

Research on Teacher Education Curriculum Design Combined with Genetic Algorithm Optimization from the Perspective of Basic Theory of Education

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Abstract: This paper is based on the perspective of basic educational theory and proposes a course design scheme based on a combinatorial genetic algorithm to address the current issues in higher education teacher education course design. First, based on the relevant factors and constraints of course design problems, the objective function, mathematical model, and fitness function for this study are determined. To address the local optimality issue in traditional genetic algorithms, the simulated annealing algorithm (SA) is introduced to optimize the genetic algorithm, thereby completing the course design work for teacher education in higher education institutions. Numerical experiments are then conducted to conduct in-depth validation and analysis of the course design for teacher education. After introducing the simulated annealing algorithm (SA), the convergence speed of the genetic algorithm (GA) was significantly improved. After 100 training runs, the algorithm could obtain the optimal solution to the course design problem, verifying the optimization effect of the simulated annealing algorithm on the genetic algorithm. Additionally, under the influence of the algorithm in this paper, the satisfaction rate of student course selection remained at 100%, demonstrating the practical application value of this algorithm in teacher education course design.

Keywords: simulated annealing algorithm; genetic algorithm; course design; fitness function

1. Introduction

The historical process of advancing the professionalization of teacher education depends, on the one hand, on the high level of self-discipline and relentless efforts of teachers in schools, and on the other hand, even more so on the collective efforts of the entire teacher education community [1-2]. Among these efforts, the design of teacher education curricula serves as a crucial implementation vehicle for the professional development and training of teachers [3]. The design of teacher education curricula forms the prerequisite and foundation for the implementation and evaluation of such curricula, and is the key to achieving the objectives of teacher education and cultivating qualified teachers [4-5]. We must first clearly recognize that how teachers “teach” depends on how they “learn.” Only by deeply understanding the essence and characteristics of teacher learning, under the guidance of basic educational theory, emphasizing teacher practice and reflection, and selecting appropriate curriculum content, can we promote teachers' professional development and lifelong learning [6-9]. However, most higher normal institutions in China currently lack reasonable theoretical guidance in teacher education curriculum design, with unreasonable selection of curriculum knowledge content and a lack of exploration into the knowledge structure of teachers during the learning process [10-12]. Therefore, the scientific nature of teacher education curriculum structure significantly influences the quality and level of professional teacher cultivation [13-14]. The linear, one-way course structure, which originated in traditional education and has been widely applied to this day with the aim of serving society, should undergo a transformation in course format in the new century [15-16]. How to design teacher education courses that meet the needs of the times is a critical issue.



The development of universities cannot be separated from teachers, and the cultivation of the teacher workforce is a key project that universities are committed to. Research on teacher education courses has received widespread attention. Literature [17] introduces a consistency model for educational curriculum design, which has high applicability to teacher professional development and school educational programs. Literature [18] applies the consistency model to teacher education curriculum design, analyzes practical examples to describe the advantages and limitations of the method, and further integrates improvement feedback into educational curriculum design to promote the continuous development of teacher professionalism. Literature [19] explores the relationship between pre-service teacher education strategies and their subject-specific pedagogical content knowledge, analyzing specific course design methods through surveys of teacher educators, aiming to provide reference suggestions for modern teacher education strategies. Literature [20] indicates that teachers' educational beliefs significantly influence the formation of their educational course orientations, meaning that when designing professional teacher courses, it is essential to fully consider the educational beliefs of the teacher group to maximize the achievement of teacher education objectives. Literature [21] emphasizes that actively engaging in innovative and teacher-centered teacher education curriculum design methods is necessary, as it can effectively promote the sustainability of teacher development, empowerment, and transformative efforts. To this end, it proposes designing teacher education curricula around professional learning communities. Although the above studies offer valuable insights and suggestions on teacher education curriculum design methods, there is limited research on specific curriculum structure optimization methods, which poses significant challenges in practical implementation.

This paper takes educational theory as the main starting point for this study, combining current university course standards to establish the relevant factors and constraints for course design, and developing corresponding solution objectives, mathematical models, and fitness functions. Related data indicates that traditional genetic algorithms suffer from issues such as slow convergence speed and local optima in teacher education course design. To address this, the simulated annealing algorithm is introduced on the basis of the traditional genetic algorithm, ultimately designing a teacher education course design scheme based on the simulated annealing-genetic algorithm. The optimization and application effects of the algorithm in teacher education course design are verified from multiple dimensions.

2. Research on Teacher Education Curriculum Design Optimized Based on Genetic Algorithms

2.1. Analysis of Teacher Education Curriculum Design

2.1.1. Factors and Constraints Related to Course Design Issues

(1) Teacher factors

Each teacher has a unique ID number, which is related to the college or department they belong to.

(2) Class factors

Each class has a unique ID number and corresponding name, which is determined based on the major, college, and year of enrollment.

(3) Course factors

Different colleges offer distinct courses based on their majors. Each course has a specific name and number. Depending on the course type, there may be requirements for the classroom, such as computer labs for lab-based courses.

School schedules are organized by week, with five days per week and four classes per day. If there are odd and even weeks, the weekly schedule may vary.

(5) Classroom Factors

Each college has its own classrooms, each with a unique identifier to distinguish their functional types. Additionally, the number of seats in each classroom is fixed.

2.1.2. Solution Objectives for Course Design Issues

Course design is an NP-complete problem. The more combinations there are, the more complex the planning problem becomes. There are currently three courses, with weekly class hours of 1, 2, and 3, respectively, denoted by F, S, and T. n denotes the number of slots in the timetable. When scheduling these three courses, the number of teacher education course design schemes for these three types of courses changes with the number of slots n in the timetable. The course calculation formula is as follows:

$$F(n) = C_n^1 (n = 1, 2, 3, \dots, 20) \quad (1)$$

$$S(n) = C_n^2 (n = 1, 2, 3, \dots, 20) \quad (2)$$

$$T(n) = C_n^3 (n = 1, 2, 3, \dots, 20) \quad (3)$$

Figure 1 illustrates the relationship between course design schemes and the number of class periods and schedule slots. When the number of class periods for a course is the same, the larger the value of n , the more course design schemes there are. When the value of n is the same, the number of course design schemes increases as the number of class periods increases. When both the value of n and the number of class periods increase simultaneously, the corresponding number of course design schemes increases sharply. In the actual course design process, the optimal solution for a single course is not necessarily the optimal solution for the timetable. Therefore, under the premise of satisfying the hard constraints, the goal is to satisfy as many soft constraints as possible, ensuring that the resulting timetable meets the requirements of most teachers and students.

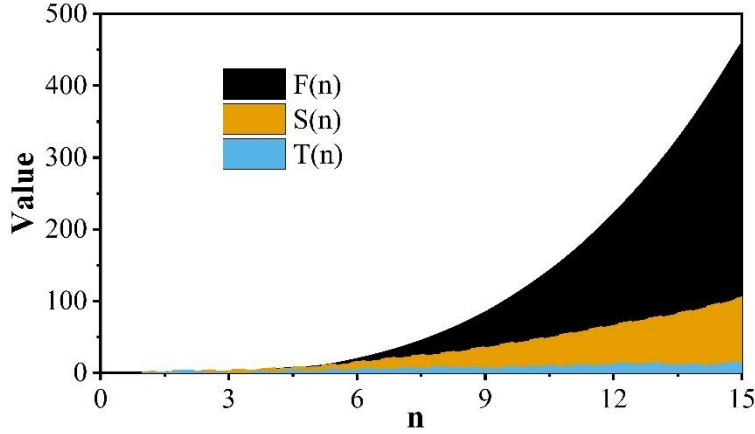


Figure 1. Diagram of changes in the class schedule combination scheme.

2.1.3. Mathematical Models of Course Design Problems

Course design is a multi-objective decision-making problem under multiple constraints. If we set the objective function as k , the constraints as m , and the decision variables as n , then the mathematical model for course scheduling is as follows:

$$\max y = f(f_1(x), f_2(x), \dots, f_k(x)) \quad (3)$$

$$\text{s.t } e(x) = (e_1(x), e_2(x), \dots, e_m(x)) \leq 0 \quad (4)$$

where: $x = \{x_1, x_2, \dots, x_n\} \in X$, $y = \{y_1, y_2, \dots, y_k\} \in Y$.

Equation (3) is the objective function of the class scheduling problem, and equation (4) is the constraint condition of the class scheduling problem. In the equation, x is the decision vector, y is the objective vector, X is the decision space formed by x , and Y is the objective space formed by y . The multi-objective optimization of the class scheduling problem is to find the maximum value of y .

The essence of the class scheduling problem is to allocate classrooms and time reasonably to teachers and classes while avoiding conflicts between these five factors. These factors can be represented by five sets: class set $C = \{C_1, C_2, C_3, \dots, C_M\}$, teacher set $S = \{S_1, S_2, S_3, \dots, S_K\}$, time set $T = \{T_1, T_2, T_3, \dots, T_D\}$, classroom set $R = \{R_1, R_2, R_3, \dots, R_N\}$, and course set $L = \{L_1, L_2, L_3, \dots, L_P\}$.

Based on the above set definitions, the following conditions must be met during the scheduling process to ensure the feasibility of the timetable.

(1) A teacher cannot teach in two classrooms at the same time:

$$R1: \sum_{p=1}^P \sum_{n=1}^N \sum_{m=1}^M x_p^l c_m r_n s_k t_d \leq 1 \quad (5)$$

In the formula: $k = 1, 2, \dots, K$; $d = 1, 2, \dots, D$;

$$xl_{p c_m r_n s_k t_d} = \begin{cases} 1, & \text{Satisfaction of conditions} \\ 0, & \text{Conditions not met} \end{cases}$$

(2) A class cannot be taught in two classrooms at the same time:

$$R2: \sum_{p=1}^P \sum_{n=1}^N \sum_{k=1}^K xl_{p c_m r_n s_k t_d} \leq 1 \quad (6)$$

Among them, $m = 1, 2, \dots, M$; $d = 1, 2, \dots, D$. It can be concluded that:

$$xl_{p c_m r_n s_k t_d} = \begin{cases} 1, & \text{Satisfaction of conditions} \\ 0, & \text{Conditions not met} \end{cases} \quad (7)$$

(3) Two courses cannot be scheduled in the same classroom at the same time:

$$R3: \sum_{p=1}^P \sum_{m=1}^M \sum_{k=1}^K xl_{p c_m r_n s_k t_d} \leq 1 \quad (8)$$

In the formula: $n = 1, 2, \dots, N$; $d = 1, 2, \dots, D$;

$$xl_{p c_m r_n s_k t_d} = \begin{cases} 1, & \text{Satisfaction of conditions} \\ 0, & \text{Conditions not met} \end{cases}$$

Formulas (5), (6), and (8) are hard constraints that must be followed in class scheduling. Only by following these hard constraints can conflicts in the class schedule be avoided and smooth class scheduling be ensured.

2.1.4. Fitness Function for Course Design Problems

Scheduling not only needs to avoid conflicts, but also ensure that the timetable satisfies most teachers and students. Therefore, an adaptability function is designed to evaluate the quality of the timetable. Typically, the adaptability function consists of the following points:

(1) Expected class period optimization

The expected class period optimization degree reflects students' satisfaction with the current class period and the efficiency of their learning. Class periods with better time slots have a higher expected class period optimization degree. Based on a survey of students' preferred class times, an expected class period optimization degree survey form was compiled, as shown in Table 1. The results indicate that the expected values for morning classes range from 0.7 to 0.9, while those for afternoon classes range from 0 to 0.6.

Table 1. Questionnaire on Expectation of Segment Optimization Degree.

Name	Monday	Tuesday	Wednesday	Thursday	Friday
1 (Morning)	0.88	0.89	0.89	0.86	0.85
2 (Morning)	0.78	0.79	0.78	0.76	0.72
3 (afternoon)	0.59	0.65	0.58	0.57	0.56
4 (afternoon)	0.28	0.29	0.27	0.27	0.26

(2) Daily Schedule Optimization Expectation

When a course has two classes per week, it is crucial to reasonably arrange the time intervals between classes to enhance teacher and student satisfaction. Therefore, the daily schedule optimization expectation is used to evaluate the quality of course daily schedule schemes. The degree of dispersion is represented by the time difference between identical courses, where 1 indicates a difference of one class period and 4 indicates a difference of four class periods.

(3) Schedule Feasibility Expectation

Combination feasibility indicates whether the timetable arrangement is reasonable and whether conflicts exist during the scheduling process, such as whether only one course is scheduled for the same classroom at the same time. Its value is either 0 or 1, with 1 indicating no conflicts in the timetable and 0 indicating that hard constraints are not met, resulting in conflicts in the timetable.

(4) Distribution Optimization Expectancy

Distribution optimization expectation indicates whether soft constraints are satisfied during the

scheduling process, such as instructors' personal needs, physical education classes being scheduled in the afternoon, and specialized courses being scheduled during optimal time slots. Distribution optimization expectation takes a floating-point value between 0 and 1.

(5) Resource Optimization Expectation

The expected resource optimization degree indicates the utilization of various school resources, with the aim of maximizing the use of school teaching resources. The resource optimization degree is a floating-point number between 0 and 1. The calculation formula is as follows:

$$e = \frac{(R - Max)}{(R - Min)} \quad (9)$$

In the formula, R represents the total number of classrooms; Max represents the maximum value for a certain type of classroom; Min represents the number of classrooms of this type that have been scheduled for classes. If the utilization rate of classrooms at the same time is higher during the scheduling process, the closer the values of Max and Min are, the higher the value of e will be. Conversely, when classroom resources are underutilized, the value of e will be closer to 0.

Based on the above analysis, the fitness function formula can be set as follows:

$$F = (a * x + b * y) * c * d * e \quad (10)$$

In the formula, x and y represent the proportions of the expected optimization degree of each period and the expected optimization degree of the daily combination in the class scheduling problem, satisfying $x + y = 1$. The specific values are determined based on actual circumstances. The optimal solution for a single course does not represent the optimal solution for the entire schedule. All courses must be scheduled to ensure that the entire schedule is optimal.

2.2. Course Design Scheme Based on Combinatorial Genetic Algorithms

Course design problems fall under the category of NPC problems. As the scale of course design continues to expand, the computational time of algorithms grows exponentially [22]. Currently, the primary research focus for addressing course design problems is the use of heuristic algorithms. Genetic algorithms are slow to search, prone to "premature convergence," and lack the ability to generate optimal individuals. Simulated annealing algorithms are characterized by their simplicity, ease of implementation, and strong algorithmic convergence. However, they are highly sensitive to parameters, converge slowly, and lack parallelism. To address these issues, this paper proposes a course design scheme for higher education teacher education that combines genetic algorithms with simulated annealing-branch and bound methods, thereby resolving course design problems in higher education teacher education.

2.2.1. Chromosome Coding

In this algorithm, chromosome encoding serves as the foundation of the algorithm and is also the first step in solving the college course scheduling problem. There are various encoding methods for chromosomes, including floating-point encoding, binary encoding, and decimal encoding. To more conveniently describe the scheduling problem, this paper adopts decimal encoding for gene encoding. The attributes of the teacher object include the affiliated institution (college), teacher ID, teacher name, title, education level, research direction, etc. The teacher ID is unique. Through the teacher ID, one can query the teacher's name, title, education level, research direction, etc.

2.2.2. Generation of the Initial Population

In this paper, each individual in the population corresponds to a class scheduling scheme. The quality of the initial population has a significant impact on the performance of the algorithm. A good initial population is a strong guarantee for the algorithm to obtain good class scheduling results. Through analysis of the class scheduling problem, we propose a method to obtain an initial population quickly. Not only is the computation time short, but the quality is also high.

2.2.3. Fitness Function Design

The constraints of the class scheduling problem include hard constraints and soft constraints. Hard constraints are conditions that must be satisfied during the scheduling process, and they serve as the standard for evaluating the feasibility of the schedule [23]. Soft constraints are conditions that can be violated during the scheduling process, and they serve as an important standard for evaluating the

quality of the schedule. In this paper, hard constraints and soft constraints are used as important components in the design of the fitness function. The design of the fitness function is as follows:

$$\begin{cases} F(i) = m_{1,i}\alpha_1 + m_{2,i}\alpha_2 + m_{3,i}\alpha_3 + m_{4,i}\alpha_4 \\ \quad + m_{5,i}\alpha_5 + m_{6,i}\alpha_6 + m_{7,i}\alpha_7 + m_{8,i}\alpha_8 \\ \text{s.t. } i \text{ satisfies hard constraints (1) to (3)} \end{cases} \quad (11)$$

Among them, $m_{1,i} \sim m_{8,i}$ respectively represent the weight values of soft constraints (1) to (3) corresponding to individual i , and $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \alpha_7, \alpha_8$ are adjustment factors that adjust the influence of different influencing factors and satisfy the following equation:

$$\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 + \alpha_5 + \alpha_6 + \alpha_7 + \alpha_8 = 1 \quad (12)$$

In this paper, the sizes of the weight adjustment factors are set to: 0.2, 0.15, 0.1, 0.05, 0.15, 0.1, 0.1, and 0.15, respectively.

2.2.4. Selecting Operations

Set individual i in the population, its fitness is F_i , and the population size is L . Calculate the sum of the fitnesses of all individuals based on the fitness of each individual in the population. The calculation formula is as follows:

$$F_{sum} = \sum_{i=1}^L F_i \quad (13)$$

Calculate the ratio of each individual's fitness to the sum of all individuals' fitness as the probability of that individual being selected. For individual i , the calculation formula is as follows:

$$p_i = F_i / F_{sum} \quad (14)$$

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

$$q_i = \sum_{t=1}^i p_t \quad (15)$$

In addition to using multiple roulette wheel selection operations, this paper also introduces partial optimal retention strategies. The fitness of individuals in the population depends on the degree to which soft constraints are satisfied. For each soft constraint, the fitness of each individual is calculated, and d individuals with better fitness that were not produced in step 5 are selected and passed on to the next generation. This ensures that the final number of individuals in the next generation, L , satisfies:

$$L = k_1 + rc * d \quad (16)$$

Among them, rc is the number of soft constraints.

2.2.5. Cross-Operation

Two individuals are randomly selected from the population and denoted as parent individual 1 and parent individual 2, respectively. n ($n \leq 20$) different integers within the interval $[1, 20]$ are randomly generated: a_1, a_2, \dots, a_n . Then, random crossover operations are performed on the partial chromosomes of individuals in the a_i ($1 \leq i \leq n$) th week.

Perform a random crossover operation on the chromosomal segment of the a_i th individual. First, randomly generate two distinct integers e_1, e_2 within the interval $[1, 25 * K]$. Then, randomly generate a number p in the interval p . If p is less than the crossover probability P_c , perform the crossover operation on the two parent individuals; otherwise, do not perform the crossover operation.

For individuals 1 and 2 that are to perform a crossover operation, select a portion of the genes within

the position interval $[e_1, e_2]$ of the partial chromosomes in week a_i as gene exchange fragments, and then exchange the gene exchange fragments of the two individuals. This produces two new individuals, denoted as offspring 1' and offspring 2'.

For the newly generated offspring 1' and offspring 2', there may be cases where the schedule does not meet the requirements of the teaching plan, so appropriate adjustments need to be made to the new individuals.

2.2.6. Variation Operations

Genetic variation refers to the process of inheritance from parent to offspring, during which certain genetic information may undergo mutations, resulting in offspring possessing genetic information not present in their parents. This leads to the emergence of new traits. For individuals with these new traits, those that are not adapted to the environment may be eliminated, while those that are adapted can continue to survive. From this, it can be seen that genetic variation can also promote population evolution.

2.2.7. Individual Optimization

The simulated annealing algorithm has a sound theoretical foundation and is characterized by its simplicity, ease of implementation, and strong convergence properties. However, the simulated annealing algorithm also has some drawbacks, such as being highly sensitive to parameters and having a slow convergence rate. To address these shortcomings, this paper proposes an algorithm that combines the simulated annealing algorithm with the branch-and-bound method for individual optimization.

(1) Neighborhood Exchange Design

In the simulated annealing algorithm, neighborhood exchange is the primary method for generating new individuals and is also a key factor in determining the quality of the algorithm. Neighborhood exchange can be represented as:

$$E(i) = \{i \oplus x \mid x \in MV(i)\} \quad (17)$$

In this context, $E(i)$ denotes the set of individuals obtained after neighborhood exchange for individual i , x denotes the neighborhood exchange operation performed by individual i , and $MV(i)$ denotes the set of all neighborhood exchange operations performed by individual i .

(2) Algorithm design combining simulated annealing and branch-and-bound methods

First, during neighborhood exchange, each individual generates two offspring individuals. For the generated offspring individuals, we use the Metropolis criterion to determine whether to accept them. When an offspring individual is accepted, it replaces the current individual, and a new round of neighborhood exchange operations is performed; when an offspring individual is rejected, the current individual is retained, and a new round of neighborhood exchange operations is performed. After the algorithm has performed gen neighborhood exchanges, we calculate the fitness values of all individuals and select the top N individuals with the best fitness. Finally, we repeat the above process for these top N individuals until the algorithm reaches the termination temperature, at which point we select the individual with the best fitness from the last generated top N individuals as the result of individual optimization.

3. Evaluation and Analysis of Teacher Education Curriculum Design Plans

3.1. Algorithm Performance Verification Analysis

To validate the algorithm proposed in this paper, we used four classic benchmark functions to test its performance. It should be noted that among the four functions, f1-f2 are single-peak functions, while f3-f4 are multi-peak functions. The specific analysis process is as follows:

3.1.1. Ablation Experiment Analysis

Under the influence of four test functions, an ablation experiment analysis was conducted on the performance of the algorithm in this paper. The results of the ablation experiment analysis are shown in Figure 2, where (a) to (d) represent test functions f1 to f4, respectively. The results show that in the test function f1, the SA (simulated annealing algorithm) and SA-GA (simulated annealing algorithm-genetic algorithm) combination algorithms have similar convergence speeds in the early stages of training. After approximately 100 training iterations, the latter accelerates its convergence speed. In the test function f2, both algorithms (GA and SA) fell into local optima and evolutionary stagnation, while the GA-SA

combination algorithm converged quickly in the early stages and found an approximate optimal solution. This shows that introducing the simulated annealing algorithm (SA) into the basic genetic algorithm (GA) can effectively improve algorithm performance, enabling it to design teacher education curriculum plans that meet user needs.

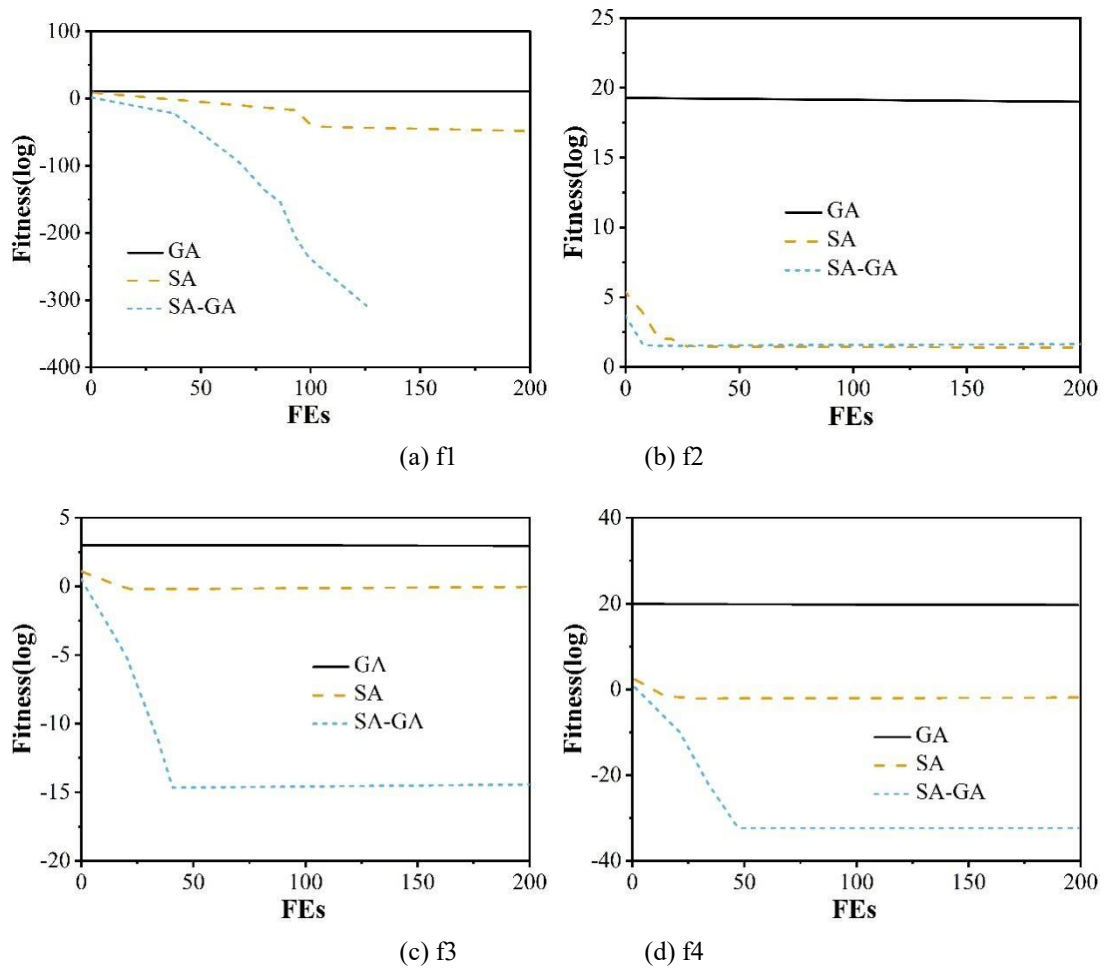


Figure 2. Analysis results of ablation experiments.

3.1.2. Comparison and Analysis of Different Algorithms

To further validate the performance of the proposed algorithm, the Adaptive Particle Swarm Optimization (APSO) algorithm and the Artificial Bee Colony with Memory (ABCM) algorithm were selected as comparison algorithms. The results of the comparative analysis between the different algorithms are shown in Figure 3. During the early stages of training, the convergence speed of the proposed algorithm on the single-peak function f1 was similar to that of the other two algorithms (APSO: Adaptive Particle Swarm Optimization algorithm, ABCM: Artificial Bee Colony with Memory algorithm). In the later stages of training, the proposed algorithm begins to converge rapidly and identifies the optimal solution. In the single-peak function f2, the three algorithms exhibit similar convergence curves and all quickly become trapped near local optima in the early stages of the algorithm. The proposed algorithm demonstrates superior performance compared to the other comparison algorithms, both in terms of final results and convergence curves, thereby validating its priority in the design of teacher education courses.

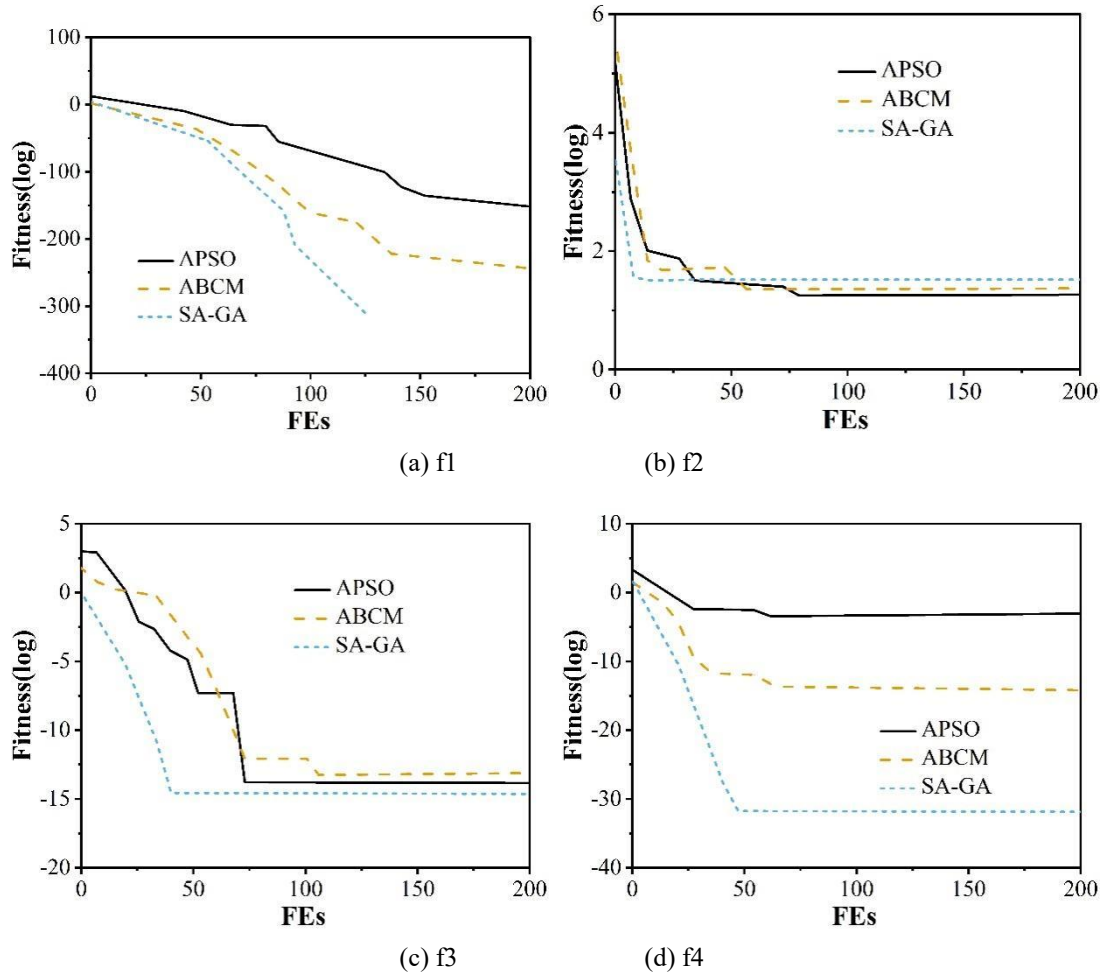


Figure 3. Comparison and analysis results of different algorithms.

3.2. Analysis of Target Results

Figure 4 shows the fitness function values of three genetic algorithms. The algorithm designed in this paper is compared with the standard genetic algorithm and the simulated annealing algorithm (SA). Among these, the standard genetic algorithm uses the roulette wheel method for selection, the random two-point crossover method for crossover and mutation operations, and the optimal individual retention method. The simulated annealing algorithm uses the neighborhood exchange method described in this paper. The encoding schemes, initial population, conflict resolution, fitness function design, and genetic algorithm parameters for the standard genetic algorithm and simulated annealing algorithm are consistent with those in this paper. The relevant numerical values are the average results of multiple experiments on the scheduling experimental data. From the analysis of the figures, it can be observed that the standard genetic algorithm converges around 120 generations. The simulated annealing algorithm converges around 160 generations, although the convergence speed is slower, the fitness function value is significantly higher than that of the standard genetic algorithm. The simulated annealing and genetic combination algorithm designed in this paper converges around 100 generations and has the characteristics of fast convergence and strong global search capabilities. This is because the local search operator performs local search optimization for specific solution objectives in the course scheduling problem. For algorithm performance, there are two metrics: global search capability and local search capability. Global search capability refers to the ability to find the optimal solution globally, while local search capability refers to the ability to derive a more optimal solution algorithm by analyzing a specific local problem based on existing solutions. In practical problems, the result values often have many local extrema points across the entire search space, making it easy to get stuck in local extrema points, i.e., the local optimal situations described earlier. The local search algorithm designed in this paper relies on the solution space for search.

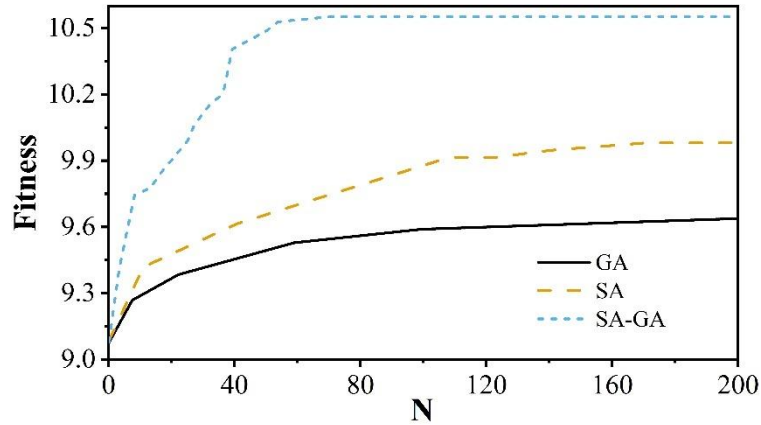


Figure 4. The fitness function values of three genetic algorithms.

Table 2 and Table 3 present the fitness function values from the perspectives of teachers and students, respectively. This is attributed to the algorithm employed in this paper, which utilizes the simulated annealing algorithm to improve the genetic operator and design the local search. In the fitness function value for “convenience for counselors to attend classes,” the proposed algorithm (0.913) outperforms the other two algorithms. This is analyzed as follows: since university counselors typically do not oversee classes of the same major or even the same grade level, the objective function of “convenience for counselors to attend classes” may conflict with other objective functions such as “classroom seat utilization rate,” “course nature interleaving,” and “physical education class scheduling time.” To increase the value of the “convenience for counselors to attend classes” objective function, simply increasing its weight value is sufficient, but this may also cause the values of other objective functions to decrease. This confirms the effectiveness of the simulated annealing-genetic combination algorithm in teacher education course design from an educational theory perspective, holding significant strategic implications for the digitalization and intelligent development of teacher education courses in higher education institutions, thereby making teacher education course design more aligned with the needs of both teachers and students.

Table 2. The fitness function value considered from the perspective of teachers.

Name	GA	SA	SA- GA
Set aside at least one day	0.78	0.766	0.922
There are at most six classes every day	0.666	0.723	0.957
Special teacher floor arrangement	0.704	0.642	0.904
Convenient for counselors to attend classes	0.652	0.686	0.913

Table 3 The fitness function value considered from the perspective of students

Name	GA	SA	SA- GA
The intervals between course days are reasonable	0.659	0.65	0.939
For each class, daily courses are evenly arranged	0.717	0.691	0.903
For each class, there are no weekly class hours More than 30 class hours	0.746	0.716	0.942
Plan the weekly classes of the class reasonably Hours	0.691	0.786	0.924
The natures of the courses are interwoven and matched	0.64	0.766	0.905
Physical education class schedule	0.659	0.706	0.923
When classes are extended, the classrooms are also updated Change the distance	0.743	0.706	0.921
One room is left vacant on each floor of the teaching building Classroom	0.716	0.602	0.916

3.3. Analysis of the Course Design Experiment Results of the Algorithm in This Paper

3.3.1. Conflict Detection and Conflict Resolution Analysis

In the course scheduling algorithm designed in this paper, conflict detection and conflict resolution are performed after initializing the population and applying genetic operations to ensure that the timetable meets both basic constraints and hard constraints. Table 4 shows the average values of course conflict detection before and after conflict resolution, based on 200 initializations of the population for the course scheduling data. As indicated by the data in the table, course conflicts inevitably occur after initializing the population in the course scheduling algorithm, with values ranging from 2 to 4,500.

Under the influence of the algorithm proposed in this paper, the number of course conflicts is reduced to 0. Thus, the algorithm proposed in this paper can resolve the conflicts currently encountered in course design for teacher education programs at higher education institutions.

Table 4. Coffee class conflict schedule.

Conflict Explanation	Before the conflict of course scheduling is eliminated	After the conflict in course scheduling is eliminated
The number of conflicts between classrooms and courses at the same time and the required classroom capacity and type	4434.1	0
The number of conflicts between teachers and courses at the same time	74.6	0
The number of conflicts between classes and courses at the same time	119.4	0
The number of conflicts between the course and its precursor courses	2.04	0
The teacher has a conflict with the regular meeting time	83.3	0

3.3.2. Analysis of the efficiency of teacher education curriculum design

This paper conducts experiments from aspects such as student course selection satisfaction, classroom utilization rate, and overall course scheduling rule satisfaction. The results of the analysis of teacher education course design efficiency are shown in Table 5. We selected two different datasets (administrative classes and flexible scheduling classes) to conduct application experiments using the simulated annealing-genetic algorithm. The experimental results show that, regardless of whether it is an administrative class or a flexible scheduling class, the student course selection satisfaction rate reaches 100%, the average overall rule compliance rate is 0.980, classroom utilization rate reaches 0.974, and course uniformity reaches 0.883.

Table 5. Analysis of the Efficiency of Teacher Education Curriculum Design.

Name	The satisfaction rate of student course selection.	Overall rule satisfaction rate	Classroom utilization rate	Course uniformity
Administrative class	1	0.984	0.965	0.838
	1	0.995	0.959	0.887
	1	0.989	0.989	0.837
	1	0.972	0.993	0.827
	1	0.962	0.986	0.913
	1	0.96	0.975	0.923
	1	0.995	0.974	0.891
Shift change	1	0.99	0.994	0.901
	1	0.98	0.995	0.934
	1	0.994	0.958	0.849
	1	0.962	0.95	0.862
	1	0.982	0.967	0.899
	1	0.971	0.958	0.873
	1	0.98	0.979	0.933

3.3.3. Course Design Satisfaction Rate Analysis

This paper applies the simulated annealing-genetic combination algorithm to the rule satisfaction rate in class scheduling. The experimental results are shown in Table 6. In the table, X1 to X11 represent the following conditions, respectively: no teacher scheduling, global fixed point, teacher class hour restrictions, teacher mutual exclusion, teachers across campuses, mutual exclusion between consecutive courses, mutual exclusion between courses on the same day, class hour priority, consecutive classes, odd and even weeks, and combined classes. Under different class scheduling rule conditions, the algorithm generally meets the rule constraints of current university intelligent scheduling systems, including teacher scheduling restrictions, class hour limits, cross-campus scheduling, conflicts between consecutive classes, consecutive classes of two or more periods, odd/even week schedules, and

combined class settings. The scheduling satisfaction rate reaches an average of over 95%, though it has not yet reached 100%. However, it can meet the current needs of university teacher education course design, fully validating the effectiveness of this algorithm in university teacher education course design applications.

Table 6. Analysis of the Satisfaction Rate of Curriculum Design.

Symbol	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
Administrative class	0.983	No	No	0.982	No	No	0.977	0.979	0.981	No	0.986
	0.99	No	No	No	No	No	0.974	0.971	0.973	No	No
	0.98	No	No	No	No	No	No	0.981	No	0.981	0.99
	0.973	No	0.982	No	No	No	0.97	0.974	0.978	No	0.972
	0.984	0.999	0.983	0.98	No	No	0.985	0.977	0.989	0.987	0.972
	0.985	0.972	0.977	0.974	No	No	No	0.983	0.98	No	0.987
	0.982	No	No	No	No	0.981	0.972	0.971	0.975	No	No
Shift change	0.98	0.983	No	No	No	No	No	No	No	No	No
	No	0.978	No	No	No	No	No	0.971	No	No	No
	No	0.984	0.982	0.986	No	No	No	0.987	0.978	No	No
	0.971	0.973	No	No	No	No	No	0.978	No	No	No
	0.988	No	0.976	No	No	No	0.975	0.984	No	No	0.979
	0.975	0.969	No	0.974	No	No	No	0.972	0.978	No	0.973
	No	No	0.976	No	No	No	No	0.977	No	No	0.975

4. Conclusion

This paper addresses the issue of course design for teacher education programs in higher education institutions under the framework of educational theory. It proposes the use of a simulated annealing-genetic algorithm combination to conduct course design for teacher education programs in higher education institutions. First, based on the relevant factors and constraints of the course design problem, an objective function is established, followed by the determination of the mathematical model and fitness function for this study. Under its influence, a course design scheme based on a genetic algorithm is designed, and the scheme is validated and analyzed. Through four test functions, it was confirmed that incorporating the simulated annealing algorithm (SA) effectively enhances the performance of traditional genetic algorithms. After 100 training runs, the algorithm identified the optimal solution to the course design problem. In terms of practical application, the course selection satisfaction rate remained at 100%, indicating that the teacher education course design based on the algorithm proposed in this paper can meet student needs.

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