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Exploration of Teaching Reform of Soil and Water Conservation and Desertification Control Specialty Based on Numerical Optimization Algorithm--Taking Soil and Water Conservation Planning and Design Course as an Example

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ABSTRACT

The specialty of soil and water conservation and desertification control has gradually become a hot and popular discipline, and the educational practitioners of this specialty must also follow the trend and actively carry out educational reform. This paper utilizes genetic algorithm to conduct in-depth research on the problem of class scheduling, and on the basis of traditional genetic algorithm, an improved adaptive genetic algorithm is proposed to be applied to the class scheduling system. Through the adaptive adjustment of genetic parameters to improve the convergence accuracy of the genetic algorithm and accelerate the convergence speed, and finally after chromosome conflict detection and repeated iterative operations, the final optimal scheduling program is obtained. The improved adaptive genetic algorithm is applied in the course scheduling system of soil and water conservation planning and design in colleges and universities. After experimental verification, the improved new adaptive genetic algorithm, under the setting of different rules of scheduling conditions, under the setting of different rules of scheduling conditions, the fulfillment rate of students' class selection reaches 100%, and the mean value of the overall rule fulfillment rate reaches 94.1%, and the overall fulfillment rate of the scheduling efficiency is improved to 96% by applying it to the intelligent class scheduling system. Finally, the professional classes were tested on the knowledge of soil and water conservation planning and design, and the remaining eight dimensions of professional knowledge were accompanied by questionnaires, and the achievement data of the test were statistically analyzed using SPSS22.0. The analysis results show that the test scores are quasi-normally distributed, and the actual pass rate of each question in the test paper is roughly close to the preset difficulty, which proves that the test paper is of good quality and the algorithm designed by the institute can basically meet the requirements.

Keywords: adaptive genetic algorithm, intelligent scheduling, teaching reform, soil and water conservation

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1. Introduction

“Soil and water conservation planning” is one of the backbone professional courses of soil and water conservation and desertification control in China, and is also a permanent course for soil and water conservation majors in agricultural and forestry colleges and universities across the country [1-2]. In view of the higher requirements of the new situation for the practice (design) of soil and water conservation planning, in view of the teaching difficulties and existing problems of this course, the practice of "soil and water conservation planning and design" course is carried out to guide students to complete different planning and design tasks, so as to continuously improve the practical content of soil and water conservation planning courses and form a scientific practice system of soil and water conservation planning courses [3-5].

Before 2000, “soil and water conservation planning” teaching, basically to “land use planning”, “integrated management of small watersheds” and other traditional watershed management planning as the main content the teaching [6]. Specifically, according to the direction and requirements of regional planning (such as national economic planning, national land planning, etc.), combined with the natural environment, resources, and socio-economic conditions of the river basin, the proportion and location of land use for agriculture, forestry and animal husbandry in the river basin should be reasonably arranged and determined, various soil and water conservation management measures should be laid out, and the labor, materials, funds, and progress required for various governance work should be arranged, technical and economic indicators should be formulated, and various measures and requirements should be put forward [7-8]. In terms of planning content, it mainly includes "land use planning", "water resources utilization planning", "agriculture, forestry, animal husbandry, sideline and special production planning", "planning and design of comprehensive soil erosion prevention and control system in river basins", "investment and benefits of river basin governance planning", and "progress of river basin management planning", etc., which require students to first master the principles of soil and water conservation, soil and water conservation engineering, soil and water conservation forestry, soil and water conservation tillage, and forestry ecological engineering [9-10]. The main content of the integrated “soil and water conservation planning and design” course includes “the concept, classification, content and work steps of soil and water conservation planning, the main techniques of soil and water conservation investigation, soil and water resources evaluation and soil and water conservation prevention and supervision, ecological restoration and comprehensive management planning methods, soil and water conservation measures Layout and typical design, soil and water conservation mapping, budget and soil and water conservation monitoring and benefit calculation methods, etc.” [11].

The traditional “soil and water conservation planning” course focuses on teaching the content and standards of planning, and the teaching method is based on one-way transmission of knowledge from teachers to students, with less feedback from students. This teaching method simplifies the rich teaching process into static, one-sided cognitive activities, and the teaching process is also ossified into a “rote” process. However, with the rapid development of modern science and technology, the real form of soil and water conservation needs and requirements increase, the traditional teaching methods need to be adjusted and reformed [12-13].

The new “soil and water conservation planning and design” course has put forward higher requirements for practical teaching (design). In order to make the teaching practice link meet the needs of production reality, it is necessary to redesign the teaching practice link, so that it can comprehensively and systematically guide students to understand and master the requirements of soil and water conservation students in planning and designing in the current production reality in China [14-15].

This paper optimizes and improves the traditional genetic algorithm, proposes an adaptive genetic algorithm to deal with the class scheduling problem, combines the improved genetic algorithm with the class scheduling system, and designs the intelligent class scheduling system. The improved algorithm is applied to the intelligent class scheduling problem, the elements and constraints of university class scheduling are analyzed, the overall functional model of the intelligent class scheduling system is established, the overall architecture design of the intelligent class scheduling system is completed, and the functional requirements of the intelligent class scheduling system are realized. After passing the system test, 42 professional students were selected to carry out soil and water conservation planning and design knowledge test and questionnaire survey, and the achievement data of the test were statistically analyzed by using SPSS22.0.

2. Optimization of course scheduling for soil and water conservation planning and design

2.1. Mathematical description of the scheduling problem

2.1.1. Analysis of the solution of the scheduling problem. Scheduling is a combinatorial planning multi-objective, multi-constraint problem seeking an optimal solution. If the optimal solution is to be found from the problem of combinatorial planning, there must be enough constraints (solution condition functions) to realize it. However, for the NP-complete problem of class schedule, it is unrealistic to find sufficient constraints, which means that the optimal solution of class scheduling is only an ideal value, and it is impossible to find the optimal value at this stage, so the idea of finding the optimal solution is discarded in favor of seeking the "relative optimality" [16].

2.1.2. Scheduling constraints:

1) Hard constraints

(1) Only 1 course may be scheduled in the same classroom during the same time period.

(2) Only 1 course can be taught in the same classroom during the same time period.

(3) Only 1 course may be taught by the same instructor in the same time slot, and a maximum of 3 different courses may be substituted by a single instructor, with the total number of classes substituted in a week not exceeding 9 class sessions (18 credit hours).

(4) Each course may have a maximum of 3 class sessions in a week, and each course may not appear in the same class 2 times on the same day.

(5) Classrooms must be large enough to accommodate the students attending the class and the classrooms must be utilized as much as possible.

(6) Different classroom types must be used for different types of classes.

2) Soft constraints

(1) Type of classroom arranged according to the type of course.

(2) Relatively even distribution of each course and scheduling in the morning or one or two afternoons whenever possible.

(3) For courses with more than two class periods per week, it is preferable that the two class periods be separated by one day.

(4) Empty classrooms and physical education classes should be scheduled in the afternoon instructional period whenever possible.

(5) Try to accommodate the special needs of individual teachers for class time.

3) Analysis of hard constraints. Hard constraints are the rules that must be observed in scheduling, once they do not comply with them, they will trigger the teaching service, and normal teaching can not

be carried out. The soft conditions can try to meet them under the condition of abundant teaching resources. According to the teaching situation in our school, each class has a fixed classroom, and the classroom accommodates more than the number of students, i.e., the class, the number of students in the class and the classroom are inherently related to each other as a whole.

2.2. Optimization Objectives to be Considered for Class Scheduling

2.2.1. Course Dispersion Optimization Objectives. Let $C_n\left(C_n \in N\right)$ denote the total number of all subjects, let the number of times course $C_i\left(C_i \in N\right)$ is scheduled in a week be $m\left(2 \le \boldsymbol{m} \le 3\right)$, and the dispersion between the $j\left(2 \le j \le m\right)$th scheduling of course C_i and the previous scheduling be k_j. The dispersion of course c_i, f_i, and the total dispersion of all subjects after scheduling, F, can be expressed as equations (1) and (2), respectively:

$$f_i = \frac{\sum_{j=2}^{n} k_j}{m * \sum_{j=2}^{n} (j-1)} \left(f_i \in (0,1)\right) \tag{1}$$

$$F = \frac{\sum_{i=1}^{C_n} f_i}{C_n} = \frac{\left(\sum_{i=1}^{C_n} \frac{\sum_{j=2}^{n} k_j}{m * \sum_{j=2}^{n} (j-1)} \right)}{C_n} (F \in (0,1)) \tag{2}$$

F is also viewed as an adaptive degree function of course discretization. The course dispersion is not calculated for courses that are scheduled only once a week. From the course dispersion formula (1) and (2), we can see that the course c_i is arranged in a different order, then the value of f_i will also change, that is, it also shows that F is also a change in quantity. The larger the value of F, the more reasonable the distribution of courses in the weekly time.

2.2.2. Increased utilization of time slots. Let the total number of scheduled courses be C_n, the number of times course C_i is scheduled in a week be m, and the importance of the j th time take the value of k_j, and the sum of the importance of all courses in a week be $5*(5+4+2)=55$, then the importance of course C_i take the value of g_i and the time utilization of all the courses be G can be expressed as equations (3) and (4), respectively:

$$g_i = \sum_{j=1}^{n} k_j \left(g_i \in (1,5m)\right) \tag{3}$$

$$G = \frac{\sum_{i=1}^{C} g_i}{C_n * 55} = \frac{\sum_{i=1}^{C} \sum_{j=1}^{n} k_j}{C_n * 55} (G \in (0,1)) \tag{4}$$

G is simultaneously viewed as the course time utilization adaptivity function. From the course time utilization equations (3) and (4), it is clear that a larger value of G indicates that the scheduling of the course occupies a better time.

2.2.3. Utilization of classrooms for classes. Let the capacity of the classroom be m_i, the number of students in the classroom where the lesson is taught be p_i, the total number of all classrooms where the lesson has been scheduled be n, the utilization rate of the individual classroom where the lesson is taught be e_i, and the utilization rate of the classroom where the lesson has been scheduled be E, then the mathematical expressions for e_i and E are:

$$e_i = \frac{p_i}{m_i}\left(e_i \in (0,1)\right) \tag{5}$$

$$E = \frac{\sum_{i=1}^{n} e_i}{n} = \frac{\sum_{i=1}^{n} \frac{p_i}{m_i}}{n} (E \in (0,1)) \tag{6}$$

E is also regarded as the adaptive degree function of classroom utilization, and it can be seen from equations (5) and (6) of classroom utilization for course classes that the larger value of E indicates the higher utilization of classroom resources.

2.2.4. Scheduling objective (adaptive) function. Adaptive function is used to measure the applicability of the schedule, feasibility and scientific objective function, a feasible schedule should make the three different adaptive function as far as possible at the same time to take the maximum value. According to the previous analysis of the scheduling factors and constraints, the objective function (adaptive function) of the scheduling problem can be constructed through the three objectives to be achieved by scheduling:

$$Z(x) = \sqrt{\sin^2 \alpha * F(x) + \frac{\cos^2 \alpha}{2} * G(x) + \frac{\cos^2 \alpha}{2} * E(x)} \tag{7}$$
$$(x \in X, Z(x) \in (0,1))$$

That is: $Z(x) = \sqrt{\sin^2 \alpha * \sum_{i=1}^{c_i} f_i(x) + \frac{\cos^2 \alpha}{2} * \frac{\sum_{i=1}^{c} g_i(x)}{c_z * 60} + \frac{\cos^2 \alpha}{2} * \frac{\sum_{i=1}^{n} e_i(x)}{n}}$

When $Z\left(x_t\right) = \max(Z(x))$, i.e., scheduling $Z\left(x_1\right) = \sqrt{\sin^2 \alpha * \max(F(x)) + \frac{\cos^2 \alpha}{2} * \max(G(x)) + \frac{\cos^2 \alpha}{2} * \max(E(x))}$ classes is taken to the optimal value, the scheduling scheme is optimal. However, this is only the ideal value, which is difficult to take.

Where X is the set of all feasible class schedules, x is a feasible class schedule, $\sin\alpha$ and $\cos\alpha$ are the weights of the function, which are also constants. And there are $\sin^2 \alpha + \frac{\cos^2 \alpha}{2} + \frac{\cos^2 \alpha}{2} = 1$, $F(x)$ is the adaptive degree function of course dispersion; $G(x)$ is the adaptive degree function of time utilization; $E(x)$ is the adaptive degree function of classroom utilization.

2.3. Mathematical modeling of the scheduling problem

The problem of scheduling is to optimize the combination of time slots, classrooms, courses, teachers, and classes in a week without conflicts, and to achieve the purpose of scheduling. It is easy to see that there are five main factors involved in scheduling, and each of the five factors constitutes a corresponding set of factors. Thus, we give the following description: the school has $T(time)$ time slot, $L(lesson)$ courses, $R(room)$ classrooms, $P(professor)$ teachers, and $C(class)$ classes. Setting

The time period collection is: $T\left\{f_1, t_2, t_3, \ldots, t_q\right\}$.

The course collection is: $L\left\{l_1, l_2, l_3, \ldots, l_k\right\}$.

The classroom collection is: $R\{r_1, r_2, r_3, \ldots, r_n\}$.

Teacher assemblies are: $P\{p_1, p_2, p_3, \ldots, p_s\}$.

Class assemblies are: $C\{c_1, c_2, c_3, \ldots, c_m\}$.

where q, k, n, s, $m \in Z$. Each teacher represents l_i courses and b_i classes $(1 \le l_i \le 3, 1 \le b_i \le 3)$. Each course corresponds to 1 class and 1 teacher. The schedule is centered on the curriculum, and the other four factors are organized around the curriculum.

2.4. *Numerical optimization solution of the scheduling problem*

2.4.1. Establishment of initial populations. A chromosome represents a possible scheduling scheme and is stored using a two-dimensional array CP(n,25). The initial population is generated, that is, multiple possible scheduling schemes are randomly generated. The steps of randomly generating a scheduling scheme chromosome are mainly as follows: for the current class 1, a teaching task schedule number 1 in the teaching time period of T1 is first filled into the current two-dimensional array CP(1,1), and then a random function is applied to generate a random number less than or equal to 25, and other teaching task codes are filled into the class time period corresponding to the generated random number, and if the currently generated random number indicates that a teaching task already exists in the time period, then a new code is regenerated and the teaching task is placed into that time period, and the above process is repeated until all the teaching tasks are all placed into the first column of the two-dimensional array, and then the original class schedule for class 1 is generated. Repeating the above process for the other classes yields the complete initial class schedule for all classes, which in turn generates the initial population. Since all the scheduling schemes within the initial population are randomly generated, there are certain contradictions and conflicts, and certain conflict detection methods are needed to detect conflicts in the population.

2.4.2. Construction of the fitness function. In the scheduling system based on genetic algorithm, the selection of the adaptation degree is a key factor in determining the merit of the schedule. Quantifying the value of the fitness is conducive to improving the quality of the solution obtained from scheduling, we construct the fitness function of the genetic algorithm through the soft constraints in the scheduling constraints, and in this subsection, we will construct the fitness function through three aspects:

1) Section weight constraints. For the section weight constraints of courses in different time periods are denoted by k_i, and the total number of courses offered by the school is denoted by n, then the section constraints can be denoted by F_1 as:

$$F_1 = \frac{1}{n}\sum_{i=1}^{n} k_i \tag{8}$$

Section weight constraints, that is, the generation of scheduling plan for each course section weights summed with the total number of courses in the university ratio, the larger the value of F_1, that is, the current scheduling plan section of the higher degree of optimization, and vice versa, the lower the degree of optimization.

2) Class time constraint. The main point in the class time constraint is that each class should be scheduled in such a way that the lessons should be evenly distributed throughout the week and should not be overly concentrated on a particular day or period of time. Now, if C_i denotes a class, d denotes the number of instructional workdays, n denotes the number of days of class per week, C_m denotes the average number of lessons taken by the class per day, and C_{avg} denotes the average number of lessons taken by the class during the week, then we have:

$$C_{avg} = \frac{\sum_{d=1}^{n} C_m}{n} \tag{9}$$

$$C_i = \frac{1}{\sqrt{\sum_{d=1}^{n} \left(C_m - C_{avg}\right)^2}} \tag{10}$$

The above is a representation of the degree of course constraints for a class, and assuming that there is x class in the whole school, the degree of course constraints for all classes in the whole school is represented by F_2:

$$F_2 = \frac{\sqrt{\sum_{i=1}^{x} C_i}}{x} \tag{11}$$

The larger the value of F_2, the more balanced the class scheduling of the corresponding scheduling plan is, and on the contrary, the lower it is, the less balanced the class scheduling plan of that scheduling plan is.

3) Classroom constraint. The classroom constraint is the utilization rate of the classroom in the school, in a scheduling plan individual, the utilization rate of the classroom is the ratio of the classes that carry out teaching activities in the current classroom to the capacity of the classroom, then the utilization rate of the classroom can be expressed as:

$$F_3 = \sum_{i=1}^{P} \sum_{j=1}^{R} \frac{P(i,j)}{capacityR_j} \tag{12}$$

where F_3 represents the third soft constraint classroom constraint.

Considering the above three constraints, section weight constraints, course constraints, and classroom constraints together, the fitness function F designed in this paper is obtained:

$$F = w_1 F_1 + w_2 F_2 + w_3 F_3 \tag{13}$$

where w_1, w_2, and w_3 are weights to regulate the weight of each constraint.

2.4.3. Design and improvement of genetic operators:

1) Set the number of individuals in the population to be set to n and the parent population $F = \{x_1, x_2, \ldots, x_n\}$, and rank the fitness of the parent individuals in the population in descending order $F' = \{f(x_1), f(x_2), \ldots, f(x_n)\}$ based on the fitness of the individuals derived from the previous computational steps, followed by Eqs. 4-8 to compute the probability that each individual in the population is selected as P:

$$P(x_i) = \frac{f(x_i)}{\sum_{i=1}^{n} f(x_i)} \tag{14}$$

2) We then calculated the cumulative probability value for each individual as:

$$q_i = \sum_{i=1}^{j} P(x_i), j = 1, 2, \ldots, n \tag{15}$$

where q_j is called the cumulative probability of the chromosome, suppose when we have five chromosomes and arrange the probability values of the individuals in smallest to largest order to get the probability values of their individuals to be selected as 0.08, 0.14, 0.22, 0.24, 0.32 respectively, then their cumulative probability is:

$$q_1=\sum_{i=1}^{1}P(x_i)=p(x_1)=0.08 \tag{16}$$

$$\begin{aligned}q_2&=\sum_{i=1}^{2}P(x_i)=p(x_1)+p(x_2)\\&=0.08+0.14=0.22\end{aligned} \tag{17}$$

$$\begin{aligned}q_3&=\sum_{i=1}^{3}P(x_i)=p(x_1)+p(x_2)+p(x_3)\\&=0.08+0.14+0.22=0.44\end{aligned} \tag{18}$$

$$\begin{aligned}q_4&=\sum_{i=1}^{4}P(x_i)=p(x_1)+p(x_2)+p(x_3)+p(x_4)\\&=0.08+0.14+0.22+0.24=0.68\end{aligned} \tag{19}$$

$$\begin{aligned}q_5&=\sum_{i=1}^{5}P(x_i)=p(x_1)+p(x_2)+p(x_3)+p(x_4)+p(x_5)\\&=0.08+0.14+0.22+0.24+0.32=1\end{aligned} \tag{20}$$

3) Spin the roulette wheel to generate a random number in interval $[0,1]$ each time, and spin it n times, and select the individual corresponding to the interval in which the random number falls.

4) Count the intervals with the highest number of selections and find the individual corresponding to interval x_i, which is the individual to be retained in the optimal retention strategy.

5) Find the least adapted individual y_j in the offspring population and replace y_i with x_i, the most adapted individual x_i in the parent F population.

6) End the selection process and continue with the next crossover and mutation operations.

Based on the above defects, we use an improved method to calculate the adaptive crossover probability and mutation probability, which is expressed as:

$$\begin{aligned}P_c&=\begin{cases}p_{c1}\dfrac{(p_{c1}-p_{c2})(0.5f_{\max}-f')}{0.5f\max-f_{\min}}, f'\le 0.5f_{\max}\\ p_{c1}, f'>0.5f_{\max}\end{cases}\\ P_m&=\begin{cases}p_{m1}-\dfrac{(p_{m1}-p_{m2})(f-0.5f_{\max})}{f\max-0.5f_{\max}}, f\ge 0.5f_{\max}\\ p_{m1}, f<0.5f_{\max}\end{cases}\end{aligned} \tag{21}$$

p_{c1}, p_{c2}, p_{m1}, p_{m2} are the coefficients, random numbers are taken in $[0,1]$ and adjusted during the optimization process and set $p_{c1}>p_{c2}$, $p_{m1}>p_{m2}$. The improved genetic algorithm improves the diversity of individuals in the population and exerts the local search ability of the variation operator.

2.4.4. Conflict retesting. After the selection operation, crossover operation and mutation operation of the genetic algorithm, the conflicts of the scheduling individuals may have been eliminated, or new conflicts may be generated, based on which, after completing the above mentioned round of genetic algorithm steps, conflict re-detection and elimination work should be carried out for the newly generated scheduling individuals.

After the completion of the above steps, that is, the completion of a genetic algorithm evolutionary process. Finally, according to the criterion of survival of the fittest, every evolution, the fitness of the newly generated offspring will be improved compared with the parent generation, if the value of the fitness of a book remains unchanged, this indicates that the approximate global optimal solution is derived.

3. Soil and water conservation planning and design course knowledge cluster paper

3.1. Intelligent Grouping Algorithm Model Design

3.1.1. Mathematical modeling of test papers. In this algorithm, a test paper is mapped as a matrix chromosome, and each test question composing the paper is mapped as a gene vector, and let each test paper have m question, and each question has 7 basic attributes as defined above, so a test paper actually determines a $m \times 7$ matrix S, and the meanings of the elements of each column correspond to the 7 attributes in turn, i.e., the objective matrix of the problem solving is:

$$S = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{17} \\ a_{21} & a_{22} & \cdots & a_{27} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m1} & \cdots & a_{m7} \end{bmatrix} \tag{22}$$

In practical paper formation, the user makes multiple requests for the paper, each of which corresponds to a constraint on the paper. To compose a high-quality test paper, the distribution of the objective matrix needs to satisfy the following test paper constraints:

1) Question type constraint: it refers to the distribution of test questions for each type of question in the test paper.

$$B_j = \sum_{i=i}^{m} R_{ij},\ Which\ R_{ij} = \begin{cases} 1 & j = a_{i2} \\ 0 & j \neq a_{i2} \end{cases} \tag{23}$$

where: B_j - the number of type j question type test questions in the test paper, a_{i2} - the type of question to which the i th test question in the test paper belongs.

2) Knowledge point-score constraint: it is the sum of the reference scores for each knowledge point test question in the test paper.

$$C_k = \sum_{i=1}^{m} a_{i6} \times T_{ik}, Which\ T_{ik} = \begin{cases} 1 & k = a_{i3} \\ 0 & k \neq a_{iz} \end{cases} \tag{24}$$

where: C_k - the score of the k nd knowledge point in the test paper, a_{i3} - the knowledge point to which the i th question in the test paper belongs, a_{i6} - the question score of the i th question in the test paper.

3) Difficulty of the paper: it is the average coefficient of difficulty of the paper. In the face of different examination requirements, in order to achieve the purpose of distinguishing the level of knowledge of the candidates, the question paper needs to be set different coefficients of difficulty.

$$DD = \sum_{i=1}^{m} a_{i4} a_{ib} \Big/ \sum_{i=1}^{m} a_{i\hbar} \tag{25}$$

where: DD - the average difficulty of all the questions in the test paper, a_{i4} - the difficulty coefficient of the i rd question in the test paper.

4) Distinctiveness of the test paper: a criterion for distinguishing the level of competence of students at different levels.

$$DP = \sum_{i=1}^{m} a_{i5} a_{i6} \Big/ \sum_{i=1}^{m} a_{i6} \tag{26}$$

where: DP - the average differentiation of all the test questions in the test paper, a_{i5} - the differentiation of the i rd test question in the test paper.

5) The total score constraint of the test paper: it is the sum of the scores of all test questions in the test paper.

$$TS = \sum_{i=1}^{m} a_{i6} \tag{27}$$

6) Total answer time constraint: the total time required for the answer to be completed.

$$TT = \sum_{i=1}^{m} a_{i7} \tag{28}$$

where: TT - the total time for the examination of the paper, a_{i7} - the reference answer time for the i rd question in the paper.

3.1.2. Objective function for grouping volumes. The distribution of the column elements in Matrix S should satisfy the user's requirements for each attribute of the test questions. When customizing the test paper, the user is required to provide the desired values of six parameters: total score of the test paper, distribution of question types, distribution of knowledge points-scores, difficulty coefficient, differentiation, and answer time. In the actual formation of the paper, the two constraints of the total score of the paper and the distribution of the question types have been satisfied in the initial population formation, so the four constraints of the distribution of knowledge points-scores, the difficulty coefficient, the differentiation and the answer time are used as the measure of the objective function, which are C_k, DD, DP, TF, respectively, and the actual parameters of the generated test paper are represented by Z, D, Q, T, and then the values of the following formulas should be calculated respectively:

1) $f_1 = \left| \frac{\sum_{j=1}^{k} |C_j - Z_j|}{k} \right|$, denotes the absolute value of the difference between the knowledge-point-score constraints given by the user and the actual values in the generated test paper, where C_j denotes the user's requirements for the scores of different knowledge points, Z_j denotes the actual values of the scores of the knowledge points in the generated test paper, and k is the number of knowledge points:

2) $f_2 = |DD - D|$, denotes the absolute value of the difference between the user's expected difficulty value and the actual difficulty value.

3) $f_3 = |DP - Q|$, indicates the absolute value between the user's expected differentiation and the actual differentiation.

4) $f_4 = \frac{|TT - T|}{T}$, indicating the absolute value between the user's expected answer time and the actual answer time of the paper.

According to the weighting coefficient method, the objective function of the group paper can be expressed as:

$$f = \sum_{i=1}^{4} f_i \omega_i \tag{29}$$

where ω_i is the weight of the i nd group paper attribute, the corresponding weights can be given according to the importance of different attributes and $\sum_{i=1}^{4} \omega_i = 1$. From the above equation, it can be seen that the smaller the value of the objective function f, i.e., the smaller the error, the more the generated test paper meets the user's requirements.

3.2. Numerical optimization for solving the grouped volume problem

3.2.1. Adaptation function design. Genetic algorithm in the evolutionary search process is based only on the fitness function, the algorithm in this paper transforms the group volume problem into finding the minimum value of the objective function f, so the fitness function can be transformed directly from the objective function, i.e.:

$$F = \sum_{i=1}^{4} f_i \omega_i \tag{30}$$

From the above equation, the smaller the value of the fitness function F, the closer the resulting individual is to the optimal solution of the problem.

In view of the repetition of test paper questions, the algorithm in this paper uses the deduplication method when the initial population is generated, which effectively avoids the generation of duplicate test questions, and extracts the corresponding number of question types according to the question type constraints, and at the same time meets the difficulty coefficient value of each chromosome, and produces the initial population of test papers that meet the three constraints of user question type distribution requirements, total score of test papers, and difficulty coefficient requirements, so as to ensure the quality of test papers and effectively reduce the number of iterations of the algorithm.

3.2.2. Design of adaptive genetic operators. In the whole genetic evolution process, the crossover probability P_c and the mutation probability P_m are the key to affect the performance of the genetic algorithm, the larger P_c and P_m are, the stronger the ability of the algorithm to generate new individuals, the fitness fluctuation between individuals becomes larger, and therefore may lead to the destruction of the optimal fitness value individuals; on the contrary, the smaller P_c and P_m are, the stronger the ability of the algorithm to make individuals tend to converge, and the average fitness of the individuals is smoother, but it may decrease the individuals' diversity and local convergence [17]. Therefore, the use of fixed P_c and P_m can not meet the needs of population evolution, in order to ensure the diversity of the population and the formation of the optimal individual at the same time, an adaptive crossover and mutation probability is used.

Adaptive Mechanisms Used Classical adaptive methods increase crossover probability P_c and variance probability P_m when the population fitness is more centralized, and decrease P_c and P_m when the population fitness is more decentralized. P_c and P_m are specifically defined as:

$$P_c = \begin{cases} k_1 \dfrac{f_{\max} - f'}{f_{\max} - f_{avg}} & f' \geq f_{avg} \\ k_3, & f' < f_{avg} \end{cases}$$
$$P_m = \begin{cases} k_2 \dfrac{f_{\max} - f}{f_{\max} - f_{avg}} & f \geq f_{avg} \\ k_4 & f < f_{avg} \end{cases} \tag{31}$$

where, f - the value of the individual's fitness, f' - the fitness value of the person with the greater fitness on both sides of the crossover, f_{avg} - the average fitness value of the group, $f_{\max}$ - the maximum fitness value of the group, $0 < k_1, k_2, k_3, k_4 \leq 1$ is a constant. The method adaptively adjusts P_c and P_m on the basis of changes in the fitness values of individuals in each generation, which accelerates the elimination of poorer individuals while protecting the optimal ones. However, the algorithm adjusts P_c and P_m on an individual basis, and in the process of evolution, it needs to calculate P_c and P_m for each individual separately, which not only affects the execution efficiency of the algorithm, but also makes the algorithm lack of overall collaboration, and is easy to fall into the local optimal solution.

3.2.3. Iterative termination conditions. This algorithm uses the following two judgment methods, both of which terminate the iteration:

1) Setting the maximum number of evolutionary generations.

2) Since the optimal individual preservation strategy is used in this algorithm, the time to terminate the iteration can be judged according to the change of the adaptation value of the best individual in each generation.

3.2.4. Algorithm Implementation Steps. The specific algorithm is realized as follows:

1) The user provides the parameters for grouping papers in the paper customization page.

2) Initialization. $t = 0$, generate initial population $Gen(t)$, set evolution counter $Gen = 0$.

3) Selection operation. Select the optimal 50% individuals in the initial population as parents.

4) Crossover operation. Generate 50% new individuals of the new population $Gen(t+1)$.

5) Mutation operation. Generate the other 50% of new individuals in the new population $Gen(t+1)$.

6) Calculate the fitness values of the individuals in the new generation of populations, perform the optimal individual preservation mechanism in ascending order, and automatically adjust the values of P_c and P_m through the calculation of the adaptive genetic operator.

7) Perform the judgment of termination conditions: 1) the genetic operation has reached the specified number of iterations: 2) the adaptation value of the optimal individual has changed less than a certain minimal value in the process of evolution in successive generations. If neither 1 nor 2 is satisfied, then $Gen(t+1) \to Gen(t)$, $t++$, go to step (4) to continue the cycle. If one of the conditions is satisfied, the iteration is terminated and the individual with the optimal adaptation value is output and the algorithm ends.

4. Experimentation and analysis of the reform of the soil and water conservation planning and design course

4.1. Intelligent Scheduling Experiment and Analysis

The original data of this section of the experiment come from the engineering practice unit "smart campus" project management platform, with Zhengzhou City, the colleges and universities for many years of class scheduling data as a reference, in the database for multiple extraction, conversion, and data cleaning to complete the pre-processing operation of the data for the experimental scheduling algorithms in this paper to provide a data base. Specific experimental data and parameters of the experiment are shown in Table 1 and Table 2.

Table 1. Experimental data

Factor	Student	Courses	Teacher	Classroom	Class
Quantity	4000	500	130	100	120

Table 2. Experimental parameter

Parameter	Initial population	Iteration number	Selection probability	Mutation probability	Cross probability
Parameter value	150	1500	0.2~0.6	New adaptation	New adaptation

4.1.1. Population size. In the traditional genetic algorithm evolution process, the number of populations is usually kept fixed constant value, this is called static parameter setting, in the new improved adaptive genetic algorithm, the size of the population and the number of iterations of the changes in the same algorithm have different effects, the size of the population size of the algorithm has a direct impact on the convergence of the algorithm.

When the number of iterations M is set to 40, 70, 140, 190, 290, respectively, the performance of the algorithm is judged, and a comparison of the results is shown in Table 3. In the table, when the number of iterations reaches 190, the value of individual fitness will appear the maximum value of 2056.

Table 3. The effect of iteration times on fitness values

Numbering	Iteration number	Maximum fitness value $f_{\max}$
1	M=40	1789
2	M=70	1793
3	M=140	1878
4	M=190	2056
5	M=290	2056

When the population size N is taken as 40, 70, 100, and 140 with unlimited number of iterations, the experimental comparison results are shown in Table 4. In the table, when the population size N reaches 140, the average running time of the algorithm is the smallest, and the time needed for scheduling classes is also the shortest. In connection with the actual scheduling problem needs, take the number of iterations M $\geqslant$ 190, N = 100, the corresponding class as a unit, to the scheduling system population size initialization.

Table 4. The impact of population scale on algorithm execution time(Unit:S)

Numbering	N=40	N=70	N=100	N=140
1	8247	6158	5572	1275
2	6875	5261	1108	687
3	649	1189	1473	989
4	577	2478	3289	473
5	199	779	1577	778
Average execution time	3309.4	3173	2603.8	840.4

4.1.2. Crossing probabilities Pc. Taking the first 1000 iterations of the process without changing the experimental base data and parameters, the variation of the adaptive crossover probability p_c for the novel improvement is shown in Fig. 1.

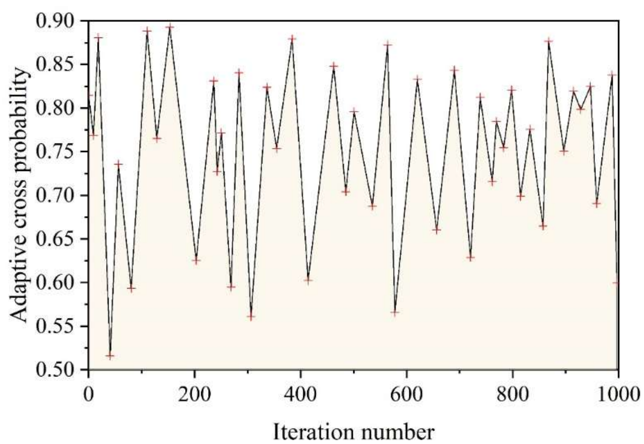

Fig. 1. Experimental results of the new adaptive cross probability PC

4.1.3. Probability of variation Pm. Taking the first 1000 iterations of the process without changing the experimental base data and parameters, the variation of the adaptive variant probability p_m for the novel improvement is shown in Fig. 2:

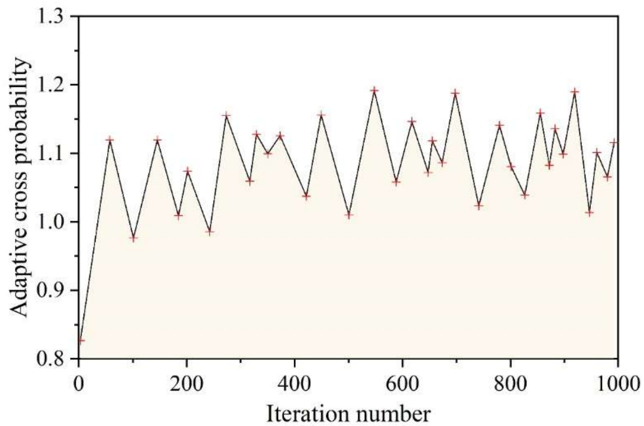

Fig. 2. Experimental results of the new adaptive mutation probability PM

4.1.4. Comparison of experimental results:

1) According to the experimental data and experimental parameters provided in Tables 1 and 2, the new improved adaptive genetic algorithm is used to verify the change of the fitness of the objective function solution as shown in Figure 3. As can be seen from the figure, using the new improved adaptive genetic algorithm, the case of the value of the fitness of the objective function has an overall advantage over the results before the algorithm is improved, so as to achieve the purpose of convergence to the optimum, which is more conducive to the search for the global optimal solution.

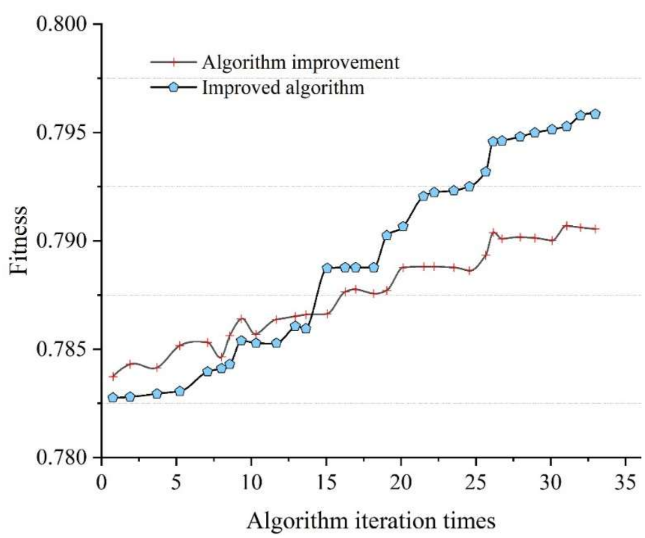

Fig. 3. The experimental results of the fitness of the target function

2) Comparison in the average fitness value, the new improved adaptive genetic algorithm and the traditional genetic algorithm, the same take the first 1000 iterations of the process, the experimental results are compared as shown in Figure 4. From the figure, it can be seen that in the same number of iterations and other experimental data, parameters are the same premise, the new improved adaptive genetic algorithm, in the size of the average fitness value, the overall than the traditional genetic algorithm's average fitness value, and with the increase in the number of iterations, the new improved adaptive genetic algorithm average fitness value of the advantage of the more obvious, the advantage of the maximum value of 506.5, which is more favorable to obtain the optimal solution.

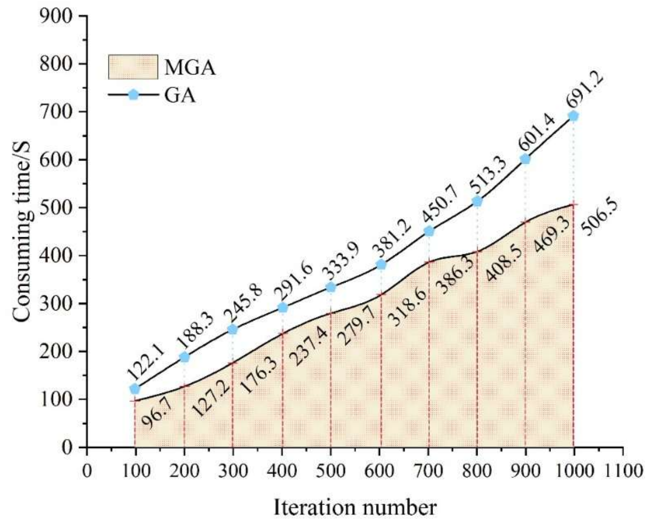

Fig. 4. Comparison of the average fitness value

3) In the process of algorithm execution, the comparison of the running time required to get the complete solution, the new improved adaptive genetic algorithm is compared with the traditional genetic algorithm, also taking the first 1000 iterations, the experimental results are shown in Figure 5. As can be seen from the figure, after a series of improvement ways such as chromosome coding, initializing the population, reconstructing the fitness function as well as the conflict detection-elimination mechanism and the improved adaptive genetic operator, the solution space of the new adaptive genetic algorithm is compressed, releasing more time for the algorithm to execute, and saving the time consumption of obtaining the complete solution space, and it is shorter than the general genetic algorithm to obtain the optimal solution, the original algorithm consumes The original algorithm consumes the longest time 797.9s, and the improved genetic algorithm consumes 596.3s, which is more conducive to obtaining the global optimal solution as quickly as possible.

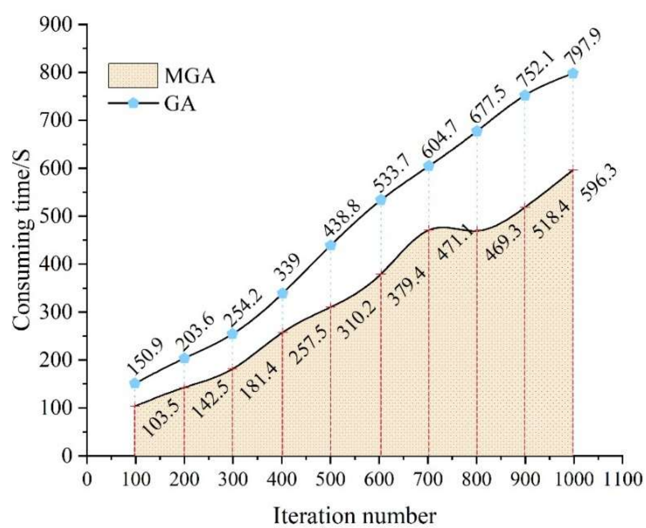

Fig. 5. Compare the results of the required time

4) In the performance evaluation of the algorithm, the quality of the scheduling scheme is compared in terms of section superiority, uniformity of class distribution, optimization of course combinations, classroom constraints, and time consumed, etc., and the new and improved Adaptive Genetic Algorithms are compared to SGA and AGA, respectively. The experimental results are shown in Table 5. As can be seen from the table, the new improved adaptive genetic algorithm is higher than the basic

genetic algorithm and the original adaptive genetic algorithm in terms of the degree of section availability (9440), the uniformity of the distribution of classroom hours (8586), the degree of optimization of the combination of courses, as well as the satisfaction of the teacher constraints, and the comprehensive evaluation of the new improved adaptive genetic algorithm is better than the performance of the original genetic algorithm.

Table 5. Different algorithms compare experimental results

	SGA	Original AGA	New improved AGA
The maximum fitness value of individual individual	/	16374	21412
Secondary excellence	8748	8870	9440
Class uniformity	7388	7798	8586
Curriculum combinatorial optimization	5128	6148	6556
Classroom constraint satisfaction	4558	5438	6530
Consuming time/s	2568	5377	6138

5) In terms of scheduling efficiency, experiments are carried out in terms of students' class selection satisfaction, classroom utilization rate, and overall scheduling rule satisfaction, and the results of specific experimental data are shown in Table 6. Two different datasets are selected in the table for experiments on the application of the new and improved adaptive genetic algorithm, and the experimental results show that the satisfaction rate of students' class selection reaches 100%, the average value of the overall rule satisfaction rate reaches 94.1%, the classroom utilization rate reaches 83.3%, and the course homogeneity reaches 0.7, regardless of whether it is in the all-administrative class or the walk-in class.

Table 6. Schedule of efficiency

Data set	Student selection rate	Overall rule satisfaction rate	Classroom utilization	Course uniformity
Administrative class	100%	95.34%	80.13%	0.7
	100%	89.51%	79.34%	0.6
	100%	82.74%	79.58%	0.6
	100%	96.78%	81%	0.7
	100%	96.81%	81.54%	0.7
	100%	94.44%	83.45%	0.6
	100%	95.29%	82.41%	0.7
Walk	100%	96.17%	85.28%	0.8
	100%	96.45%	85.56%	0.7
	100%	93.28%	82.71%	0.7
	100%	96.22%	87.3%	0.6
	100%	96.31%	87.54%	0.8
	100%	93.61%	87.51%	0.7

6) Table 7 shows the list of scheduling satisfaction rate under the conditions of setting different scheduling rules. It basically meets the rule constraints of intelligent scheduling in universities, the teacher does not schedule, the limitation of class time, the conflict between two sections before and after the course, two or more consecutive courses, and single and biweekly schedules, and the scheduling satisfaction rate reaches the average value of 96%.

Table 7. Schedule of the rule satisfaction rate

Data set	The teacher doesn't schedule	Global fixed point	Teacher class restriction	The course is mutex	Class priority	Single double week	Teacher mutex
Full office	98.13%	100%	Nothing	Nothing	96.57%	Nothing	100%
	99.24%	100%	Nothing	95.57%	90.12%	Nothing	Nothing
	98.77%	100%	Nothing	Nothing	77.62%	100%	Nothing
	Nothing	100%	Nothing	Nothing	96.55%	Nothing	100%
	95.45%	100%	98.43%	95.23%	97.37%	100%	100%
	97.62%	100%	97.39%	Nothing	90.25%	Nothing	100%
	96.31%	98.89%	Nothing	89.71%	92.97%	Nothing	100%
Walk the cattle	100%	100%	Nothing	Nothing	Nothing	Nothing	Nothing
	Nothing	100%	Nothing	Nothing	92.78%	Nothing	Nothing
	Nothing	100%	97.66%	Nothing	86.59%	Nothing	Nothing
	97.45%	100%	Nothing	Nothing	92.58%	Nothing	43%
	97.88%	100%	Nothing	Nothing	90.71%	Nothing	100%
	Nothing	100%	Nothing	Nothing	81.41%	Nothing	Nothing

4.2. Intelligent Grouping Experiment and Analysis

In this section, 42 students of a university majoring in soil and water conservation and desertification control (1) class were taken as an example to carry out a questionnaire survey and knowledge test on the professional knowledge of soil and water conservation planning and design course to understand their professional learning, 42 questionnaires were distributed and 42 questionnaires were recovered, with an effective rate of 100%.

4.2.1. Distribution of data characteristics for knowledge indicators. In order to understand the various distributional characteristics of the results of the test and questionnaire results of the professional knowledge test of soil and water conservation planning and design course, descriptive statistics of the test result data of the test paper of professional knowledge test of soil and water conservation planning and design course were carried out with the help of SPSS software.

The distribution statistics of the raw results of the soil and water conservation planning and design knowledge test of the professional (1) class are shown in Table 8, with the range of difference (i.e., the full distance) of 47, the maximum value of 122, the minimum value of 74, the mean value of 93.736, which meets the standard of passing line of 90 points, the median of 93.2, and the plurality of results (i.e., the table of the "mode of ", the same below) is 84, the standard deviation is 9.7632, the skewness is positive, indicating that there are more scores located to the left of the mean than those located to the right of the mean, and the kurtosis is positive, indicating that the distribution of soil and water conservation planning and design knowledge scores is more sharp compared to the normal distribution. Its fitted normal curve is shown in Figure 6.

Table 8. The original grade of the course statistics

N	In effect	42
	deletion	0
Mean value		93.736
Standard mean error		0.9876
median		93.200
mode		84.0[a]
Standard deviation		9.7632
variance		115.754
Degree of bias		0.456
Standard deviation error		0.354
kurtosis		0.031
Standard peak error		0.695
range		47.0
Minimum value		74.0
Maximum value		122.0

a. Multiple ways exist. Minimum values have been shown.

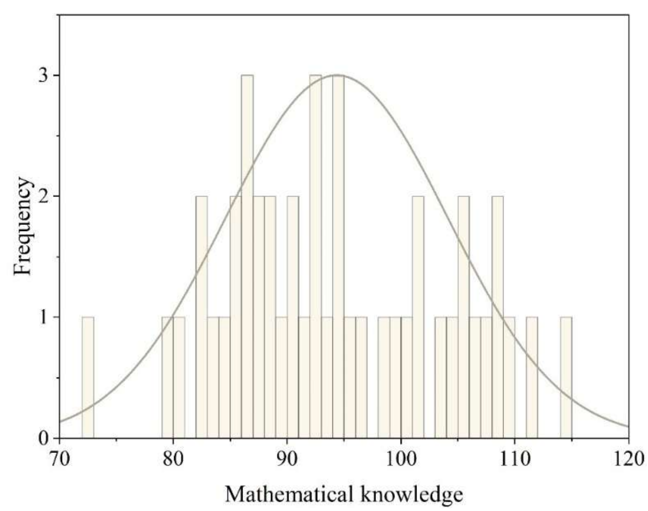

Fig. 6. The fitting normal curve of the original result

Table 9 shows the distribution of percentages corresponding to the knowledge of soil and water conservation planning and design scores converted into five grade value scores. It can be seen from the table that the highest percentage of students, 52.5%, scored between 90-120 points (grade value of 4), while 42.9% of the students did not reach the passing line of 90 points (grade value of 3 and below).

Table 9. Percentage distribution of original grades

-		Frequency	Percentage	Effective percentage	Cumulative percentage
In effect	3	18	42.9	42.9	42.9
	4	22	52.5	52.5	96.4
	5	2	4.8	4.8	100
	Total	42	100	100	

4.2.2. Cross-sectional comparison of the average level and degree of dispersion of indicators. If the original results of soil and water conservation planning and design knowledge are converted, The calculated mean value is 3.229 and the standard deviation is 0.437 (3.23 and 0.44 if two decimal places are retained), which are compared with the mean and standard deviation of the other 8 indicators, and the numerical collation is shown in Figure 7, Professional Knowledge (PK), Learning Engagement (LP), Memory Strategy (ME), Refinement Strategy (ES), Learning Regulation Strategy (LR), Knowledge Transfer (KT), Communication and Cooperation (CC), Reflective Innovation (RI), and Learning Resource Utilization (LR). From the figure, it can be concluded that the best overall level of performance is reflective innovation (3.561), followed by learning participation (3.501) and memory strategy (3.498), and the worst performance is the use of learning resources (3.19), and in terms of the degree of dispersion, the data is most concentrated in professional knowledge, most dispersed in reflective innovation, and the dispersion of communication, cooperation and knowledge transfer is right behind reflective innovation. After that, it can be seen that the individual differences of students in this test class are large and polarized.

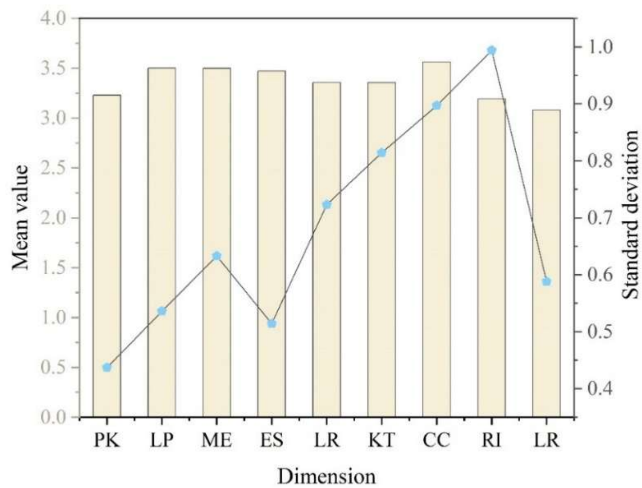

Fig. 7. The average and standard deviation of each measure

4.2.3. Comparison of the actual difficulty of each question in the test paper with the preset difficulty. The actual difficulty of each question of the test paper was calculated, i.e., the difficulty of each question was expressed in terms of the percentage of points scored on each question. Based on the data, a comparison about the actual difficulty of the test questions and the preset difficulty was compiled as shown in Figures 8 and 9.

As can be seen from Figure 8, out of the 25 questions in the test paper, 7 questions were actually at a lower difficulty level than the preset difficulty level (28%), and the remaining 18 questions were in line with the preset difficulty level (72%), which shows that the preset situation at the level of difficulty is relatively good.

As can be seen in Figure 9, there is a discrepancy between the score rate of some questions and the expected difficulty value corresponding to the preset difficulty level. It was analyzed that the reason for this discrepancy was that the three levels of difficulty in the text were set more broadly, making the gap between the expected difficulty values at each level larger, while the score rates of the questions were based on the answers, and it was unlikely that all of their values would fall exactly around the expected difficulty values.

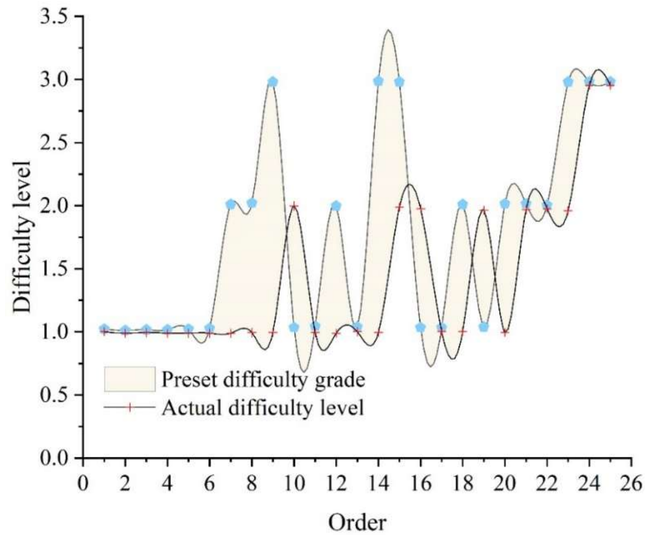

Fig. 8. Comparison of difficulty level and preset difficulty level

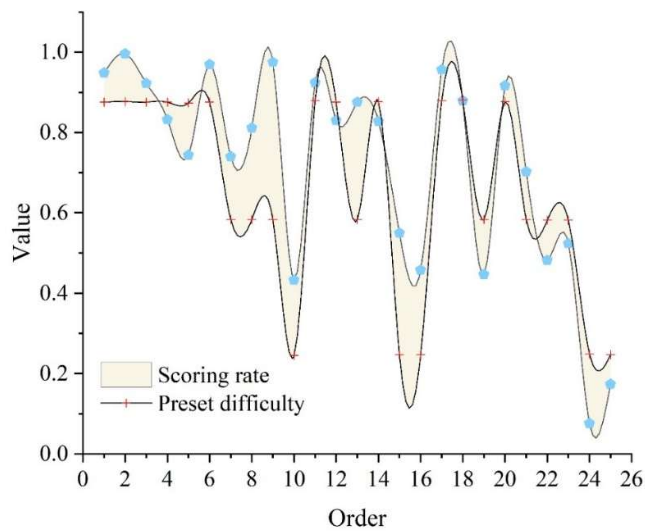

Fig. 9. Comparison of actual score ratio with preset difficulty

4.2.4. Level of professionalism. Based on the test data of the nine measures of mathematical literacy, the total scores of students' mathematical literacy in Class X were calculated and obtained. The distribution of the total scores is shown in Figures 10 and 11, with the largest number of students at level 4 grade (3 < total score ⩽ 4), 33 students, or 78.6%, and at level 3 grade (2 < total score ⩽ 3), 6 students, or 14.3%, and no students at level 2 grade (1 < total score ⩽ 2), or at either end of the spectrum -i.e., students at level 1 grade (0 < total grade ⩽ 1) and level 5 grade (4 < total grade ⩽ 5). Accordingly, it can be concluded that the overall level of expertise of the students in class (1) is good.

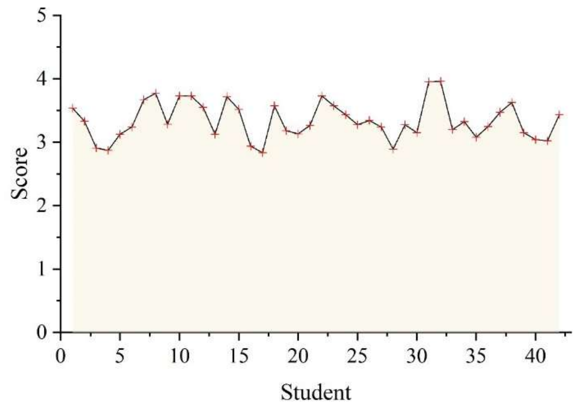

Fig. 10. The professional knowledge of the subjects

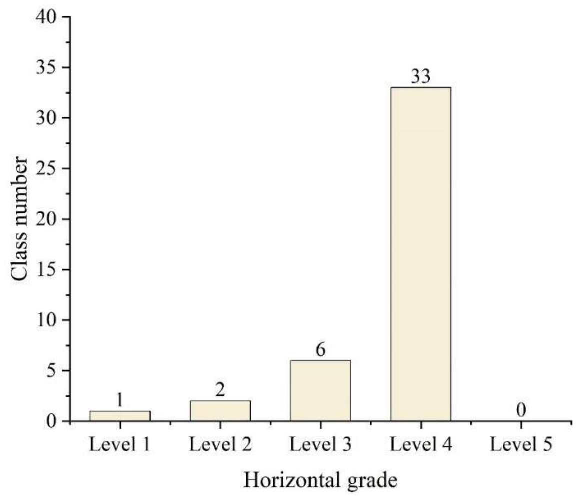

Fig. 11. The level of professional knowledge is graded

5. Conclusion

1) The experimental results of the improved new adaptive genetic algorithm show that compared with the traditional genetic algorithm, compared with the traditional genetic algorithm, the improved new adaptive genetic algorithm not only ensures the diversity of the population, but also can quickly obtain the global optimal solution, avoid precocious maturity and early convergence, improve efficiency, and the overall performance is better than that of the original adaptive genetic algorithm.

2) By comparing the total scores of the students in class (1) in soil and water conservation planning and design and the corresponding level grades, it is found that most of the students' professional knowledge is at the level of "level 4" (3<total score ≤4), and most of the students at this level have the ability to adapt the knowledge they have learned to new contexts on the basis of their understanding of the concepts of the objects of soil and water conservation planning and design. The majority of students at this level have the ability to adapt their knowledge to new situations based on their understanding of the concepts of soil and water conservation planning and design objects. There were no exceptionally good students in the test ("Level 5" grade, 4 < total score ≤ 5), indicating a relatively good and concentrated level of expertise in the Soil and Water Conservation Planning and Design course in this class.

In summary, it is proved that the application of the class scheduling system based on improved adaptive genetic algorithm proposed in this paper is effective.

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