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Article

Simulated Annealing Algorithm for Solving the Optimal Configuration of Graduate Curriculum System and Competency Development Objectives

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Abstract: The arrangement and scheduling of courses is one of the basic tasks of academic management in higher education institutions, and the quality of graduate school class schedules is related to whether the teaching task can be executed normally. The article models the college scheduling problem and the grouping problem, and proposes a college solution algorithm based on the combination of genetic algorithm and simulated annealing-branching limit method. The algorithm promotes the continuous genetic evolution of the population in a better direction, and at the same time uses the idea of combining the simulated annealing algorithm with the branching limit method to carry out individual optimization, so as to jointly solve the problem of the postgraduate curriculum system and ability cultivation objectives. Finally, the experimental results show that from the average value of the results of 8 runs of the three algorithms, the average number of iterations of this paper's algorithm is 34, the running time is 7.47 seconds, and the optimal solution value is 0.8088. It has a certain degree of superiority compared with the basic simulated annealing algorithm and the original adaptive simulated annealing algorithm, and verifies the effectiveness of this paper's algorithm in solving the postgraduate curriculum system and ability cultivation objectives.

Keywords: simulated annealing; genetic algorithm; branch-and-bound method; curriculum system

1. Introduction

At present, graduate students have shown vigorous development under the dual role of university expansion and the development of disciplinary scale [1]. But at the same time, many defects in the process of postgraduate training has also been significantly amplified in the process of the surge in the number of students. There are some professional colleges and universities that ignore their own training conditions and indiscriminately set up additional specialties and courses, thus affecting the quality of the training of postgraduate capabilities [2-4]. Coupled with the continuous expansion of universities in recent years, the gold content of graduate education is reduced [5]; on the other hand, employers are dissatisfied with the quality of postgraduate talent in colleges and universities, and all these phenomena make society question the quality of postgraduate training in colleges and universities at present [6]. In this process, for the individual master's degree students, many students who chose to continue graduate school to avoid the pressure of choosing a career, are still facing greater employment pressure [7-9].

In view of the above phenomena, both experts in the field of education, or professional teachers, or related practitioners, have reflected on the training of graduate students in colleges and universities, in order to find a new way out. In this process, the curriculum system, as an important part of education, occupies a key position [10]. On the one hand, the curriculum system represents the goal of professional faculties for the cultivation of graduate students' ability [11]. Both teachers' teaching and students' learning are guided by the curriculum system. On the other hand, the curriculum system, as the most important link in the teaching process, has a decisive role in the final quality of talent training [12-13]. The curriculum system determines the quality of academics and the strength of national talents at the macro level, and shapes the educational content and philosophy of faculties at the micro level [14].

In view of the open character of the curriculum system, the development of society will have a corresponding impact on the content, form, teaching methods and other factors of the curriculum. Especially since the new century, as human society enters into a new era of informationization and globalization, the cause of science education also requires corresponding adjustments and changes [15-17]. These changes are reflected in the curriculum system, which means that the demand for compliant talents increases, and the new ideas of curriculum system construction are more open, diversified communication, information fusion, and disciplinary intersection and so on [18-20]. Comprehensive analysis found that the ability cultivation goal determines the construction of curriculum system, and the curriculum system in turn affects the ability cultivation goal [21]. Competency cultivation objectives and curriculum system are connected with social demand through graduates, social demand is the key and competency cultivation objectives are the direction [22-25]. The curriculum system should be set around the ability cultivation goal so as to better serve the social demand. Therefore, through scientific methods, exploring the optimal configuration between the curriculum system and the ability cultivation objectives can provide a useful guiding basis for solving the limitations of graduate talent cultivation in colleges and universities.

The article firstly analyzes the problem of scheduling and ability cultivation in depth, and constructs a model of the optimal configuration of the postgraduate curriculum system and ability cultivation objectives. On this basis, a college solution algorithm based on the combination of genetic algorithm and simulated annealing-branching limit method is further proposed, which improves the genetic operation process of genetic algorithm by utilizing the robustness and adaptability of genetic algorithm, and promotes the genetic evolution of the population to a better direction continuously. At the same time, the branch-limit method is introduced, and the algorithm combining simulated annealing algorithm and branch-limit is proposed for individual optimization operation, which jointly solves the problem of the curriculum system and ability cultivation objectives of postgraduate students in colleges and universities. In the experiments, this paper uses five test functions to simulate the experiments of this paper's algorithm, and compares the optimization results of the basic genetic algorithm, the original adaptive genetic algorithm and this paper's algorithm in the problem of scheduling classes under the same experimental conditions. Finally, experimental analysis is conducted to verify whether this paper's algorithm is able to generate higher-quality test papers when solving the postgraduate scheduling problem.

2. Model of the optimal configuration of the postgraduate curriculum system and competence training objectives

2.1. Analysis of Curriculum System Problems

2.1.1. Description of scheduling problems

Course scheduling is a very complex task that requires a great deal of patience as many factors need to be considered throughout the process. In the actual course scheduling process, various conflicting problems need to be solved and various conditions need to be determined, including teaching facilities, teachers and other factors. The scheduling problem can be simplified as a combined planning problem for teachers, classrooms, classes, courses and time, and a more reasonable schedule can be constructed through certain constraints. However, the scheduling problem is very complex, not only need to consider the hard requirements, but also need to consider some of the “preferences” of teachers or students, with the increase of “preferences”, the optimization problem will become more complex and difficult to solve. There are two main types of constraints in solving such problems. The first type of constraint is a hard constraint, which is mandatory and cannot be violated. In other words, when a solution conflicts with a hard constraint, the solution should be eliminated from the conflict or regenerated into a solution that satisfies the constraint. Hard constraints contain the following cases:

① The same class can only be taught in the same time slot.

② The same teacher can only teach one course at a time.

③ Only one course can be taught in a classroom at a time.

④ The number of seats in a classroom must be large enough to accommodate all students.

Soft constraints mainly refer to user preferences, which make the schedule more reasonable and humanized. Common soft constraints are teacher's preference for lecture time. These constraints should be satisfied as much as possible during the course scheduling process. In the actual scheduling process, the scheduling algorithm does not find the ideal optimal solution, at this time to take a compromise program, in the case of meeting the basic hard constraints, the solution that meets more soft constraints as the final feasible solution. This type of problem belongs to the constrained optimization problem in mathematics, without loss of generality, this type of problem can be described as:

$$\begin{cases} \min F(d) = (f_1(d), f_2(d), \ldots, f_m(d))^T \\ \text{s.t. } g_j(d) \le 0, j = 1, 2, 3, \ldots, p \\ h_j(d) = 0, j = p+1, \ldots, q \end{cases} \tag{1}$$

where d denotes the decision variable, $d \in D$, and D is the search space consisting of d . $f(x)$ is the objective function, m is the number of objective functions, and a multi-objective optimization problem is a multi-objective optimization problem when $m > 1$ and a single-objective optimization problem when $m = 1$. $g_j(d) \le 0$ and $h_j(d) = 0$ denote the inequality constraints and equation constraints, respectively, $g_j(d) \le 0, j = 1, 2, 3, \ldots, p$ denotes the existence of p inequality constraints, $h_j(d) = 0$, $j = p+1, \ldots, q$ represents the $q - p$ equational constraints.

When solving constrained optimization problems, the equational constraints are generally converted to inequality constraints for solution:

$$G_j(d) = \begin{cases} \max\{g_j(d), 0\}, & 1 \le j \le p \\ \max\{|h_j(d)| - \delta, 0\}, & p+1 \le j \le q \end{cases} \tag{2}$$

The total violation of all constraints by individuals in the population can be expressed as:

$$G(d) = \sum_{i=1}^{p} w_i G_i(d) \tag{3}$$

where δ is the tolerance parameter and w_i is the weight of the i th constraint. The solution is feasible when the total violation of constraints of population individuals is 0, otherwise it is infeasible.

2.1.2. Mathematical model of the scheduling problem

Scheduling is the process of arranging a reasonable amount of time and space for classes, teachers, and courses to ensure that scheduling meets all reasonable common and individual requirements for time and humane and efficient use of space. On this basis, arrangements are made to achieve the global optimum of all objectives as far as possible. It is assumed that there are n decision variable parameters, k objective functions and m constraints in the scheduling problem. Based on the relationship between the decision variables, objective functions and constraints, the optimal objective of the scheduling problem is:

$$\max imize\ o = f(d) = (f_1(d), f_2(d), \ldots, f_k(d)) \tag{4}$$

$$subject\ to\ c(d) = (c_1(d), c_2(d), \ldots, c_m(d)) \le 1 \tag{5}$$

$$d = (d_1, d_2, \ldots, d_n) \in D, o = (o_1, o_2, \ldots, o_n) \in O \tag{6}$$

where d denotes the decision vector, o denotes the objective $o = f(d) = (f_1(d), f_2(d), \ldots, f_k(d))$ vector, D stands for the decision space consisting of d , and O stands for the objective space consisting of o . The $c(d)$ is a constraint on the possible range of the decision vector.

The problem of school scheduling is to place the teacher's classroom activities under certain conditions of teaching resources and following certain mandatory conditions that must be fulfilled. Teaching activities are organized under soft constraints where teachers cannot be present in different classrooms at the same time. The essence of scheduling is to make a teacher teach in a particular classroom according to a reasonable allocation of time and to avoid conflicts. Assuming that there are five sets of teachers, classrooms, classes, courses and time, the set of teachers: $L = \{L_1, L_2, \ldots, L_i\}$, the set of classrooms: $R = \{R_1, R_2, \ldots, R_j\}$, the set of classes: $C = \{C_1, C_2, \ldots, C_k\}$, the set of courses: $U = \{U_1, U_2, \ldots, U_p\}$, and the set of times: $T = \{T_1, T_2, \ldots, T_m\}$. Each solution is a set consisting of (L, R, C, U, T) .

The hard constraint in the scheduling problem can be expressed as follows:

A teacher can teach in only one classroom at a time:

$$\sum_{p=1}^{P}\sum_{j=1}^{J}\sum_{k=1}^{K}u_p c_k r_j l_i t_m \le 1 \tag{7}$$

Only one course can be scheduled in a classroom at any one time:

$$\sum_{p=1}^{P}\sum_{k=1}^{K}\sum_{i=1}^{I}u_p c_k r_j l_i t_m \le \tag{8}$$

A class can only be in one classroom at a time:

$$\sum_{p=1}^{P}\sum_{j=1}^{J}\sum_{i=1}^{I}u_p c_k r_j l_i t_m \le 1 \tag{9}$$

For example, Condition 2 expresses that the l_i teacher teaches the course u_p in the c_k class in the r_j classroom at time t_m. If the result is greater than 1, it indicates that multiple courses exist in the same classroom, violating the hard constraint. The other conditions are similar. The above three hard constraints must be obeyed to make the class schedule meet the basic requirements.

2.2. A model for organizing papers with the goal of developing competencies

In general, due to the nature of the examination, objectives, scope of application and other factors, there are different requirements for the test paper. In order to meet the requirements of the actual examination, the content of the specific test paper must be adjusted accordingly, and in the process of combining test papers, the influence of multiple constraints should be considered when selecting test questions [26]. In this context, this paper constructs a mathematical model of grouping papers to ensure the rationality, practicality and scientificity of grouping papers.

In the actual process of grouping papers, if each test question is affected by n indicators, such as a_1 test scores, a_2 difficulty, a_3 question types, a_4 knowledge points, etc., we can denote them by $A = A(a_1, a_2, a_3, \ldots, a_n)$, where a_i denotes the i th test question indicator. Such a set of test papers contains m test questions, which we can denote by $T = (A_1, A_2, A_3, \ldots, A_m)$, so that a complete set of test papers constitutes a matrix as shown in equation (10):

$$T = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \tag{10}$$

In order to ensure that the test paper is reasonable, practical and scientific, the test paper matrix T needs to satisfy the following constraints:

Test paper score constraint: the teacher sets the total score S of the test paper as shown in equation (11):

$$S = \sum_{i=1}^{m} a_{i1} \tag{11}$$

Where S denotes the total score of the test paper, and a_{i1} denotes the score of the test questions.

Test paper difficulty constraint: the difficulty of the test paper is one of the main constraints in the grouping of the paper, which affects the quality of the paper, as shown in equation (12):

$$D = \frac{1}{m}\sum_{i=1}^{m} a_{i2} \tag{12}$$

Where D denotes the difficulty coefficient of the test paper and a_{i2} denotes the difficulty coefficient of the test questions, and the difficulty of each question is determined at the time of entering the test questions.

Score constraint for each question type: the proportion of the score of each question type in the test paper to the total score of the test paper, as shown in equation (13).

$$G = \frac{1}{S}\sum_{i=1}^{x} a_{i3} \tag{13}$$

Where G denotes the proportion of each question type to the total score, S denotes the total score of the test paper, and a_{i3} represents the question type of the test.

Knowledge point constraint: the sum of the scores of a knowledge point in the test paper, as shown in equations (14) and (15).

$$M_k = \sum_{i=1}^{m} P_{i1} \times a_{i4} \tag{14}$$

$$P_i = \begin{cases} 1, (a_{i4} = k) \\ 0, (a_{i4} \neq k) \end{cases} \tag{15}$$

Where M_k denotes the sum of the scores of the k th knowledge point in the test paper and a_{i4} denotes the knowledge point to which the test question belongs.

The main indicators of the quality of a set of test papers are difficulty, validity, reliability and differentiation. In order to ensure the quality of the test paper, the main measures in this paper are: determining the question types and scores, stabilizing the difficulty of the test paper and the coverage of knowledge points, and ensuring the standardization of the test questions.

Difficulty, reflecting the degree of difficulty of this test paper, is one of the important indicators of test paper evaluation. Under the premise of ensuring that each test question has its own difficulty, it is also necessary that the overall difficulty of the test paper meets the requirements of the examination, which is usually different at different levels. The formula for calculating the statistical difficulty P of test questions is shown in (16):

$$p = 1 - \frac{\overline{R}}{S_i} \tag{16}$$

Where $\overline{R}$ indicates the average score of the test question, S_i indicates the score of the test question. From the formula and the table, when $\overline{R}$ is larger, the smaller P is, indicating that the average score of the question is high, the difficulty is smaller the question is easier. On the contrary, the more difficult the test question is.

Validity, which mainly refers to the reasonableness of the content of the test paper, indicates whether the knowledge points in the examination paper are consistent with the examination objectives of this examination, which can reflect the degree of the candidates' mastery of the knowledge they have learned. The higher the validity, the more accurate the judgment of this examination on the knowledge framework of the students to be assessed. Among the main factors affecting the validity of the test paper include: whether there is a clear examination objective, whether there are reasonable test questions, and whether there is coverage of knowledge points in line with expectations.

Reliability, mainly measures the degree of reliability of the test results. Reliability refers to the degree of consistency and stability of the test scores obtained when the same set of test papers is used to repeat the test on the candidates, the higher the reliability means that the higher the quality of the test paper, the higher the degree of reliability.

Differentiation, an indicator of the level of competence of candidates, a reliable test paper can accurately show the differences in the knowledge mastery of different candidates.

3. Hybrid simulated annealing algorithms for class scheduling and paper grouping solving

3.1. Overall idea of algorithm design

This paper proposes a college class scheduling algorithm based on the combination of genetic algorithm and simulated annealing-branching limit method, and the process of solving the group volume model is similar to class scheduling. The flow of the class scheduling algorithm proposed in this paper is shown in Figure 1.

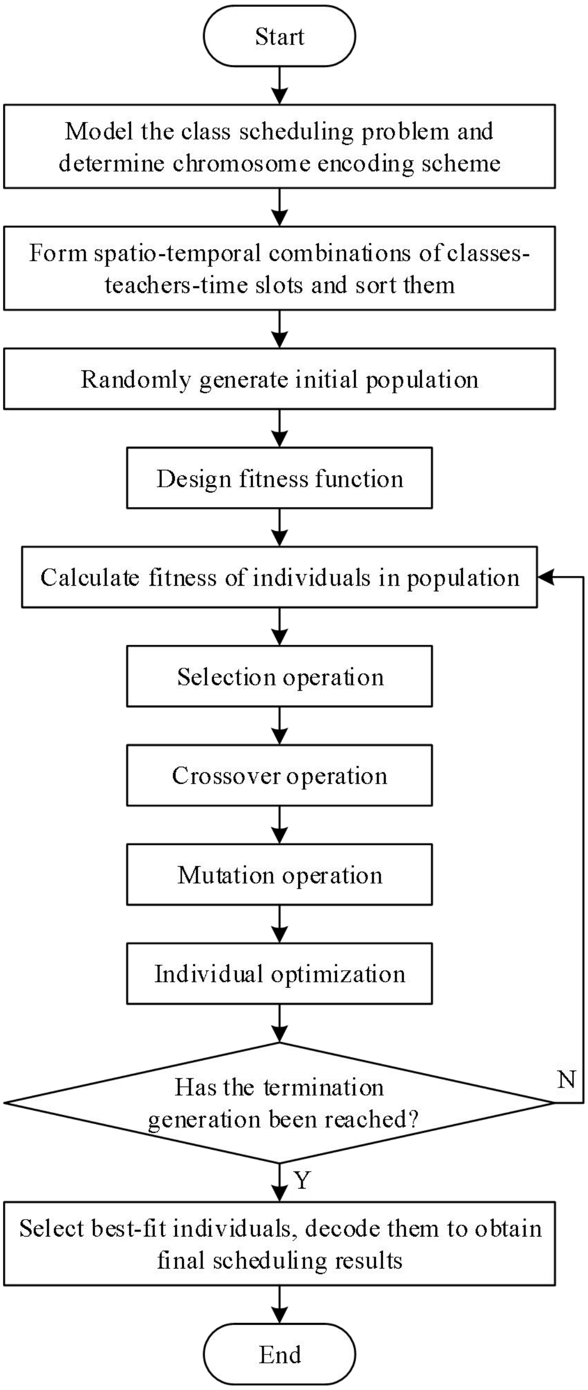

Figure 1. The process of the course scheduling algorithm proposed in this article.

3.2. Chromosome coding

In this paper, decimal coding is used for genetic coding. The attributes of the teacher object include affiliation, teacher number, teacher's name, title, education, and research direction. The teacher number is unique. By using the teacher number, the name, title, education, research direction, etc. of the teacher can be queried.

3.3. Initial population generation

In this paper, each individual in the population corresponds to a scheduling scheme. The basic process of population initialization is:

Step 1: Form a course-teacher-class instructional event based on school and college schedules.

Step 2: Form the spatio-temporal combination of campus-classroom-time period based on campus, classroom and time period.

Step 3: Sort the teaching events, in accordance with the requirements of "first special and then common, first more people and then less people", first arrange the fixed classrooms and time slots, then arrange the courses with special classrooms or time slots, and finally arrange the common courses.

Step 4: According to the scheduling order of teaching events, we also sort the time and space combinations of campus - classroom - time slot. The ordering is done first by campus. Within each campus, we sort by "special then general". Classrooms in the same category are sorted by classroom capacity from largest to smallest.

Step 5: When scheduling teaching events to the corresponding time-space combinations, first select all the classrooms and time slots that satisfy the hard constraints to form a set, and then randomly select a campus, classroom, and time slot from the set, and schedule the teaching events of the teacher, class, and course to that time-space combination.

Step 6: Perform step 5 sequentially until all instructional events have been scheduled to form a viable individual.

Step 7: Repeat the above steps to generate N individuals to form the initial population.

3.4. Adaptation function design

In this paper, the constraints in the scheduling algorithm are selected as the main components of the fitness function [27]. In this paper, hard and soft constraints are used as the important components of the design of the fitness function. The design of the fitness function is as follows:

$$\begin{cases} \mathrm{F}(i) = \mathrm{m}_{1,i}\alpha_1 + \mathrm{m}_{2,i}\alpha_2 + \mathrm{m}_{3,i}\alpha_3 + \mathrm{m}_{4,i}\alpha_4 \\ \qquad + \mathrm{m}_{5,i}\alpha_5 + \mathrm{m}_{6,i}\alpha_6 + \mathrm{m}_{7,i}\alpha_7 + \mathrm{m}_{8,i}\alpha_8 \\ \text{s.t.i satisfies hard constraints 1 throu gh 8} \end{cases} \tag{17}$$

Where $\mathrm{m}_{1,i} \sim \mathrm{m}_{8,i}$ represents the weight value of individual i corresponding to the soft constraints ① to ⑧, respectively, and $\alpha_1,\alpha_2,\alpha_3,\alpha_4,\alpha_5,\alpha_6,\alpha_7,\alpha_8$ is a regulating factor that regulates the influence of different influencing factors and satisfies the following equation:

$$\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 + \alpha_5 + \alpha_6 + \alpha_7 + \alpha_8 = 1 \tag{18}$$

3.5. Selection operations

In the algorithm of this paper, the probability of an individual in the population being selected is proportional to the size of its fitness. The greater the fitness of an individual, the greater the chance that it will be selected and passed on to the next generation. Conversely, the less likely it is to be selected and passed on to the next generation.

First, let us assume that an individual i in the population, whose fitness is F_i, and the size of the population is L, then the roulette selection operates as follows:

Step 1: Based on the size of the fitness of each individual in the population, find the sum of the fitnesses of all individuals. The formula for this is as follows:

$$F_{sum} = \sum_{i=1}^{L} F_i \tag{19}$$

Step 2: Calculate the ratio of the fitness of each individual in the population to the sum of the fitnesses of all individuals as the probability of that individual being selected. For individual i, the formula is calculated as follows:

$$p_i = F_i / F_{\mathrm{sum}} \tag{20}$$

Step 3: the cumulative probability of each individual among all individuals is calculated. For individual i, its cumulative probability:

$$q_i = \sum_{i=1}^{i} p_i \tag{21}$$

Step 4: A circular roulette wheel is divided into L blocks of regions based on the cumulative probability of each individual.

Step 5: A random generation is used to generate a number x on the $[0,1]$ interval, if $q_{i-1} < x \leq q_i$, then individual i is selected and inherited to the next generation. Repeat this operation L times to obtain L individuals that constitute a new generation.

3.6. Cross-operation

In this paper, a multipoint crossover operation based on under weekly frequency is proposed. The steps of multipoint crossover operation under weekly based are as follows:

Step 1: Two individuals are randomly selected from the population and are denoted as Parent Individual 1 and Parent Individual 2. $n(n \leq 20)$ distinct integers are randomly generated in the interval $[1,20]$: $a_1, a_2, \ldots, a_n$. Then, random crossover operations are carried out on a portion of the chromosomes of week $a_i\ (1 \leq i \leq n)$ in each of the individuals.

Step 2: Perform a random crossover operation for a portion of chromosomes in the a_i th week. First, two different integers $\varepsilon_1, \varepsilon_2$ in the interval $[1, 25 * K]$ are randomly generated. Then, a number p on the interval $[0,1]$ is randomly generated, and the crossover operation is performed on the two parent individuals when p is less than the crossover probability P_c. Otherwise, no crossover operation is performed.

Step 3: For the part of the chromosome in the a_i th week of Individual 1 and Individual 2 where the crossover operation is to be performed, select part of the genes in the interval of position $[\varepsilon_1, \varepsilon_2]$ as the gene exchange fragments, and then exchange the gene exchange fragments of the two individuals. Thereby, two new individuals are generated, denoted as zygote 1' and zygote 2'.

Step 4: For the newly generated offspring 1' and offspring 2', there may be a class schedule that does not meet the requirements of the instructional program, so the new individuals need to be corrected appropriately. The strategy of correction is more deletion and less replacement. Thus, child generation 1 and child generation 2 are obtained.An example of multipoint crossover operation under weekly based is shown in Fig. 2.

Parent Generation 1

	Classroom 1	Classroom 2	Classroom 3
Time Period 1	course1		course3
Time Period 2	course4	course2	
Time Period 3		course5	course6

Parent Generation 2

	Classroom 1	Classroom 2	Classroom 3
Time Period 1	course2	course6	
Time Period 2			course3
Time Period 3	course4	course1	course5

Multi-Point Intersection Operation

Parent Generation 1'

	Classroom 1	Classroom 2	Classroom 3
Time Period 1	course1	course6	
Time Period 2	course4		course3
Time Period 3		course1	course6

Parent Generation 2'

	Classroom 1	Classroom 2	Classroom 3
Time Period 1	course2		course3
Time Period 2		course2	
Time Period 3	course4	course5	course5

Corrective Operation

Generation 1

	Classroom 1	Classroom 2	Classroom 3
Time Period 1	course5	course6	
Time Period 2	course4		course3
Time Period 3		course2	course2

Generation 2

	Classroom 1	Classroom 2	Classroom 3
Time Period 1	course6		course3
Time Period 2		course2	
Time Period 3	course4	course5	course1

Figure 2. An example of multi-point crossover operation based on week.

3.7. Variant operations

Combined with the actual situation of the scheduling problem, the mutation operation based on weekly multipoint symmetric rotation is used. The operation process is as follows: first, for the individual i to be mutated, randomly generate $m(m \leq 20)$ different integers in the interval $[1,20]$: $b_1, b_2, \ldots, b_m$. A multipoint symmetric rotation operation is performed sequentially on a portion of the chromosome at the $b_i(1 \leq i \leq m)$ week in individual i. A random number on the interval $[0,1]$ is randomly generated. For the mutation operation, two gene points are randomly selected as inverted loci within the partial chromosome of the b_i th week of individual i. Finally, the partial genes are symmetrically rotated according to the inverted sites until the operation ends after the mutation operation has been performed on all m partial chromosomes, resulting in a new individual.

3.8. Individual optimization

3.8.1. Neighborhood Switching Design

In the simulated annealing algorithm, neighborhood exchange is the main way to generate new individuals and also an important factor in determining the quality of the algorithm. Neighborhood exchange can be expressed as:

$$E(i) = \{ i \oplus x | x \in MV(i) \} \tag{22}$$

where $E(i)$ denotes the set of individuals after neighborhood swapping for individual i, x denotes the neighborhood swapping operations performed by individual i, and $MV(i)$ denotes the set of all neighborhood swapping operations for individual i.

In this paper, we propose a weekly-based multi-location neighborhood exchange. The exchange process can be described as follows: for the individual i to be exchanged, randomly generate $k(k \le 20)$ different integers in the interval $[1, 20]$: $x_1, x_2, \ldots, x_k$. Sequentially, a multi-location neighborhood exchange is performed on the partial chromosomes of the $x_i(1 \le i \le k)$ th week of individual i. The steps of week-based multi-location neighborhood exchange are shown in Fig. 3.

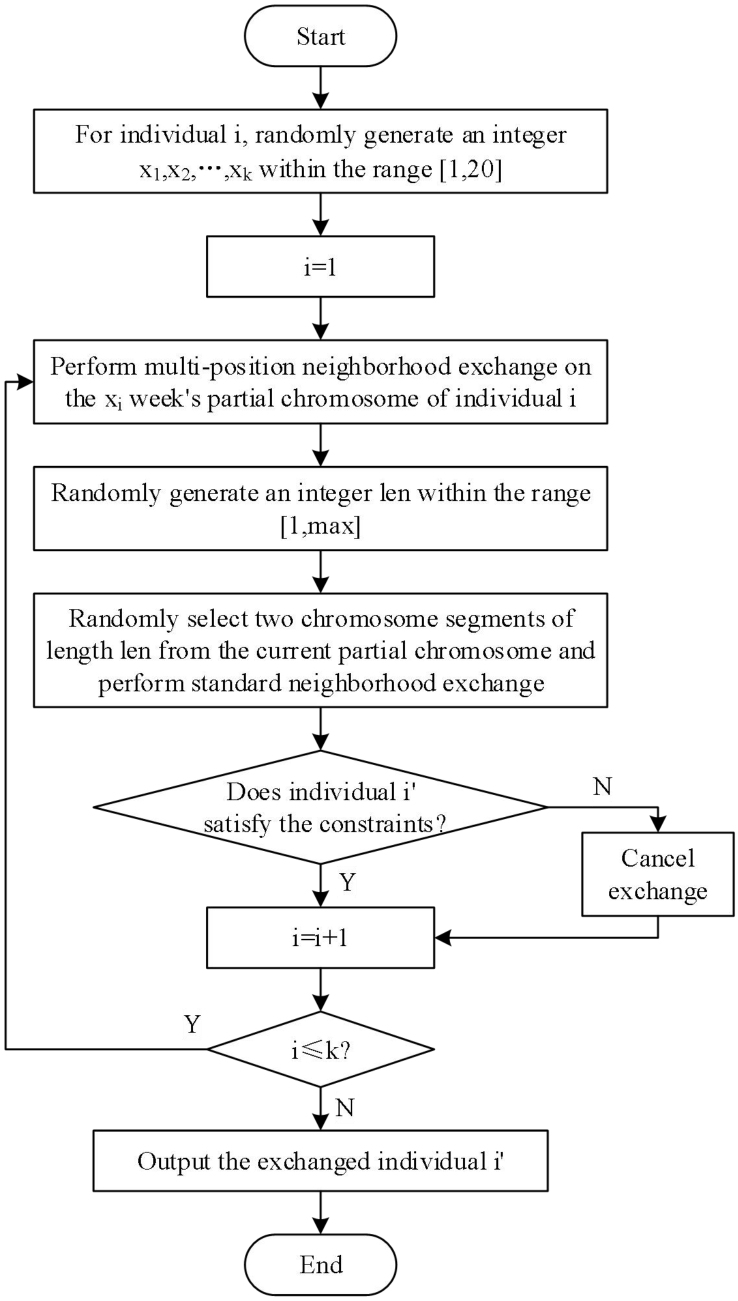

Figure 3. A process of multi-location neighborhood exchange based on the number.

3.8.2. Algorithm Design of Simulated Annealing Algorithm Combined with Branch-and-Limit Approach

In this paper, an algorithm combining simulated annealing algorithm and branch-and-bound method is proposed [28]. The flowchart of the algorithm combining simulated annealing algorithm and branch-and-bound method is shown in Fig. 4.

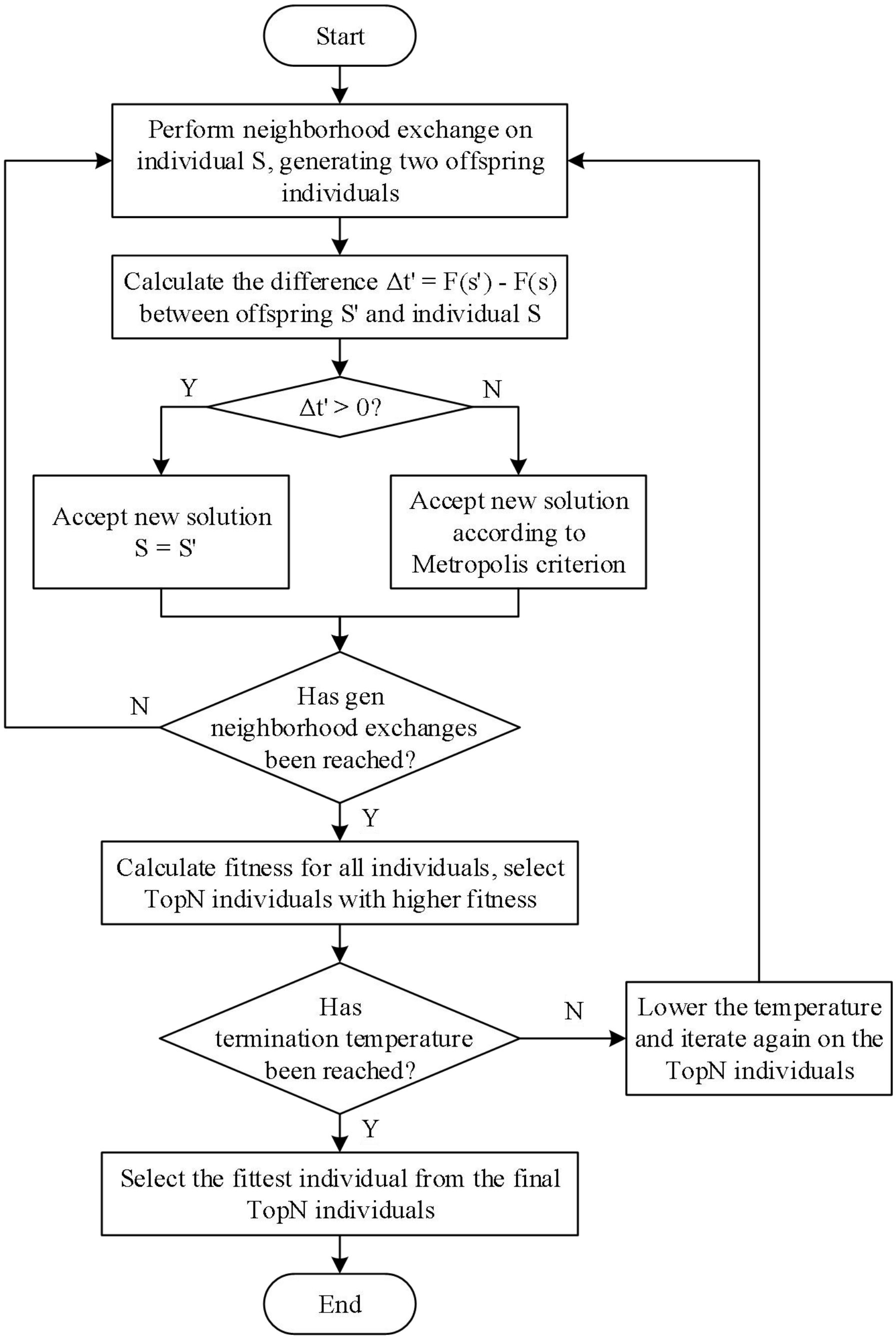

Figure 4. The algorithm of simulated annealing algorithm and branch limit method.

4. Experimental results and analysis

4.1. Simulation experiments

4.1.1. Test functions

In order to test the optimization effect of the scheduling algorithm proposed in this paper, PSO and

GA algorithms are selected for comparative experiments and five nonlinear functions are introduced for testing.The five test functions are Sphere, Rosenbrock, Ackley, Griewank and Rastrigrin functions. Except for the Rosenbrock function which has a minima at the global optimal solution [1, 1, ..., 1], the rest of the test functions have minima at the global optimal solution [0, 0, ..., 0], and the minima are all 0, and the function optima are all 0 as well.

4.1.2. Results and analysis

Numerical simulations of the five test functions using the algorithms of this paper, PSO and GA algorithms are performed to verify the feasibility of the algorithms of this paper. The main parameters are set as follows: population size 45, maximum number of iterations 1200, function dimension 32, initial maximum value of inertia weight in PSO algorithm is 0.8, initial minimum value of inertia weight is 0.5, c_1=1.53, c_2=1.53. K=0.8 in annealing algorithm, and the initial temperature is 10,000°C. The crossover probability in the genetic algorithm is 0.8 and the variance probability is 0.3. In order to verify the superiority and feasibility of the algorithm in this paper, the optimization curves for the Sphere, Griewank, Rosenbrock, Ackley, and Rastrigrin functions are derived by comparing and analyzing the five nonlinear test functions, Sphere, Griewank, Rosenbrock, Ackley and Rastrigrin function optimization curves are shown in Figs. 5-9. As can be seen from the figure, compared with the particle swarm algorithm and genetic algorithm, the algorithm in this paper has obvious advantages in the optimization of high-dimensional functions, hybrid algorithm is easy to jump out of the local optimal solution, to avoid the phenomenon of “precocity” and has the advantages of fast convergence speed, which overcomes the shortcomings and shortcomings of the traditional PSO algorithm and GA algorithm.

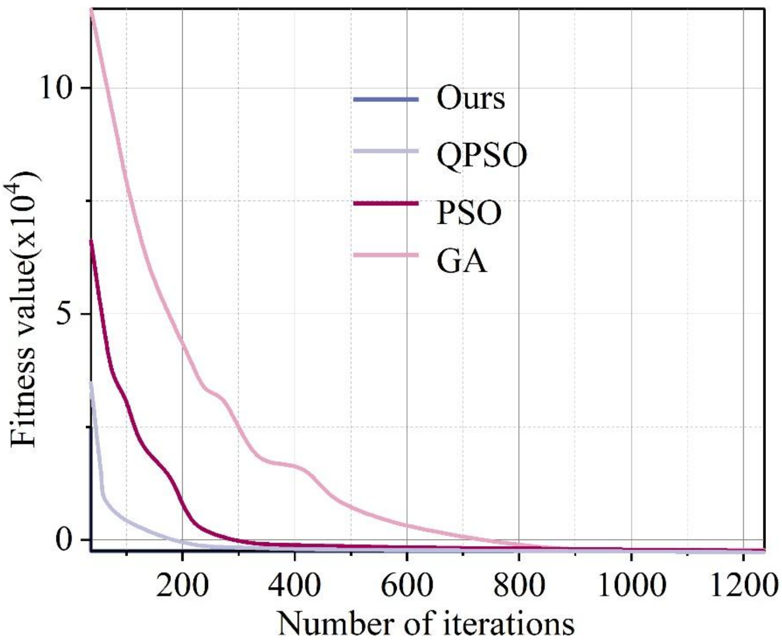

Figure 5. Sphere function optimization curve.

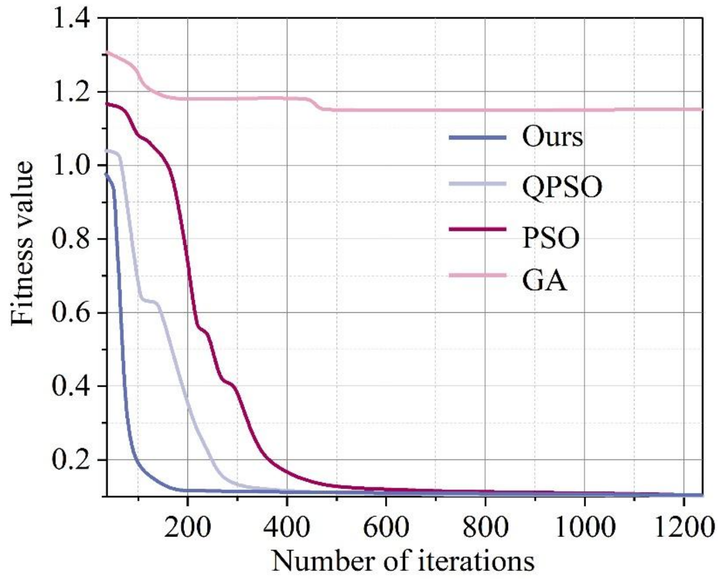

Figure 6. Griewank function optimizes the curve.

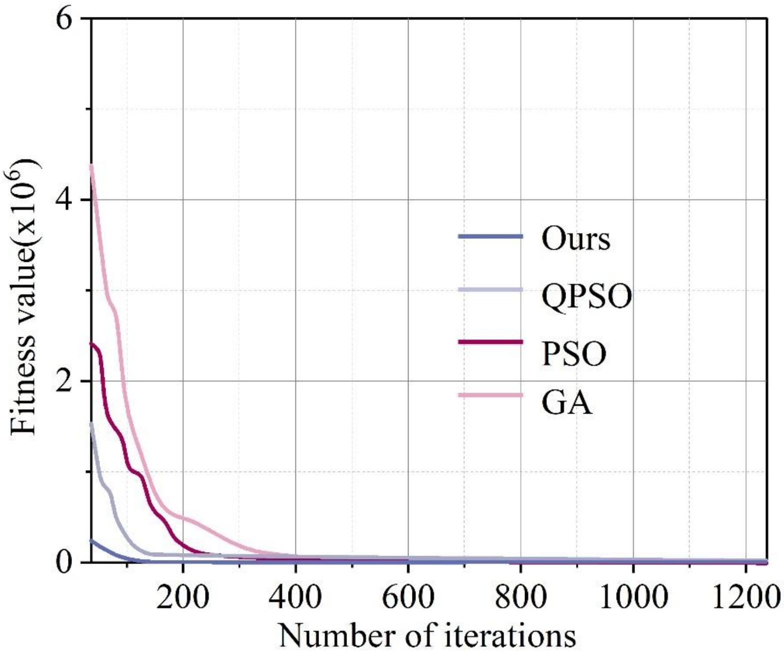

Figure 7. Rosenbrock function optimization curve.

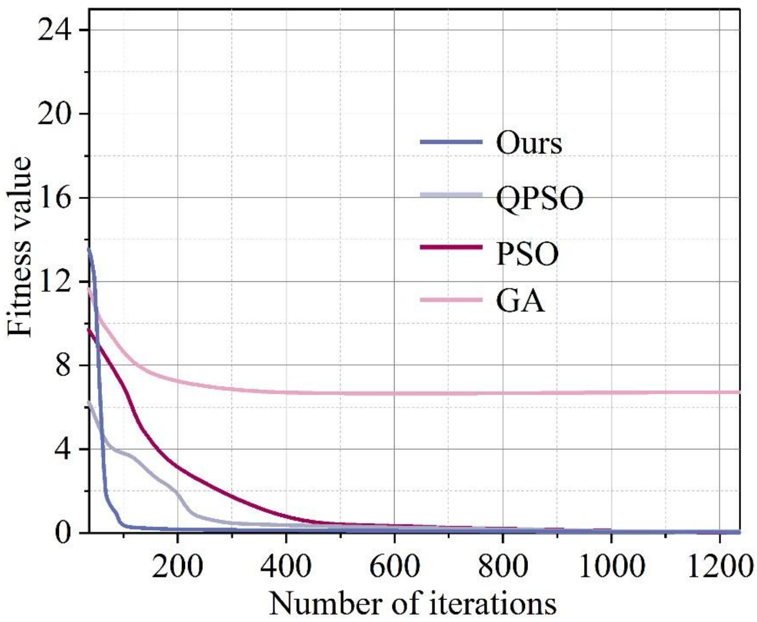

Figure 8. The Ackley function optimization curve.

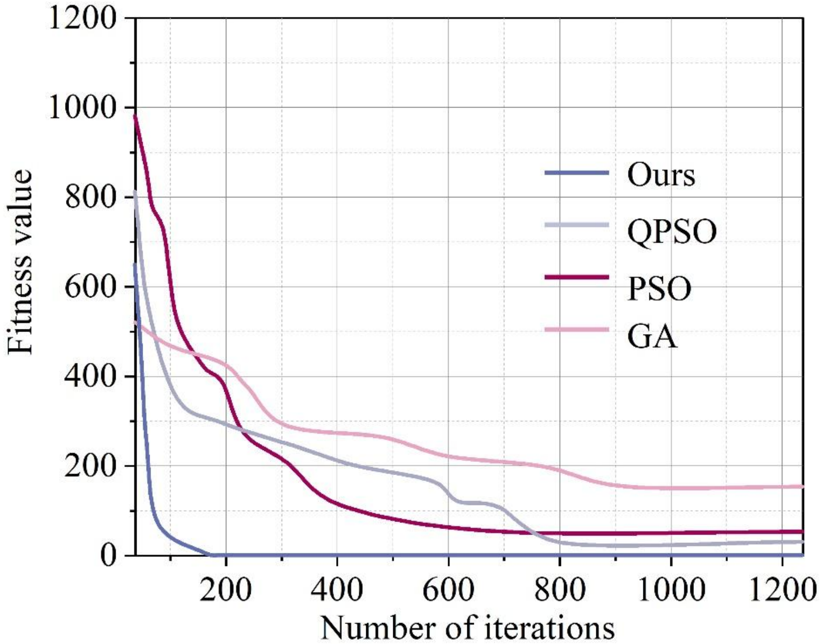

Figure 9. Rastrigrin function optimization curve.

4.2. Cultivation of Graduate Student Curriculum System

4.2.1. Selection of population size and number of iterations for hybrid simulated annealing algorithm

In the hybrid simulated annealing algorithm proposed in this paper, apart from the fact that the crossover point, crossover probability, and mutation probability are adaptively updated to the appropriate values as the evolutionary situation changes, the number of iterations and the population size are the other two important parameters that affect the effectiveness of the algorithm. In the experiment, the performance of the algorithm is observed by taking T=40, T=80, T=100, T=160 respectively. The effect of different number of iterations is shown in Table 1.

Table 1. The influence of different iterations.

Serial number	Number of iterations	Maximum fitness value
1	40	1885
2	80	1899
3	100	2110
4	160	2110

In hybrid simulated annealing algorithm, the initial size of the population also has a great impact on the convergence of the algorithm, which is observed by taking M=40, M=100, and M=160 without limiting the number of iterations, respectively. The effect of population size on scheduling efficiency is shown in Table 2.

Table 2. The affection on the timetable of the population size(unit:sec).

Serial number	$M^{=40}$	$M^{=100}$	$M^{=160}$
1	8970	5784	1225
2	7018	1143	816
3	974	1736	1110
4	246	3549	644
Average time	4302	3053	948.75

It can be seen in the table that the highest adaptation value will be achieved when the number of iterations is 100. When the population size is 160, the time spent on class scheduling is the shortest, so according to the scheduling problem and the needs of the actual project, M = 100 and T ≥ 100 are chosen as the population size and the number of iterations for this experiment. Correspondingly, the class as a unit as the initialization of the population size of the scheduling system.

4.2.2. Objective function solution and change in mean value

The objective function of the scheduling problem is solved using a hybrid simulated annealing algorithm without changing other parameters and experimental background data. The changes in the objective function solution and mean values are shown in Figure 10. From the figure, it can be seen that the hybrid simulated annealing algorithm has good convergence in the design and optimization of the scheduling problem.

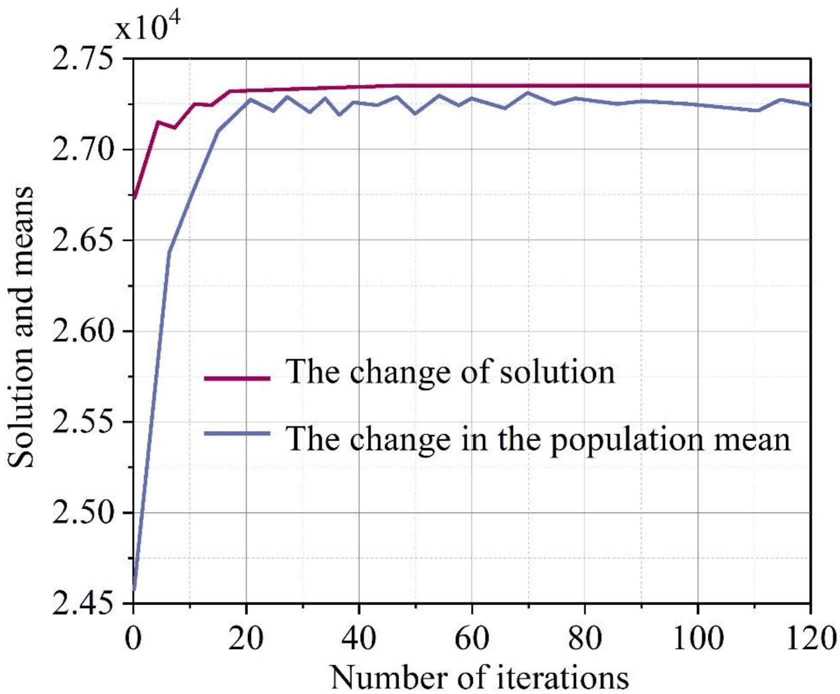

Figure 10. The variation of the solution and mean of the objective function.

4.2.3. Experimental results for cross probability

Using the hybrid simulated annealing algorithm without changing the other parameters and the experimental background data, the crossover probability varies as shown in Figure 11.

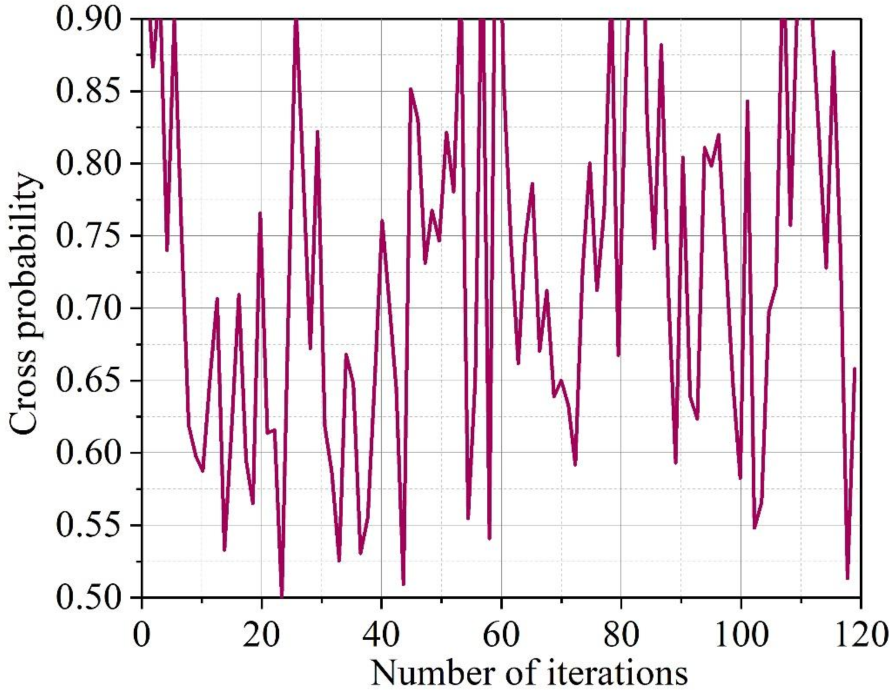

Figure 11. The change of the crossover probability.

4.2.4. Experimental results on the probability of variation

Using the hybrid simulated annealing algorithm without changing the other parameters and the experimental background data, the variation of the variance probability is shown in Figure 12.

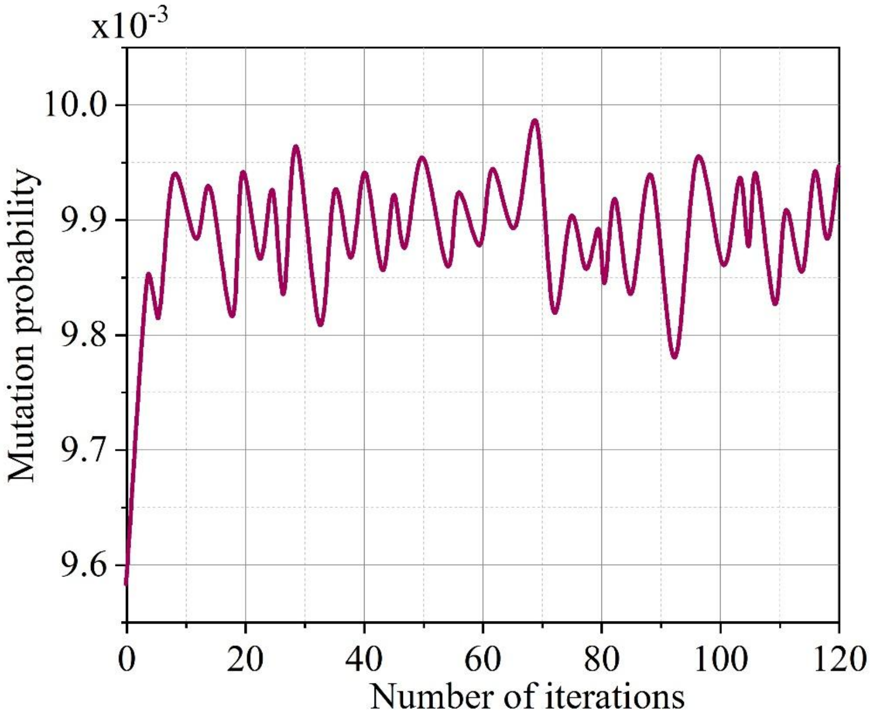

Figure 12. The change in the probability of mutation.

4.2.5. Comparison of genetic algorithms

(1) Comparison of objective function optimization

For the objective function of the scheduling problem in this paper, the basic simulated annealing algorithm, the ordinary adaptive simulated annealing algorithm algorithm and the algorithm in this paper are used to solve it respectively. The background of the experiment and the control parameters of the algorithm are kept consistent, and the crossover probability of the basic genetic algorithm is taken as p_c =0.8, p_m =0.2. The comparison of the objective function optimization is shown in Table 3. From the table, it can be seen that the hybrid simulated annealing algorithm has a considerable improvement in convergence compared to the base simulated annealing algorithm and the original adaptive simulated annealing algorithm in the optimization experiments of the scheduling problem.

Table 3. Objective function optimization comparison.

Algorithm	Convergent average iterative algebra	Local convergence degree	Maximum individual fitness	Average individual fitness
Basic simulated annealing algorithm	Unable to converge	/	/	/
Original adaptive simulated annealing algorithm	155	16	18262	1763
This algorithm	121	2	22153	20693

(2) Algorithm Performance Evaluation

The scheduling performance evaluation and comparison is shown in Table 4. From the table, it can be seen that although the operation time of this paper's algorithm is increased compared to the basic simulated annealing algorithm and the original adaptive simulated annealing algorithm, it is better than the first two simulated annealing algorithms in terms of the value of the maximum fitness of the population, the superiority of the number of sections in the scheduling, the uniformity of daily distribution of the scheduling, and the teacher's satisfaction, and this paper's algorithm is 953 and 39.

Table 4. Evaluation and Comparison of Course Scheduling Performance.

Evaluation project	Basic simulated annealing algorithm	Original adaptive simulated annealing algorithm	This algorithm
The maximum fitness value of an individual in the population	/	18048	22031
The quality of the class schedule	9178	9414	9725
The uniformity of the old distribution of course scheduling	7839	8680	9012
Teacher satisfaction	5970	6884	6923
Operation time /s	3058	5709	6934

4.2.6. Visualization of experimental results

The scheduling table based on the method of this paper is shown in Table 5. As can be seen from the results, in the scheduling algorithm proposed in this paper, the scheduling is more humanized. It is mainly reflected in the following: for the courses that have to be taken every day, try to have longer intervals, and arrange them in the morning yesterday and in the afternoon today. For operational courses (e.g., maintenance electrician), the algorithm in this paper arranges the theory class followed by the operational class, which is more helpful for students to learn and master the course content. Social activities classes are arranged on Wednesdays to relieve students' course pressure and make them more satisfied. Therefore, the scheduling algorithm proposed in this paper can meet the actual needs.

Table 5. Class schedule.

Room number	1-19	Monday	Tuesday	Wednesday	Thursday	Friday
1	One or two classes	Maintenance electrician	Application of CAD	Variable frequency technology	The operation of the enterprise power supply system	Maintenance electrician
2	Three or four classes	Career guidance	Application of CAD	The operation of the enterprise power supply system	Maintenance electrician	Maintenance electrician
3	Five or six classes	Variable frequency technology		Club activities	Maintenance electrician	
4	Seven or eight classes					
5	Nine or ten classes					

4.3. Experimentation with the grouping system

4.3.1. Experimental data sets

In this paper, the electrical course is used as an example for test paper generation. Before the beginning of the experiment, firstly, the test question data were crawled, secondly, in order to meet the constraints of the group paper as much as possible, and to prove the superiority of this paper's algorithm in solving the problem of the group paper, the test questions were classified into chapters by using the simple Bayesian algorithm, i.e., the labeling of the knowledge points, and finally, the difficulty coefficients of the test questions and the differentiation value were randomly assigned by using the random random function. Among them, there are 800 test questions in the exercise library, 300 multiple choice questions, 200 fill-in-the-blanks questions, 200 short answer questions, and 100 calculation questions.

4.3.2. Comparative analysis of experiments

After determining the algorithm parameters and group scrolling constraints, this paper implements the algorithm using Java language and establishes a correspondence with the group scrolling mathematical model for experimental analysis. The experimental simulation in this section is divided into four parts, and the experimental results are analyzed to verify the performance of the algorithm of this paper in solving the group scrolling problem.

(1) Experiment 1: Comparison of optimal solution fitness values of algorithms

The comparison of the optimal solution fitness values is shown in Figure 13. When the algorithm iterates to 20 times, the optimal solution adaptation value of the basic simulated annealing algorithm is about 0.7252, the optimal solution adaptation value of the original adaptive simulated annealing algorithm is about 0.7621, and the optimal solution adaptation value of the algorithm in this paper is already about 0.8123, which is about 0.0871 higher than that of the basic simulated annealing algorithm, and about 0.0502 higher than that of the original adaptive simulated annealing algorithm. It is about 0.0502 higher than the original adaptive simulated annealing algorithm. With the increase in the number of iterations and the continuous evolution of the population, it can be found that when 43 generations, this paper's algorithm has reached convergence with a value of about 0.8676, while the basic simulated annealing algorithm and the original adaptive simulated annealing algorithm continue to iterate to find the optimal. Therefore, the algorithm of this paper is able to achieve better results in the optimal solution value and generate better quality test papers.

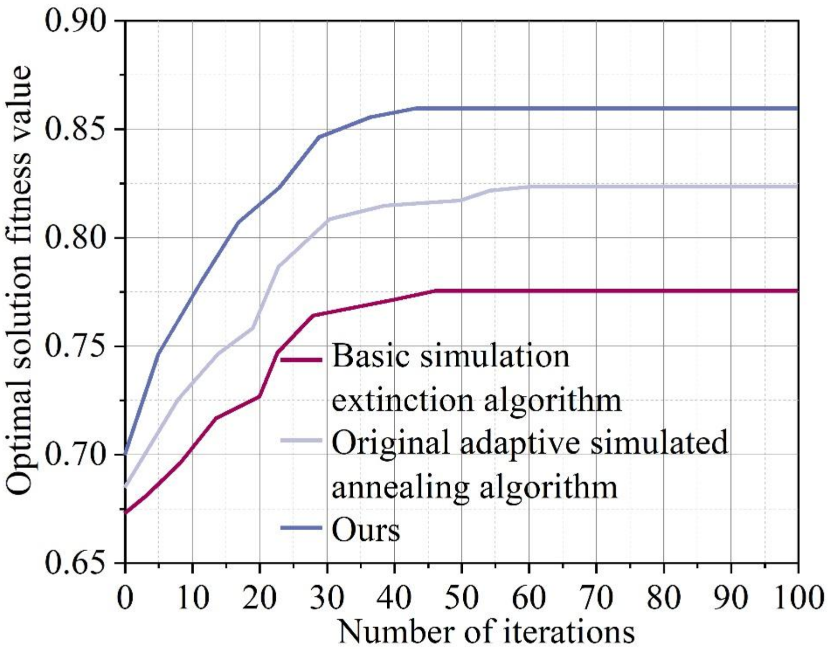

Figure 13. Comparison of the fitness values of the optimal solutions.

(2) Experiment 2: Evaluation and Analysis of Indicators

The fitness function of the group paper problem is composed of the evaluation of the difficulty coefficient, the evaluation of the knowledge point coverage, and the evaluation of the differentiation degree of the paper, so the experiment measures the quality of the paper generated by this paper's algorithm by comparing the difference between the values of these constraints indicators and the expected values. The difficulty coefficient, knowledge point coverage and differentiation evaluation are shown in Table 6. As can be seen from the table, the difficulty coefficient of the test paper generated by this paper's algorithm is 0.511, and the difference with the expected value is 0.022. Analysis shows that, in terms of the difficulty coefficient, the difference of this paper's algorithm is obviously lower than that of the basic simulated annealing algorithm and the original adaptive simulated annealing algorithm, and at the same time, the difficulty coefficient of the original adaptive simulated annealing algorithm and the algorithm of this paper are below 0.6, which means that the overall difficulty of the test paper generated by the original adaptive simulated annealing algorithm and this paper algorithms generate question papers of moderate overall difficulty. Although the basic simulated annealing algorithm is also within the range, the difficulty coefficient is slightly lower, and the overall difficulty of the generated test paper is simpler, in terms of the absolute value of the difference with the expected value, this paper's algorithm is closer to the expected value than the original adaptive simulated annealing algorithm, so the use of this paper's algorithm for the grouping of the paper, the overall difficulty of the paper is more in line with the expected effect. This paper's algorithm generates test papers with a knowledge point distribution rate of 0.802, and the difference with the expected value is 0.18. Analysis shows that in terms of the knowledge point distribution rate, the difference between this paper's algorithm and the original adaptive simulated annealing algorithm is significantly lower than that of the basic simulated annealing algorithm, and the value of the knowledge point distribution rate is larger. The differentiation of the test paper generated by this paper's algorithm is 0.585, and the difference with the expected value is 0.005. Analysis shows that in terms of differentiation, the difference between this paper's algorithm and the original adaptive simulated annealing algorithm is significantly lower than the basic simulated annealing algorithm, and the value of differentiation is larger. Therefore, the test papers generated by the algorithm in this paper are more able to illustrate the students' mastery of the knowledge points. In summary, as a whole, the test papers generated by this paper's algorithm are more in line with the expected results and are of better quality.

Table 6. Difficulty coefficient, knowledge point coverage and discrimination evaluation.

	Comparison item	Expected value	Basic simulated annealing algorithm	The original adaptive simulated annealing algorithm	This algorithm
Difficulty coefficient	Difficulty coefficient	0.515	0.226	0.414	0.511
	The absolute value of the difference	--	0.326	0.132	0.022
Knowledge point coverage	Distribution rate of knowledge points	1	0.616	0.837	0.802
	The absolute value of the difference	--	0.404	0.189	0.18
Degree of discrimination	Degree of discrimination	0.621	0.501	0.465	0.585
	The absolute value of the difference	--	0.088	0.095	0.005

(3) Experiment 3: Comparison of algorithm average fitness values

The comparison of the algorithms' average fitness values is shown in Figure 14. As can be seen from the figure, in terms of the average fitness of the population, with the increase in the number of iterations, the average fitness values of the three algorithms are gradually increasing, but as a whole, the average fitness of this paper's algorithms is higher than that of the original adaptive simulated annealing algorithm and the basic simulated annealing algorithm, and ultimately this paper's algorithms are able to reach about 0.8253. In summary, from the aspect of the average adaptation of the population, utilizing the algorithm of this paper to group volumes, the quality is better.

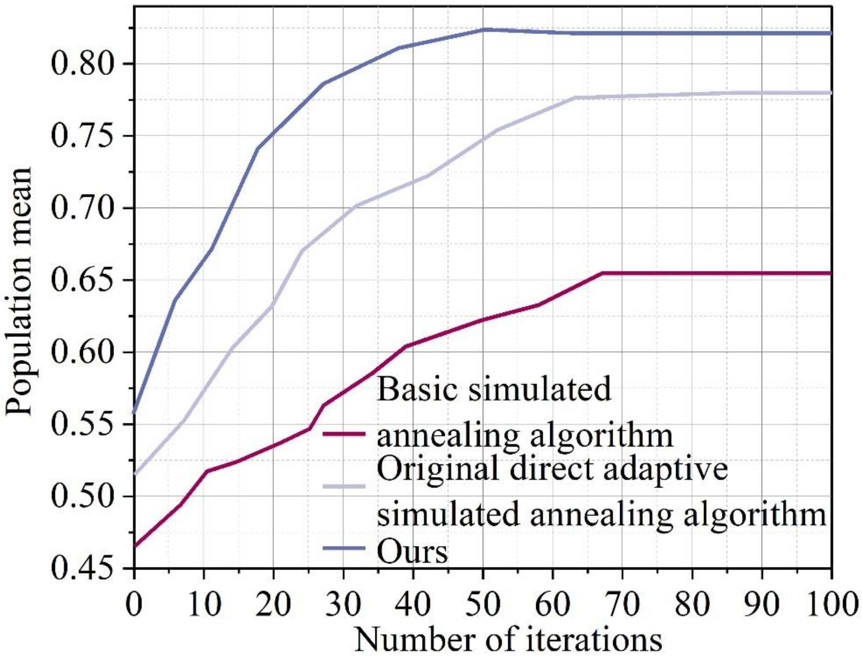

Figure 14. Comparison of the average fitness values of algorithms.

(4) Experiment 4: Comparison of the average performance of the three algorithms

The basic simulated annealing algorithm, the original adaptive simulated annealing algorithm, and this paper's algorithm are each executed 8 times, to obtain the optimal number of iterations, the running time (in seconds) and the optimal solution fitness value of the three algorithms each time the execution is completed, and to obtain the average of the results of the 8 experiments, and the comparison of the average performance of the three algorithms is shown in Table 7. According to the average value of the eight running results in the table, the average number of iterations of this paper's algorithm is 34, the running time is 7.47 seconds, and the optimal solution value is 0.8088. Therefore, the algorithm of this paper's algorithm achieves the goal of a better fitness function value in the model in terms of the efficiency of the algorithm and the quality of the solution in solving grouped volume problems. This also proves that this paper's algorithm can generate higher quality test papers when solving the group paper problem, which is more suitable for solving the group paper problem, and meets the teachers' expectations of the difficulty of the test paper, the degree of coverage of the knowledge points, and the differentiation, which is somewhat superior compared with the other two algorithms.

Table 7. Comparison of the average performance of the three algorithms.

	Basic simulated annealing algorithm			The original adaptive simulated annealing algorithm			This algorithm		
Operation frequency	Iteration number	Running time	Optimal solution	Iteration number	Running time	Optimal solution	Iteration number	Running time	Optimal solution
1	45	5.211	0.6571	53	6.255	0.7772	32	7.247	0.8105
2	46	5.19	0.6531	53	6.427	0.7725	36	7.387	0.8075
3	45	5.305	0.6575	54	6.584	0.7752	33	7.706	0.811
4	47	5.227	0.6515	53	6.1	0.7746	35	7.502	0.8126
5	45	5.465	0.6524	52	6.537	0.7694	32	7.444	0.808
6	46	5.319	0.6525	54	6.333	0.7756	36	7.314	0.808
7	46	5.414	0.6514	52	6.13	0.774	35	7.552	0.8061
8	47	5.505	0.6499	53	6.346	0.773	33	7.609	0.8068
Average	45.88	5.3295	0.6532	53	6.339	0.7739	34	7.470	0.8088

5. Conclusion

As people pay more and more attention to the quality of education for graduate students in colleges and universities, more and more scholars begin to study how to realize the optimal configuration of the course system and ability training objectives. This paper proposes a solution method based on the combination of genetic algorithm and simulated annealing-branching limit method, and applies it to the problem of scheduling optimization and ability cultivation group volume. The conclusions drawn through experiments are as follows:

After comparing the simulation experiments of five nonlinear benchmark functions, the article finds that the algorithm in this paper has better optimization ability in nonlinear complex function optimization, showing the advantages of high adjustment accuracy and fast convergence speed, and at the same time, it avoids the phenomenon of “precocious” and the problem of falling into the local optimum.

From the comparative analysis of the experimental results of class scheduling, this paper's algorithm in teacher satisfaction than the basic simulated annealing algorithm and the original adaptive simulated annealing algorithm 953 and 39, that is, based on this paper's algorithm class scheduling results are more able to meet the needs of students and teachers. And when the more courses taken, the better the results of intelligent scheduling.

In the comparison experiment of the average adaptation value of the algorithm, the average adaptation of this paper's algorithm is higher than that of the original adaptive simulated annealing algorithm and the basic simulated annealing algorithm, and the final version is able to reach about 0.8253. This verifies that the algorithm in this paper is able to generate higher quality test papers when solving the graduate student scheduling problem.

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