching mode, the paper's group paper technology is placed in the online assessment to realize the all-round reform of yoga course Civics teaching. The research results show that the improved genetic algorithm (IGA) in this paper has a higher grouping efficiency and quality compared with the traditional genetic algorithm (GA), and saves about 52.7% in the grouping time. At the same time, using the social network analysis method to analyze the online-offline hybrid teaching mode of this paper, we are able to derive the student objects that need to be focused on based on the results of the analysis of the centrality of the point degree and the centrality of the middle of the point degree. The experimental class adopting the teaching mode of this paper has an excellent class performance rate of 100% under the test of group paper technology, which fully demonstrates that the teaching reform method proposed in this paper for the ideology of yoga course in colleges and universities has significant practical application effects.

Keywords: group paper technology, multi-objective optimization, genetic algorithm, social network analysis, yoga course civic-mindedness

1. Introduction

At present, the teaching content of yoga courses in colleges and universities is often limited to the learning of college students' yoga asana movements and the enhancement of special physical qualities, and the attention and integration of ideological education are not enough, focusing on skills and light on theories, and lack of guidance around the ideological link, which shows little ideological connotation, and therefore cannot form a complete system [1-4].

✉ Corresponding author.
E-mail address: jiangkun1268@163.com (K. Jiang).
Received 05 March 2024; Revised 20 April 2024; Accepted 05 December 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-318

Most of the yoga courses in colleges and universities are welcomed by students, and students are more likely to cooperate in the learning process, and their teaching will seldom be a problem, but they will seldom be linked to the ideological education [5-6]. Nowadays, most of the yoga courses in colleges and universities have mature teaching planning, but in the construction of the Civic and Political construction of some colleges and universities yoga courses lack of attention, do not play the advantages of yoga class, lack of effective Civic and Political construction of the assessment link [7-10]. Although the construction of ideology and politics can not directly bring some help to the teaching of yoga courses in colleges and universities, but in the process of long-term development, the construction of ideology and politics can realize the improvement of the teaching level of the stable institutions, to ensure that the direction of development is in line with the interests of long-term development [11-14]. At the same time can effectively reduce the risk of various yoga course personnel training, yoga courses in colleges and universities nowadays is more important to improve the assessment of the learning outcomes of the construction of the ideology and politics [15-17]. Based on the concept of "course political thinking", should be "political education" as a guide, according to the characteristics of the yoga program, digging deep into the yoga curriculum contains elements of political thinking as well as educational value, and moral education, aesthetic education, intellectual education elements skillfully integrated into the content of teaching and learning, the formation of a complete yoga curriculum system [18-21].

This paper establishes a mathematical curve model based on the binomial distribution function of discrete random variables for reflecting the difficulty distribution of the test paper, and constructs the group paper model according to the proposed global constraints to realize the multi-objective optimization of the process of the Civic-Politicalization of yoga courses for colleges and universities. To improve the traditional genetic algorithm, such as the problem of "easy maturity", the multi-objective optimization model established in this paper is solved by the improved genetic algorithm. The intelligent grouping technology of this paper is embedded in the online teaching module of yoga course for the political thinking of colleges and universities, and combined with the offline yoga asana teaching and extension teaching, etc., to explore the method of teaching reform for the political thinking of yoga course in colleges and universities. Comparing the performance of the improved genetic algorithm and the traditional genetic algorithm in terms of scrolling efficiency, the rationality of the improvement of the genetic algorithm in this paper is demonstrated, and the scrolling technology and the online and offline mixed teaching mode are applied to the experimental class of yoga course in the College of Physical Education, and the effectiveness of the teaching reform method proposed in this paper is discussed in the context of the Social Vanguard Network Analysis, which can provide a reference to speed up the process of promoting the political thinking of the yoga course in colleges and universities.

2. Intelligent grouping of papers for yoga course civics

2.1. Roll-up techniques

2.1.1. Quality factors for examination papers. The quality of a test paper depends on two indicators: the difficulty of the test paper and the differentiation of the test paper, which together control the overall quality of the test paper, the basic component of which is the test questions.

1) Difficulty and Distinctiveness of Test Questions:

(1) Difficulty of test questions. The so-called test question difficulty refers to the probability of the tested population losing scores based on the current test questions. Differences in the differences in the way scores are calculated determine differences in the test question difficulty formula. The method of calculating the difficulty of objective questions is shown in Equation (1), in which the difficulty of a test question is denoted by Q, the number of people who successfully passed the test on that question is denoted by R, and the total number of tested people is denoted by N. The difficulty of subjective

questions is calculated as shown in formula (2), in formula (2), the difficulty of the test question is represented by Q, the average score of the tested group in the question is represented by X, and the full score of answering the question correctly is represented by K:

$$Q = 1 - \frac{R}{N} \tag{1}$$

$$Q = 1 - \frac{\bar{X}}{K} \tag{2}$$

The difference in difficulty of the test questions is generally represented by 5 levels, the correspondence of which is shown in Figure 1. In the figure, L1-L5 represent the 5 levels of easy, easier, average, more difficult and difficult, respectively. From the figure, it can be seen that easy corresponds to a difficulty interval of 0.0-0.2, easier corresponds to a difficulty interval of 0.2-0.4, average corresponds to a difficulty interval of 0.4-0.6, more difficult corresponds to a difficulty interval of 0.6-0.8, and difficult corresponds to a difficulty interval of 0.8-1.0.

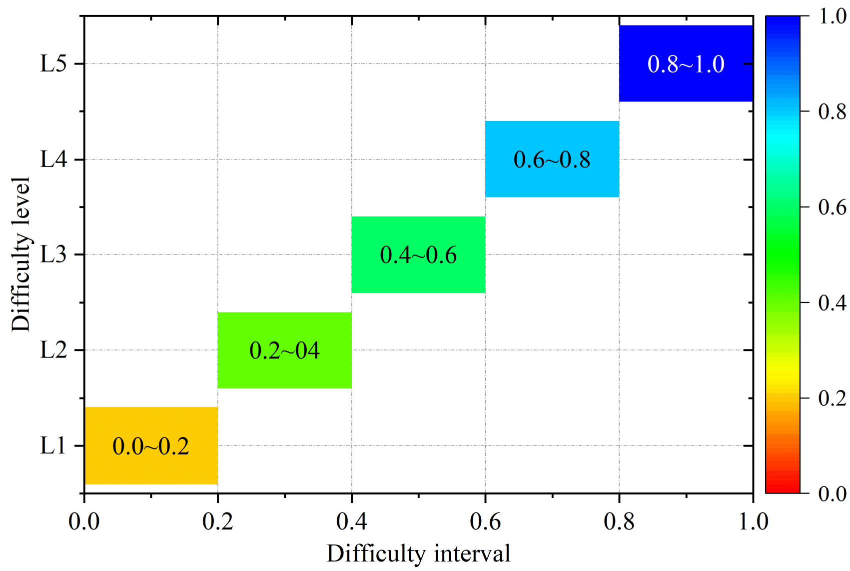

Fig. 1. Correspondence of difficulty level

(2) Distinctiveness of test questions. This index is used to reflect the ability of the test questions to the test takers. The calculation of the degree of differentiation usually takes the high and low grouping calculation method, and the calculation formula is shown in formula (3), and the degree of differentiation of the test questions is denoted by D:

$$D = \frac{\bar{X}_H}{Z} - \frac{\bar{X}_L}{Z} \tag{3}$$

The mean score of high scoring subjects is denoted by $\bar{X}_H$, the mean score of low scoring subjects is denoted by $\bar{X}_L$, and the full score value of the current test question is characterized by Z. Too low a distinction indicates a propositional failure, and the distinction is equipped with a corresponding evaluation criterion, which is shown in Fig. 2. In the figure, E1-E5 represent five differentiation evaluation levels: unqualified, modified usable, qualified, good and excellent, respectively. When the differentiation degree of the test question is less than 0.2, it indicates that the differentiation degree of the test question is unqualified. When the differentiation degree is 0.2~0.4, it indicates that the differentiation degree of the test question can be used after modification. When the differentiation scale is 0.4 to 0.6, it indicates that the test question is a passable test question in terms of differentiation. When the differentiation of the test question is 0.6 to 0.8 and 0.8 or more, it indicates that the test question is a test question with excellent differentiation.

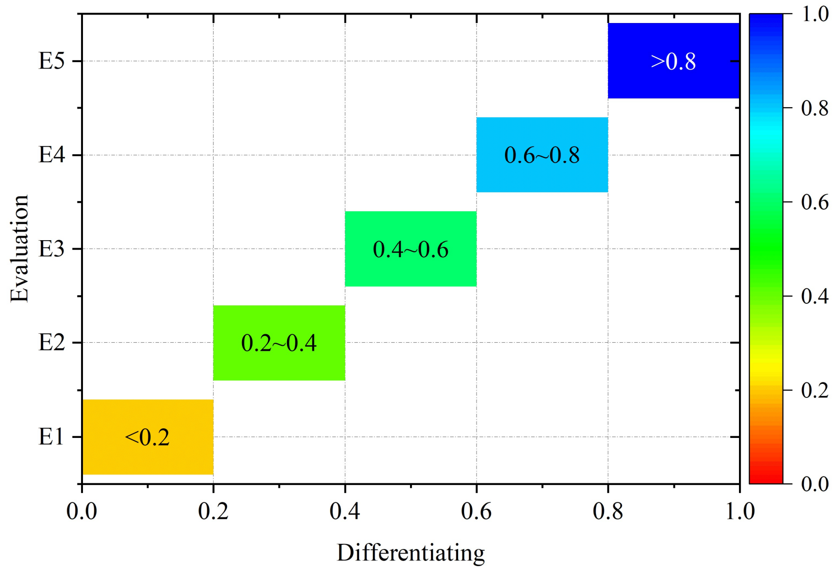

Fig. 2. Distinguishing evaluation of test questions

2) Difficulty of the question paper and differentiation of the question paper:

(1) Test paper difficulty. It refers to the overall rate of marks lost on the test paper by the tested population. It is calculated as shown in formula (4):

$$P = \frac{\sum_{i=1}^{n} P_i k_i}{Z} \tag{4}$$

The total number of questions in the question paper is denoted by n in the formula, the question difficulty of the i question is denoted by P_i, the mark value of the i question is denoted by k_i, and Z represents the total score of the question paper, which has the value of $\sum_{i=1}^{n} k_i$.

(2) Distinctiveness of the test paper. Is an indication of the extent to which the current question paper conforms to the syllabus and is expressed by the formula shown in (5):

$$D = \frac{\sum_{i=1}^{n} D_i k_i}{Z} \tag{5}$$

The differentiation of the ith question in the formula is denoted by D_i.

The difficulty of the paper and the differentiation of the paper work synergistically; normal differentiation does not exist with abnormal difficulty, and the difficulty coefficient is usually between the interval of 0.4 and 0.6, implying excellent differentiation.

2.1.2. Test paper development constraints. Assume that B is a test group attribute matrix of the form shown in (6):

$$B = \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ \cdots & \cdots & \cdots & \cdots \\ b_{s1} & b_{s2} & b_{s3} & b_{s4} \end{bmatrix} \tag{6}$$

The test paper indicators involved in this paper are mainly based on the following conditions.

1) Score points corresponding to knowledge points. Here, the set I_1 is used to represent the key knowledge, and the set I_2 is used to represent the sub-focus knowledge, and the corresponding score ranges are $[L_1, u_1]$ and $[L_2, u_2]$, then the constraints on the scores can be expressed as equation (7):

$$\begin{cases} L_1 \le \sum C_{2i} b_{i2} \le u_1 \\ L_2 \le \sum C_{3i} b_{i2} \le u_2 \end{cases} \tag{7}$$

This constraint specifies the score requirements that should be met for different levels of knowledge. The composition of the focus and sub-focus knowledge sets and the specific range of score values are determined by the proposing instructor.

2) Difficulty distribution. The expectation of the difficulty distribution for the different levels should conform to a normal distribution.

3) Paper structure. The total marks of the paper and the question types of the paper together form the structure of the paper.

(1) Total marks of the paper. The total score of the examination paper can generally be calculated using formula (8). The total marks of the question paper are given by the teacher who sets the questions in the process of organizing the paper:

$$K = \sum_{i=1}^{\infty} b_{i2} \tag{8}$$

In the above formula, the total number of questions in the test paper is denoted by m, and the mark for question i is denoted by b_{i2}.

(2) Test paper questions. The need used to set the corresponding question types that should meet the total mark constraint is expressed in equation (9):

$$Q_t = \sum_{i=1}^{\infty} C_{4i} \cdot b_{i2} \tag{9}$$

where Q_t denotes the score of the tth question type, and the value of this variable is given by the proposing teacher.

(3) Coverage of knowledge points. The method of calculating the coverage of knowledge points is expressed in equation (10):

$$R = \frac{\textit{The knowledge already included in the test set}}{\textit{The sum total of knowledge that the test should contain}} \ge r \tag{10}$$

Where R denotes the coverage of knowledge points, the maximum value of R is equal to 1 when the knowledge points contained in the test set cover the entire syllabus, and in general, the value of r is taken to be more than 0.8.

2.2. Modeling and Processing of Grouped Volumes

2.2.1. System volume organization mode. Volume formation system can be divided into four processes: demand analysis, volume formation model establishment, establishment of mathematical models and solving mathematical models. The success of the mathematical model establishment relates to the efficiency of the whole algorithm implementation, and even affects the robustness of the scrolling system. In this paper, a mathematical curve model based on the binomial distribution function $B(n, p)$ of discrete random variables is established to reflect the difficulty distribution of test papers [22], and the model is represented as follows:

$$P(k) = C_n^k p^k (1-p)^{n-k} \tag{11}$$

Where k denotes an integer from 0 to n. Let $p = \frac{\text{Expected average value}}{\text{Full score value}}$ and $n = \text{Difficulty factor} + 1$, and in this way, $P(k)$ can be found.

The basis of the paper model lies in the difficulty level of the test scores, which vary in terms of competency requirements and chapter scope. Differences in the difficulty coefficients of the test scores are resolved by the model described above, and by taking into account the differences in the difficulty of the test questions and the scope of the chapters in which the test questions are located, the pattern of grouping the papers is determined as follows:

1) Total marks for the paper MFZ: i.e. the total marks for the questions in the paper.

2) Answer time: This is used to control the overall difficulty and number of questions in the paper and is usually set at 2 hours.

3) Difficulty distribution: if the difficulty set of the paper is $L = \{1, 2, \cdots, m\}$, and the total score of the i th difficulty is $\alpha_i = \{i = 1, 2, \cdots, m\}$, the relationship between the total score of difficulty and and MFZ is:

$$MFZ = \alpha_1 + \alpha_2 + \cdots + \alpha_m \tag{12}$$

4) Quantity and Marks: Quantity refers to the number of question types and the number of test questions under each question type. Score is the sum of the marks of each question type. Assuming that the set of question types in the question paper $T = \{1, 2, \cdots, n\}$ and the total number of marks for the x th category of question types is denoted as $t_x = \{x = 1, 2, \cdots, n\}$, the relationship between the various types of question types and the total number of marks of the question paper can be expressed as:

$$MFZ = t_1 + t_2 + \cdots + t_n \tag{13}$$

5) Distinction distribution: if the set of paper distinctions is $Q = \{1, 2, \cdots, h\}$, and the total score for the first y distinctions is $\beta_y = \{y = 1, 2, \cdots, h\}$, then the relationship between the distinctions and the total score of the paper is:

$$MFZ = \beta_1 + \beta_2 + \cdots + \beta_h \tag{14}$$

6) Chapter distribution: assuming that the set of paper chapter distributions is $W = \{1, 2, \cdots, d\}$, and the total score for the z range is denoted as $\gamma_z = \{z = 1, 2, \cdots, d\}$, the relationship between the chapter distributions and the total score of the paper is denoted as:

$$MFZ = \gamma_1 + \gamma_2 + \cdots + \gamma_d \tag{15}$$

7) Distribution of competency requirements: Assuming that the set of test questions for the competency requirements of the paper is $O = \{1, 2, \cdots, r\}$, and the total score for the k th competency requirement is $\delta_k = \{k = 1, 2, \cdots, r\}$, the relationship between the competency requirements and the total score of the paper is:

$$MFZ = \delta_1 + \delta_2 + \cdots + \delta_r \tag{16}$$

The process of grouping test questions involves many uncertainties such as the choice of question types, competence requirements, distribution of knowledge points, difficulty of test questions, etc., and the purpose of grouping test papers is to use the above conditions for fixing these uncertainties.

2.2.2. Modeling the grouping of volumes. In order that the extraction of test questions can be terminated in a limited time and the paper forming process is relatively scientific, global constraints are proposed in this paper. In this way, the paper-grouping process becomes a multi-objective optimization problem that maximizes the user's satisfaction. Simplifying the constraint set can achieve the purpose of improving the efficiency of the algorithm. The total score, answer time and question type are preset before the paper formation, so the constraints of the test paper can be simplified into four dimensions: difficulty of the test question, differentiation of the test question, the chapter to which the test question belongs and the ability requirement of the test question, and their corresponding objective subfunctions are as follows:

$$\min f_1 = \sum_{x=1}^{n} | s\alpha_x |, \min f_2 = \sum_{y=1}^{h} | s\beta_y |, \min f_3 = \sum_{z=1}^{d} | s\gamma_z |, \min f_4 = \sum_{k=1}^{r} | s\delta_k | \tag{17}$$

Where $| s\alpha_x |, | s\beta_y |, | s\gamma_z |, | s\delta_k |$ denote the absolute value of the difficulty of the test questions, the differentiation of the test questions, the chapters to which the questions belong, and the deviations of the test questions' competence requirements, respectively, and the deviations refer to the deviations of the actual values in the test papers from the required values. The following mathematical model for automatic paper grouping is established [23]:

$$\min F = (f_1 + f_2 + f_3 + f_4) = \sum_{x=1}^{n} | s\alpha_x | + \sum_{y=1}^{b} | s\beta_y | + \sum_{z=1}^{d} | s\gamma_z | + \sum_{k=1}^{r} | s\delta_k | \tag{18}$$

3. Improved Genetic Algorithm Based Group Volume Model Solving

3.1. *Sub-question coding*

This paper adopts the real number encoding method to uniquely identify a test question by its question number in the database, which not only meets the one-to-one encoding requirement, but also does not have redundancy, is simple and straightforward, and saves the trouble of encoding and decoding. On this basis, an additional identification is added for each type of question, which is combined with the question number to form the encoding, and this approach ensures that the number of questions of different types of test questions is kept within a certain range when crossover and mutation are carried out.

Suppose that to compose a Yoga Course Civics paper containing multiple choice, judgment, fill-in-the-blank, and question and answer questions, each question type is given a unique identifier: A for multiple choice, B for judgment, C for fill-in-the-blank, and D for question and answer. Then an individual can be denoted as $[Ai, Bj, Cp, Dq]$, where i, j, p, q denote the question numbers of the test questions in the question bank, respectively. For example, if an individual contains 3 multiple-choice questions, 4 fill-in-the-blanks questions, 2 quiz questions, and 3 judgment questions, the coding of the individual is represented as:

$$\underbrace{A1, A2, A10}_{\text{Multiple choice}}, \underbrace{B3, B4, B7}_{\text{True or False}}, \underbrace{C5, C6, C8, C9}_{\text{Gap filling}}, \underbrace{D11, D12}_{\text{Essay question}} \tag{19}$$

When the genetic algorithm performs crossover and mutation, it should try to satisfy that it is done with the same type of questions.

3.2. *Initializing populations*

Firstly, the search range of the question bank is determined according to the knowledge points included in the grouping conditions. According to the grouping conditions, the average difficulty coefficient of the extracted questions should be satisfied:

$$|H-h|\leq w \tag{20}$$

Where H is the difficulty coefficient required by the group paper, and h is the average difficulty coefficient of the questions extracted from the single-question type. w is a permissible error value determined according to the size of the search range of the question bank.

At the same time in order to be able to cover the knowledge points to try to meet the requirements of the group paper, the number of knowledge points contained in the extracted questions should be satisfied:

$$|K-k|\leq v \tag{21}$$

Where K is the total number of knowledge points required to be included in the question paper and k is the number of knowledge points actually included in the question type.

3.3. Design of the Adaptation Function

As can be seen from the previous section on how the initialized population is selected, it is already optimal in terms of the distribution of question types and number of questions without having to make another judgment. Therefore the main factors to consider when judging the fitness of an individual are the difficulty coefficient and knowledge points. At the same time, in order to make the grouped test paper can maximally meet the requirements of the grouped paper, the adaptability function should also consider the difference between the proportion of test question scores of each difficulty coefficient in the total score of the test paper and the requirements of the grouped paper. Set weights for these three attributes as a priority, prioritizing the constraints with the greatest weight. Here the weighting ratio is set as difficulty coefficient>knowledge points>difficulty ratio, and the weighting values are 0.5, 0.3, and 0.2, respectively.

Accordingly the fitness function is expressed as shown in equation (22):

$$F=\sqrt{0.5|(H-h)|+0.3d+0.2u} \tag{22}$$

where H is the target difficulty coefficient of the paper, h is the average difficulty coefficient of the individual, u is the knowledge fit of the individual, and d is the difficulty fit of the individual.

The average difficulty coefficient of an individual is:

$$h=\sum_{t=1}^{n}a_t g_t/G \tag{23}$$

where a_t is the difficulty coefficient of the test question, g_t is the score of the test question, and G is the total score of the individual.

The individual's difficulty fit is:

$$d=\sum_{l=1}^{l}(|D_j-F_l|/F_j) \tag{24}$$

where l is the total number of difficulty levels, D_j is the proportion of test scores for the j th difficulty level to the total number of individual scores, and F_i is the proportion of the j th difficulty level required by the test paper.

The individual knowledge point fit is:

$$u=\sum_{k=1}^{m}(|N_k-P_k|/P_k) \tag{25}$$

Where m is the number of knowledge points required by the group paper, N_k is the proportion of the total marks of the k th knowledge point included in the test question to the total marks of the paper, and P_k is the proportion of the k th knowledge point required by the group paper. Using this fitness function the lower the fitness value, the closer the individual is to the objective function.

In this paper, the exponential proportional change method is used to adjust the size of the fitness value appropriately. The formula for the exponential proportional change method is:

$$F' = e^{(-\beta F)} \tag{26}$$

Where F' is the value of adaptation after the change of exponential proportion, β is the coefficient of variation, and F is the value of adaptation. As can be seen from the formula, the smaller the F value the larger the transformed F' value. The smaller the value of β, the smaller the difference between the fitness values of the changed individuals, which can increase the diversity of the population at the beginning of the iteration. The larger the value of β, the larger the difference between the fitness values of the changed individuals, and the faster the convergence of the population at the later stage of the iteration. Therefore the value of β in the exponential proportional change method is a fixed value obviously can not be well applied to the group volume process. In this paper, we use the change strategy of exponential form and propose the formula of β as:

$$\beta = e^{(-\sigma)} \tag{27}$$

In general the value of σ decreases as the iteration proceeds, and it can be concluded that the value of β is gradually increasing.

3.4. Genetic conditioning

The genetic algorithm of the genetic algorithm as well as the iteration termination conditions are designed according to the grouping needs of the yoga course oriented Civics studied in this paper.

3.4.1. Selection of operators. Stepl: First calculate the number NUM_i that each individual should inherit to the next generation, Eq:

$$NUM_i = N \cdot F_i / \sum_{i=1}^{N} F_i \tag{28}$$

Where N is the number of individuals in the population, F_i is the fitness of an individual, and the integer part of NUM_i, I_i, is the number of individuals inherited to the next generation.

Step2: Set the sum of the fitnesses of the individuals as F, and use $F_i - I_i \cdot F / N$ to reset the fitness value for the individuals in the population. According to the new fitness values, the individuals to be inherited to the next generation are randomly determined using a roulette wheel algorithm. The number of individuals required is shown in equation (29):

$$N - \sum_{i=1}^{N} I_i \tag{29}$$

3.4.2. Intersection operators. The coding approach used in this paper is based on question types for coding, and crossover and variation can be similarly based on question types. The process of crossover is to first take out two individuals randomly from a population, group them by question type, and randomly select a point in the same group to exchange and get a new individual. In this paper, we take the crossover probability $P_c = 0.8$.

In order to ensure that the distribution of question types in the initialized population is not destroyed, the crossover operation in this paper is carried out in question types, assuming that the coding of two individuals is:

$$\underbrace{A1, A2, A10}_{\text{Multiple choice}}, \underbrace{B3, B4, B7}_{\text{True or False}}, \underbrace{C5, C6, C8, C9}_{\text{Gap filling}}, \underbrace{D11, D12}_{\text{Essay question}} \tag{30}$$

$$\underbrace{A21, A22, A23}_{\text{Multiple choice}}, \underbrace{B33, B34, B37}_{\text{True or False}}, \underbrace{C45, C46, C48, C49}_{\text{Gap filling}}, \underbrace{D51, D52}_{\text{Essay question}} \tag{31}$$

Then when the crossover was performed, the crossover was performed with the question types as groupings, and the results of the crossover were as follows; the number of test questions under each question type did not change:

$$\underbrace{A1, A2, A23}_{\text{Multiple choice}}, \underbrace{B3, B4, B37}_{\text{True or False}}, \underbrace{C5, C6, C8, C49}_{\text{Gap filling}}, \underbrace{D11, D52}_{\text{Essay question}} \tag{32}$$

$$\underbrace{A21, A22, A10}_{\text{Multiple choice}}, \underbrace{C45, C46, C48}_{\text{True or False}}, \underbrace{C45, C46, C48, C9}_{\text{Gap filling}}, \underbrace{D51, D12}_{\text{Essay question}} \tag{33}$$

3.4.3. Variational operators. When performing a variation, the new test questions used for replacement likewise need to ensure that the questions remain the same. Assume that the mutation probability $P_m = 0.06$. Assume that individuals are coded as follows:

$$\underbrace{A21, A22, A10}_{\text{Multiple choice}}, \underbrace{B33, B34, B7}_{\text{True or False}}, \underbrace{C45, C46, C48, C9}_{\text{Gap filling}}, \underbrace{D51, D12}_{\text{Essay question}} \tag{34}$$

The individual contains 12 test questions, first randomly generate the variation points and use the $rand(1,12)$ function to randomly generate the value m to find the m th test question in the individual. The identification of the test question code is used to determine the type of that test question, and a test question is randomly drawn from the data array under that type under the condition that it meets the final hit time. If the draw fails then open the last hit time to a time 5 minutes prior to the current time to ensure that no duplicate test questions are drawn, and replace the drawn test questions.

3.4.4. Iterative termination conditions. In this paper, we use the combination of two common methods to end the algorithm, first set the maximum value of the number of iterations 150 and the minimum value of 50, when the number of iterations is greater than 50 and less than 150, judgment of the optimal individual in the population does not carry out the exponential change in the fitness value is less than 0.20 can end the iteration. Otherwise, continue to carry out the judgment of the previous step until the maximum value of the number of iterations is reached, ending the iteration. At this time, the individual with the minimum fitness is the optimal solution.

4. Modularization-based online-offline hybrid teaching model

In order to realize the comprehensive reform of the teaching of yoga course civics, this paper builds a hybrid teaching mode of online and offline on the basis of the intelligent paper forming technology, combining the characteristics of yoga course civics. Online teaching relies on the online education platform to integrate online teaching resources such as videos and electronic documents, focuses on the theoretical teaching of yoga course civics, and utilizes this paper's intelligent paper-grouping technology to generate test papers to test students' yoga course civics learning content. The offline teaching focuses on teachers leading students to practice yoga, linking theory to practice in the process of practicing, so as to facilitate students to more deeply comprehend the elements of the Civics and Politics of Yoga course, and thus to improve the teaching quality and teaching effect of the Civics and Politics of Yoga course.

4.1. Modularization of teaching content

In terms of teaching content, we mainly choose representative and classic elements of yoga curriculum ideology and politics, such as value leadership and spirit shaping, physical and mental health and social responsibility, cultural confidence and cross-cultural understanding, practical norms and character internalization, lifelong sports and overall development, etc. Modularization contains two levels: first, horizontal module is to take each ideology and politics element as a module. The vertical module is to divide the teaching content from top to bottom into four sub-modules: basic knowledge module, ideology and methodology module, practice module, and expansion module:

1) Basic Knowledge Module. It mainly introduces the basic knowledge of yoga, such as its origin, development history and schools, and at the same time integrates the concepts of harmony and balance between body and mind in traditional Chinese philosophy, such as the Taoist idea of "unity of heaven and man". Students will understand the rich cultural connotation of yoga, and realize that yoga is not only a way of physical exercise, but also contains philosophical ideas. Through the introduction of traditional Chinese philosophical concepts, we help students build up cultural confidence and enhance their sense of identity with local culture.

2) Ideology and Methodology Module. In the process of teaching yoga breathing methods and asanas, explain the importance of concentration, persistence, self-discipline and other methods of thought. Students will be guided to experience how these ways of thinking can help overcome difficulties and cultivate the quality of perseverance in yoga practice. This module is designed to integrate ideological education into specific teaching sessions, so that students, while mastering the skills of yoga, can realize the positive ideological methods contained therein, and improve their own psychological quality and quality of will.

3) Practice Module. Students are arranged to practice yoga asanas, group mutual help practice and yoga demonstration activities. In practice, we emphasize the values of teamwork, respect for others and tolerance of differences, and encourage students to help each other and make progress together. Through practical activities, students can transform theoretical knowledge into practical actions, cultivate communication skills and collaborative spirit in teamwork, and enhance interpersonal skills and sense of social responsibility in respect and tolerance.

4) Expansion Module. Self-made students participate in public welfare yoga activities, such as yoga teaching for the elderly and special groups in the community. Students are guided to explore the relationship between yoga and healthy lifestyles and social responsibility, and are encouraged to conduct independent research on the value and application of yoga culture in contemporary society. The Extension Module aims to broaden students' horizons and cultivate their sense of caring and creative thinking skills. Through participation in public welfare activities, it enhances students' sense of social responsibility, and through exploration and research, it improves students' in-depth understanding of yoga culture and their ability to apply it comprehensively.

4.2. Online Teaching Resources Creation

The implementation of blended teaching requires the support of quality course resources. The offline teaching resources need to use the excellent teaching materials of yoga course ideology and politics. Online course resources need to be based on offline teaching materials combined with talent cultivation requirements to increase teaching resources. Based on the talent training objectives, teaching modules and students' learning process, diversified curriculum resources for students' development are constructed in three aspects, namely, knowledge module, special practice test module (using the grouping technology proposed in this paper), and expansion module, to provide support for students' online independent learning and the implementation of blended teaching.

4.3. Online and offline hybrid teaching model

The architecture of the online-offline hybrid teaching mode is shown in Figure 3. Combined with the online learning platform, the online-offline hybrid teaching mode with students as the main learning body is adopted. Specific teaching is carried out in accordance with the pre-course - in-course - post-course. Before class, students can choose the corresponding learning module for online preview and query information, and organize the problems. During the class, the teacher explains the key points and problems raised by students, guides students to complete the yoga practice tasks, and organizes group discussions and assigns practical topics in combination with the teaching content. After class, the study group discusses the knowledge and practice of yoga course Civic Teaching and submits relevant reports, and the teacher should give timely guidance to the extracurricular expansion.

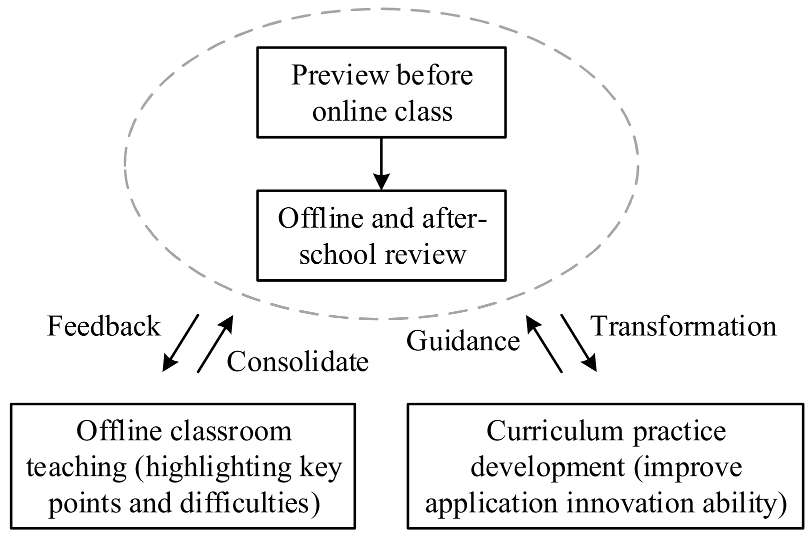

Fig. 3. Online and offline hybrid teaching mode

5. Experimental results and analysis

5.1. Analysis of grouping experiments

In this paper, we carry out automatic grouping experiments by improving the genetic algorithm on the basis of improving the initial population, coding scheme and so on. The changes of fitness value and evolution time in the evolution process of traditional genetic algorithm and improved genetic algorithm are compared respectively, and the changes of fitness value in the evolution process using different crossover probability P_c and variance probability P_m are also observed, and the results of the experiments are as follows.

The distribution of the number of questions in each chapter of the test bank is shown in Fig. 4, and the distribution of difficulty is shown in Fig. 5. C1-C10 in the figure respectively indicate the yoga culture traceability and national spirit, yoga philosophical thought and life wisdom, self-discipline and perseverance in asana training, breathing practice and physical and mental harmony, teamwork and mutual help spirit in yoga, self-knowledge and emotion management in yoga practice, the concept of unity of heaven and man in yoga and traditional culture, and yoga's historical inheritance and cultural self-confidence in yoga in yoga course civic and political teaching content, Positive thinking meditation and concentration cultivation, the practice of yoga spirit in life and social responsibility in 10 chapters, L1-L5 as mentioned above indicates five levels of difficulty of the test questions: easy, easier, average, more difficult, and difficult.

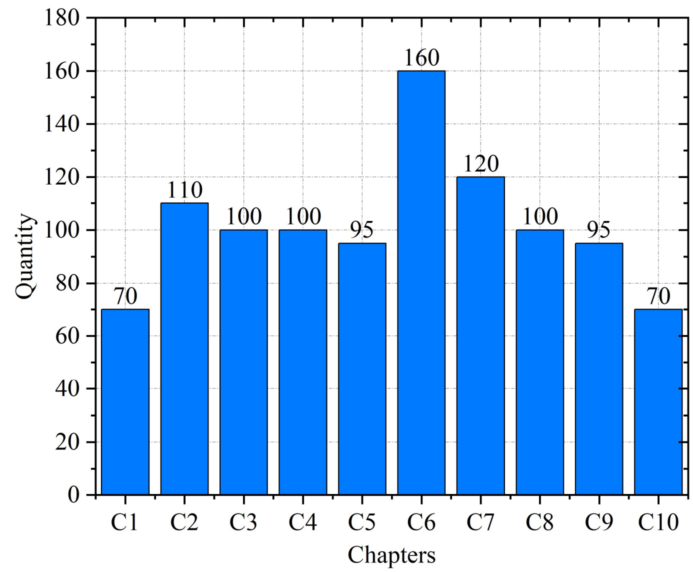

Fig. 4. Distribution of question quantity on each chapter

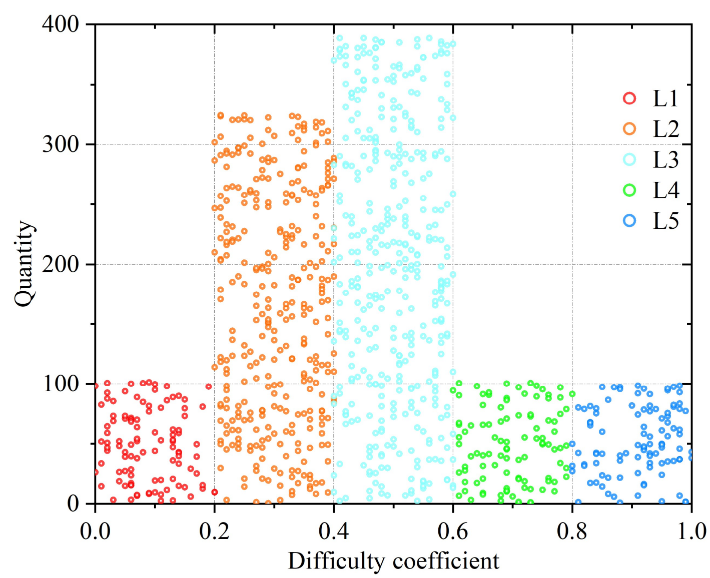

Fig. 5. Test difficulty distribution

As per the requirement, on the basis of the experiment, a test paper is to be generated based on the improved genetic algorithm. In order to verify the improved effect of the algorithm, a test paper is also generated using the traditional genetic algorithm. The running results of both are shown in Figure 6. From the figure, it can be seen that at the 0th iteration, the optimal fitness of the two algorithms is exactly the same. However, after the 0th iteration, the efficiency and effectiveness of the improved genetic algorithm to group papers is higher than that of the traditional genetic algorithm.

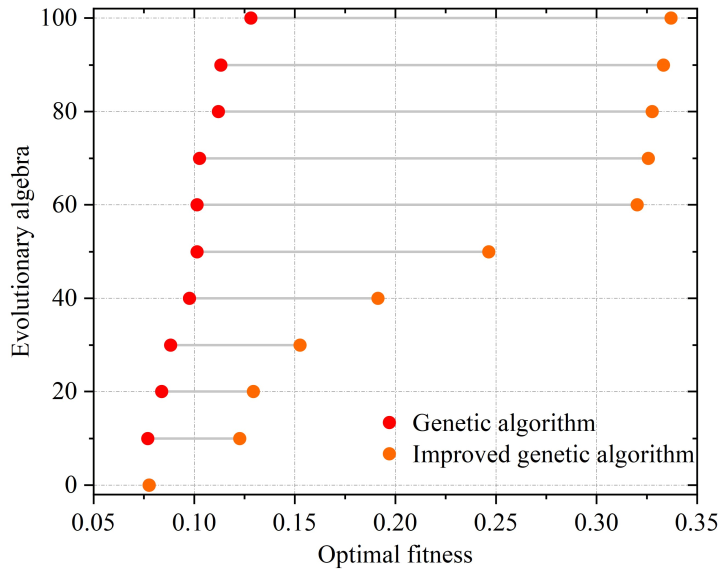

Fig. 6. Comparison of genetic algorithm and improved genetic algorithm

The group paper requires that the question types include multiple choice, judgment, fill in the blanks and question and answer questions, in which the number of questions of each type is 20, 10, 10, 5 respectively, and the mark value of each sub-question of each question type is 1, 2, 2, 8 respectively, then the requirement of distribution of marks for each chapter of the Yoga Curriculum Civics paper is shown in Figure 7. The first half of the brackets in the figure is the chapter and the second half is the marks allocated to each chapter. From the figure, it can be seen that the algorithm allocates higher marks in the chapters of Self-knowledge and Emotion Management in Yoga Practice (C6) and Concept of Celestial Integration in Yoga and Traditional Culture (C7), which are 20 and 25 marks, respectively, indicating that the paper focuses on these two aspects of the teaching of Civics and Politics in Yoga Course.

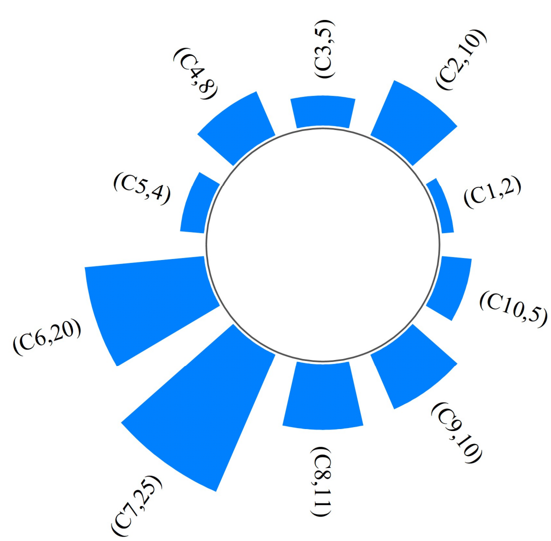

Fig. 7. Distribution of scores for each chapter in the test paper

The paper requires a total score of 100 points, a difficulty coefficient of 0.5, an examination time of 120 minutes, three indicators with weights of 0.5, 0.3, 0.2, the number of populations $n = 100$, an initial crossover probability $P_c = 0.7$, and an initial variance probability of $P_m = 0.3$. Under the premise that the above conditions are satisfied, the improved and traditional genetic algorithms are used to conduct 10 grouping experiments respectively, and the results of generating the time used to satisfy the grouping requirements are shown in Fig. 8. GA in the figure represents the traditional genetic algorithm, IGA represents the improved genetic algorithm in this paper, and the numbers in the outer circle in the figure are the number of group scrolls. From the figure, it can be seen that the time of the improved genetic algorithm in 10 times of grouping is significantly smaller than the traditional genetic algorithm, in which the average time of the improved genetic algorithm for 10 times of grouping is 44.6 s, and the average time of the traditional genetic algorithm is 94.3 s. Compared with this, the grouping time of the improved genetic algorithm is reduced by 52.7%, which has a significant performance advantage.

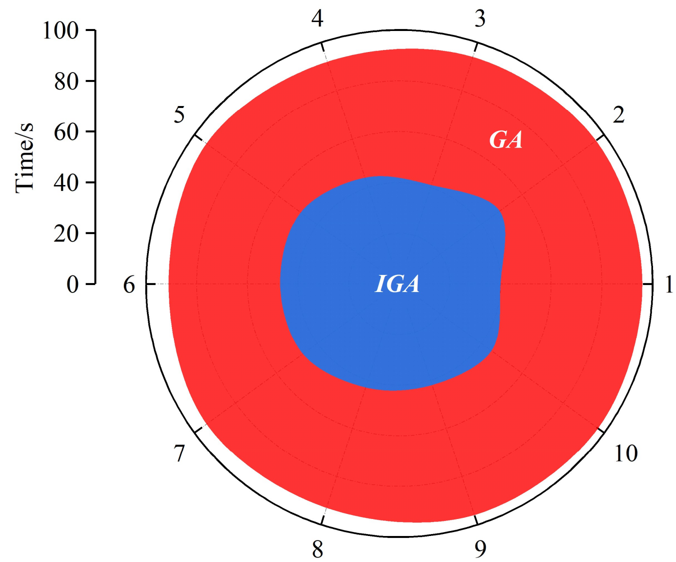

Fig. 8. Comparison of performance for different algorithm

Different P_c values are used to carry out the intelligent grouping experiments of the improved genetic algorithm, and the results are shown in Fig. 9. From the figure, it can be seen that different parameters P_c have a greater effect on the fitness. When $P_c = 0.5$ or so, the algorithm's fitness is lower overall, while when $P_c = 0.8$ or so, the algorithm's fitness is higher overall.

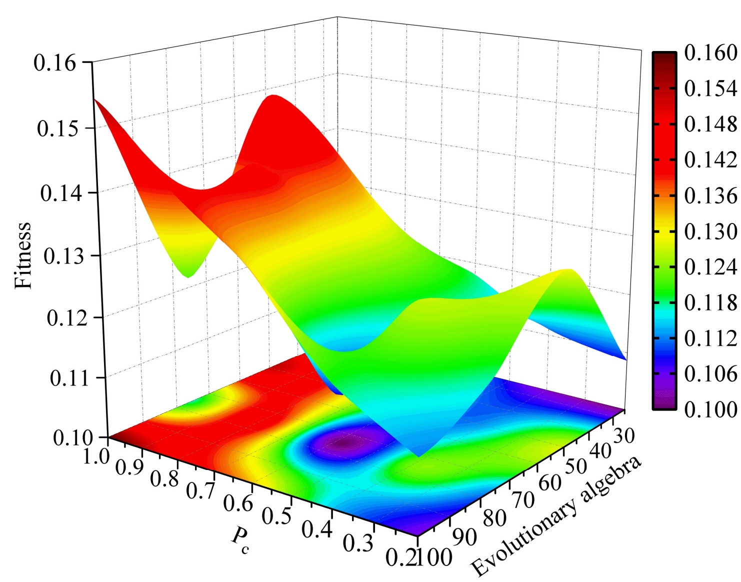

Fig. 9. The effect of parameters P_c on fitness

Similarly, different values of P_m are used for the intelligent grouping experiment ($P_c = 0.8$), and the results are shown in Fig. 10. From the figure, it can be seen that under the premise of $P_c = 0.8$, the effect of parameter P_m on the algorithm's fitness is closely related to the algorithm's number of evolutionary generations. When the number of algorithm evolutionary generations is above 70, the algorithm adaptation under $P_m = 0.1$ is the highest.

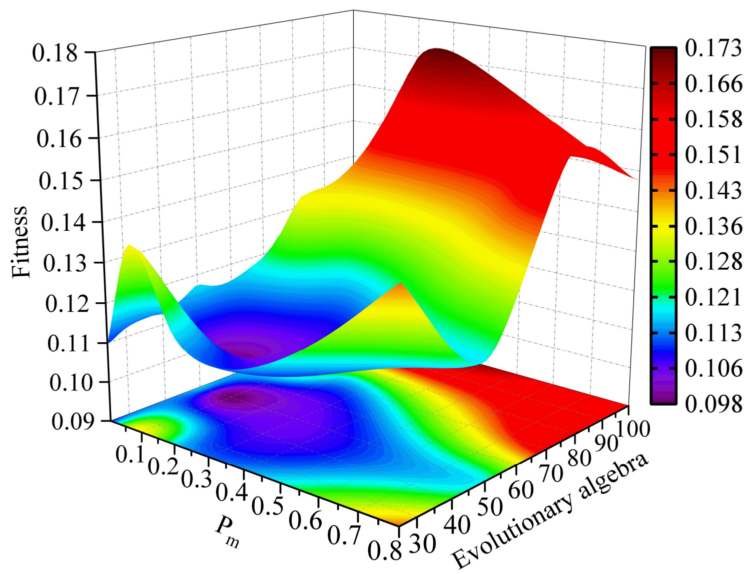

Fig. 10. The effect of parameters P_m on fitness

When the population size $n = 30$, $P_c = 0.8$, $P_m = 0.1$, the comparison of the optimal and average adaptation is shown in Figure 11. When the population size $n = 80$, $P_c = 0.8$, $P_m = 0.1$, the comparison of the optimal fitness and average fitness is shown in Fig. 12. Through the above comparison, the efficiency of the improved genetic algorithm is significantly higher than the traditional genetic algorithm, and it has good application in the grouping of yoga course Civics.

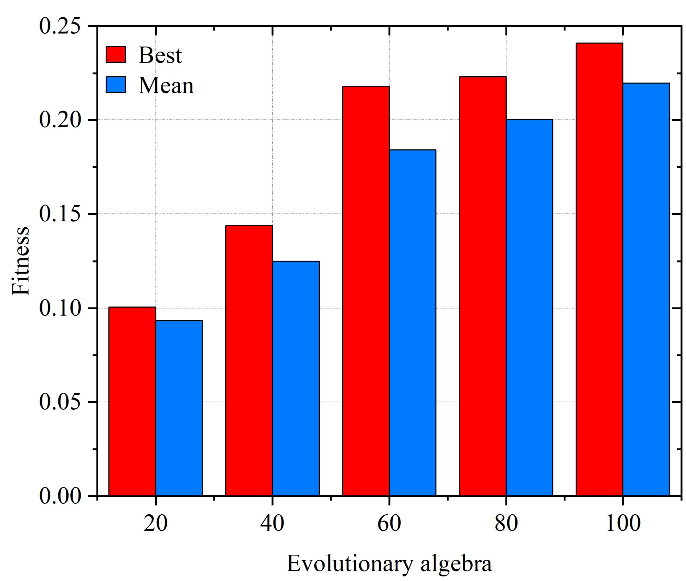

Fig. 11. Comparison of fitness between best and mean($n = 30$)

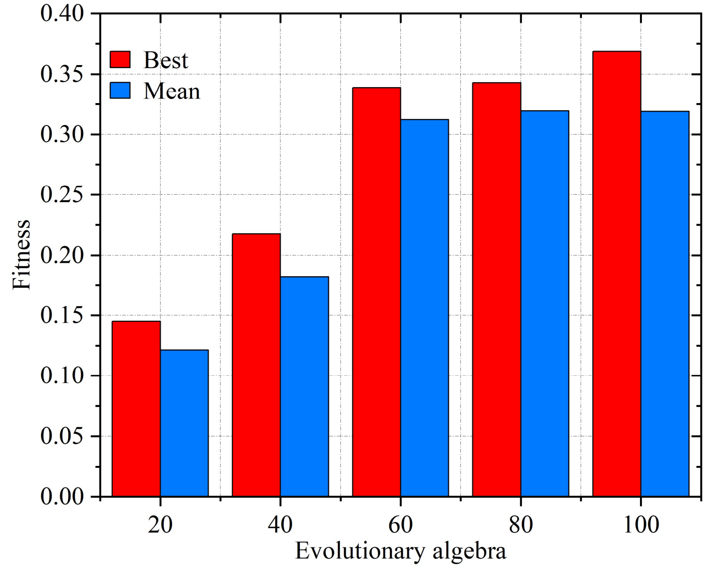

Fig. 12. Comparison of fitness between best and mean($n = 80$)

5.2. Social Network Analysis of Online-Offline Hybrid Teaching and Learning

This paper takes 20 students participating in the yoga course in the first year of the College of Physical Education as the research object (hereinafter referred to as the experimental class). The comprehensive foundation of the students in this class is relatively good in the whole grade, and traditional teaching is difficult to meet the students' needs for the knowledge of yoga course's Civics and Politics. In order to further mobilize students' enthusiasm and meet individualized needs, the online-offline hybrid teaching provided in this paper was carried out in this class.

5.2.1. Basic network properties. According to the counseling relationship between the students in the experimental class, the basic attributes of the class network were obtained by using Ucinet 6.5 measurements as shown in Table 1, and the network of associations between the 20 students is shown in Figure 13. In this regard, the following basic conclusions can be obtained: (1) The network is relatively sparse. On the one hand, the network density value is 0.157, which is relatively sparse. On the other hand, the average distance is 3.283, which means that it takes an average of 3.283 people to realize the connection between every 2 students. The network transmissibility is 0.94%, which is less efficient. Therefore, there is still much room for improvement in promoting mutual help among students. (2) Network cohesion is high. The clustering coefficient of the network is 0.362, that is, the number of stable triad groups in the network accounts for 36.2%, indicating that there is a “small group” in the class. In the actual teaching process, according to the “small group” group collaboration or discussion, is conducive to enhancing the teaching effect. (3) Network reciprocity is high. The reciprocity of the network is about 0.323, that is, there is 32.3% two-way consulting relationship in the network, and the atmosphere of mutual learning between students is better. (4) The overall centrality of the network is low. Although there is no isolated node in the network, the intermediate centrality potential is 20.46%, which indicates that the central tendency of the class is not too strong, and the learning among students is relatively more balanced, and there is no student who has an absolute advantage in the learning of this course.

Table 1. The basic properties of the experimental class network

Network parameter	Parameter value
Network density	0.157
Mean distance	3.283

Node number	20
Side number	67
Clustering coefficient	0.362
Transitivity	0.94%
Reciprocity	0.323
Intermediate potential	20.46%

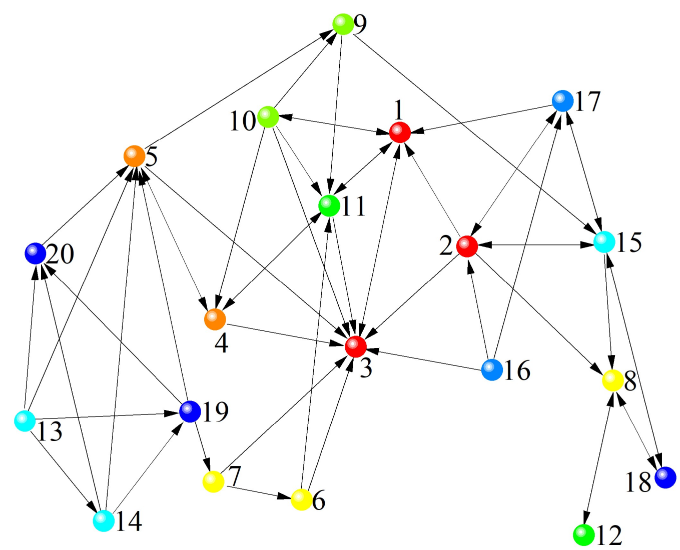

Fig. 13. The association network of the students in the experimental class

5.2.2. Centrality analysis:

1) Point degree centrality analysis. In directed graphs, the degree of each point can be divided into point in degree and point out degree, point degree centrality is the sum of the in degree and out degree of a node in the network [24], the network point degree centrality and intermediate centrality are shown in Table 2. Among them, the maximum value of out-degree is 6, and the members include student 17, whose standardized out-degree is 15, which indicates that the student takes the initiative to establish active learning relationships with 15% of the students in the class, and tends to ask more than one of his/her classmates for advice when he/she encounters a problem. The largest in is 11 (student 3), which has a standardized in of 51, meaning that the student has provided counseling services to 51% of the students in the class. This student plays an important role in answering the queries of other students in the class. The point with the largest centrality of the point degree is student 3 (12), who has a greater degree of in than out, showing a net input-as-consulted correlation. There are still students such as student 4 whose in-degree is less than the out-degree, indicating that these students are weak in answering questions and relatively unmotivated in active learning, and need to be given more attention in the teaching and learning process.

Table 2. Network point center and intermediate center degree

Network node	Degree of emergence	Degree of entry	Point center	Normalized degree	Standardized admission	Intermediate center
1	3	4	10	20	23	27.676
2	5	2	9	20	20	16.772
3	1	11	12	10	51	53.080
4	4	3	9	15	29	75.129
5	2	6	10	15	33	105.368

6	3	0	3	10	5	1.444
7	2	1	4	10	0	2.796
8	5	6	9	20	31	53.709
9	4	1	7	20	9	104.653
10	3	4	7	15	13	5.652
11	2	4	8	15	23	2.201
12	1	3	7	15	20	2.531
13	4	2	4	20	2	0.000
14	1	1	4	20	8	0.000
15	5	2	9	20	26	96.707
16	3	0	3	20	2	1.362
17	6	4	5	15	18	4.106
18	3	4	6	15	13	9.540
19	3	1	7	20	8	3.857
20	1	4	6	10	14	2.260

2) Analysis of the centrality of the middle of the point. The centrality of points reflects members' ability to control “resources”, and the centrality of points in the experimental class is shown in Table 2. The top 6 members of the experimental class are: 5 (105.368), 9 (104.653), 15 (96.707), 4 (75.129), 8 (53.709), and 3 (53.080) in order of centrality. The centrality of the above members' points is significantly higher than that of the other students, indicating that the above students' opinions and suggestions are conducive to facilitating the communication and interaction of other students, and that they play the role of a bridge and leader of collaborative communication in this course.

5.3. Analysis of learning outcomes

Taking the test scores of the test papers under the group paper technique of this paper as the evaluation standard, it can test the students' interest and effect in learning the Civics of Yoga course. The average scores of the experimental class students' two tests through this paper's group paper technology at the midterm and the end of the semester are taken as the final scores of the students in the class, and the specific results are shown in Table 3. The average score of the whole class in the experimental class is 92.88, the highest and lowest scores are 99.58 and 84.53 respectively, and the whole class has reached the standard of excellence (80) or above, with an excellence rate of 100%. It shows that the use of the paper's grouping technology and modularized online and offline hybrid teaching mode can achieve good results in the teaching of yoga course Civics.

Table 3. Test grade of experimental class

Member	Score	Std	Member	Score	Std	Member	Score	Std
2	99.58	0.71	17	95.31	4.13	15	89.76	12.08
11	98.64	2.12	9	94.72	5.26	16	88.23	8.41
4	97.42	3.01	3	94.15	6.91	13	87.64	9.83
19	97.06	2.22	1	92.58	8.12	14	87.19	10.12
18	96.83	3.74	5	92.43	10.23	6	86.42	12.56
20	96.52	3.20	12	91.12	8.14	7	84.53	8.74
8	96.48	5.49	10	91.08	6.09			
Class average score:92.88			Class average Std:6.56					

6. Conclusion

In this paper, the intelligent grouping technology is used as an entry point to construct a multi-objective optimization model for the Civics and Politics of yoga courses in colleges and universities, and the improved genetic algorithm is used to solve the problem. Establishing the online and offline hybrid teaching mode, and analyzing the teaching effect of the mode by combining the social network analysis method, the research results show that:

1) The improved genetic algorithm used in this paper to solve the multi-objective optimization model of paper formation has obvious superiority in the efficiency and quality of paper formation compared with the traditional genetic algorithm. the average time of the improved genetic algorithm in the 10 paper formation experiments is 44.6s, while the average time of the traditional genetic algorithm is 94.3s, which is a saving of 52.7% of the time of the formation of papers. It shows that the improved genetic algorithm in this paper can more effectively realize the automated grouping of yoga course Civics teaching, and its automatically generated test papers can also more effectively examine the real level of students.

2) The test scores of the experimental class adopting this paper's paper-forming technology and online-offline hybrid teaching mode are all above 80 points, and the excellence rate of the test scores of the whole class reaches 100%. It shows that the effectiveness of this paper's yoga course ideology teaching reform method can significantly promote the process of yoga course ideology in colleges and universities.

Funding

This research was supported by the Education and Teaching Reform Research Project (Curriculum Ideological and political special project) of Shaanxi Fashion Engineering University (project No. 2024SZZX025).

References

[1] Zhang, H. (2022). THE INFLUENCE OF YOGA TEACHING ON COLLEGE STUDENTS'PHYSICAL AND MENTAL HEALTH. Psychiatria Danubina, 34(suppl 5), 265-265.

[2] Weng, T. (2024). A Developmental Study of Yoga Courses and Yoga Teaching in General Colleges and Universities. Frontiers in Educational Research, 7(5).

[3] Zheng, H. (2023). The Problems of Yoga Courses in Colleges and Universities and the Countermeasures: Evidence from China. International Journal of New Developments in Education, 5(18).

[4] Quinn, B. P., & Maddox, C. B. (2024). The body doesn’t lie: Yoga and embodiment in the higher education classroom. Teaching in Higher Education, 29(6), 1425-1441.

[5] Wang, Y. (2017, July). Research on the Sustainable Development of Yoga Teaching in Colleges and Universities. In 2017 3rd International Conference on Economics, Social Science, Arts, Education and Management Engineering (ESSAEME 2017). Atlantis Press.

[6] Gorvine, M. M., Zaller, N. D., Hudson, H. K., Demers, D., & Kennedy, L. A. (2019). A naturalistic study of yoga, meditation, self-perceived stress, self-compassion, and mindfulness in college students. Health Psychology and Behavioral Medicine, 7(1), 385-395.

[7] McCartney, P. (2017). Politics beyond the yoga mat: Yoga fundamentalism and the ‘vedic way of life’. Global Ethnographic, 4, 1-18.

[8] Godrej, F. (2017). The neoliberal yogi and the politics of yoga. Political Theory, 45(6), 772-800.

[9] Shaw, A., & Kaytaz, E. S. (2021). Yoga bodies, yoga minds: contextualising the health discourses and practices of modern postural yoga. Anthropology & Medicine, 28(3), 279-296.

[10] Sood, S. (2020). Towards a critical embodiment of decolonizing yoga. Race and Yoga, 5(1).

[11] Gautam, A., & Droogan, J. (2018). Yoga soft power: How flexible is the posture?. The Journal of International Communication, 24(1), 18-36.

[12] Rosen, A. (2019). Balance, yoga, neoliberalism. Signs and Society, 7(3), 289-313.

[13] Jain, A. R. (2020). Peace love yoga: The politics of global spirituality. Oxford University Press.

[14] Di Placido, M. (2022). Modern yoga research as a discursive formation. Bulletin for the Study of Religion, 50(2), 60-72.

[15] Atudorei, M. C., & Swenninger, K. (2018). Discourse Analysis of the Public Communication Campaigns About the Yoga Teacher Gregorian Bivolaru. World Journal of Social Sciences and Humanities, 4(1), 20-60.

[16] Kemmerer, S. (2022, December). Facing the Emergency DownDog–On the Political Appropriation of Yoga. In Kairos: A Journal of Critical Symposium (Vol. 7, No. 2, pp. 10-24).

[17] Kelly, C. (2017). Stress in the higher education sector: causes and yoga-mindfulness interventions. Journal of Yoga and Physiotherapy, 3(3), 1-14.

[18] Khatun, S., Ansary, K., & Adhikari, A. (2022). Attitude towards yoga education among undergraduate students. EPRA International Journal of Multidisciplinary Research (IJMR), 8(12), 9-13.

[19] Smith, S., & Atencio, M. (2017). "Yoga is yoga. Yoga is everywhere. You either practice or you don't": a qualitative examination of yoga social dynamics. Sport in Society, 20(9), 1167-1184.

[20] Samanta, S., & Bakshi, R. (2017). A study of global peace: based on Sri Aurobindo's political thinking, integral yoga and national integration. International Journal of Scientific Research and Management, 5(6), 5591-5615.

[21] Rashedi, R. N., & Schonert-Reichl, K. A. (2019). Yoga and willful embodiment: A new direction for improving education. Educational Psychology Review, 31, 725-734.

[22] Man Zhang,Yili Hong & Narayanaswamy Balakrishnan. (2018). The generalized Poisson-binomial distribution and the computation of its distribution function. Journal of Statistical Computation and Simulation,88(8),1515-1527.

[23] Wang Yan. (2022). A Study of Intelligent Paper Grouping Model for Adult Higher Education Based on Random Matrix. Mathematical Problems in Engineering,2022.

[24] Yang Yang,Dong Yuxiao & Chawla Nitesh V. (2014). Predicting node degree centrality with the node prominence profile. Scientific reports,4(1),7236.