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Using Genetic Algorithm to Enhance Path Planning for Resource Allocation in Civic and Political Education Courses

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Abstract In this study, a hybrid genetic algorithm (HGGA) improved based on greedy strategy is proposed for the path planning problem of resource allocation for Civic and Political Education courses. The improved genetic algorithm is proposed based on the greedy strategy to increase the correction operation for perfect and imperfect solutions. Combined with the special needs of Civic and Political Education in value shaping and ideology dissemination, the resource content composition, classification organization and dynamic adaptation mechanism are optimized. Experiments show that HGGA has optimal convergence probability, convergence speed, optimal convergence extreme value and average convergence extreme value in the test function compared with the comparison algorithm, and the solution accuracy is better. The traditional genetic algorithm has to be iterated to about 30 generations to find the optimal solution under the calculation of the algorithm, while the HGGA algorithm can find the optimal solution under the calculation of its algorithm as long as it is iterated to about 23 generations. In the final exam at the end of the teaching experiment, the passing rate of the experimental group class was 7.5% higher than that of the control group class, and the excellence rate was 2.5% higher compared to the control group class. The results of the mean score t-test showed that the mean score of the experimental group was 7.97 points higher than that of the control group at the end of the experiment, and there was a significant difference in the students' performance in Civics and Political Science ($p=0.019$, $p<0.05$). The mean scores of students in the experimental group classes were higher than those in the control group classes in the three dimensions of behavioral attitudes, affective tendencies, and value orientations, and significant differences emerged in the dimensions of affective tendencies ($p=0.013$) and value orientations ($p=0.035$) ($p<0.05$).

Index Terms civic education, curriculum resource allocation, genetic algorithm, greedy strategy

I. Introduction

Civic and political education in colleges and universities aims to cultivate students' sense of social responsibility and patriotism, and it is an important position for higher education in the new era to realize the establishment of morality and nurture people on the basis of improving the comprehensive quality of students, which not only concerns students' personal growth and development, but also relates to the future of the country and the nation [1]-[4]. In the context of the new era, as China's education reform continues to advance, the allocation of curriculum resources for the Civic and Political Science course in colleges and universities, as a key course for establishing morality and building people's moral character, is also facing new challenges and opportunities [5], [6]. On the one hand, due to the increasing number of students in colleges and universities, the related teaching resources in the process of teaching in colleges and universities are not able to meet the requirements of the number of students after the expansion of enrollment, which hinders the development of the teaching activities of ideological and political courses [7]-[9]. On the other hand, there is a general lack of teaching resources sharing ability in the teaching process of colleges and universities, and students can't access basic education resources to understand the relevant theoretical knowledge and enrich themselves, resulting in a waste of resources [10]-[12]. In the face of increasingly tense educational resources, how to reasonably allocate and utilize limited educational resources to improve the teaching effect of Civics and Politics courses has become an important issue for universities [13], [14].

This paper firstly establishes a framework model for analyzing the allocation of curriculum resources, incorporating the ideological propagation law of ideological education. A hybrid genetic algorithm with improved greedy strategy is proposed to solve the problem of uneven distribution of initial population and local optimal convergence. Control experiments are set up to verify the effectiveness of the improvement scheme in this paper. Through the analysis of teaching experiments, the feasibility of the proposed algorithm in optimizing the path planning of course resource allocation in Civic and Political Education is explored.

II. Civic education course resource allocation based on HGGA algorithm

With the further deepening of the new curriculum reform, the application of educational resource websites in the teaching of primary and secondary school subjects is also expanding. The quality of curriculum resource configuration of educational resource websites is related to the quality of educational resource websites and the effect of the utilization of curriculum resources. With the acceleration of the digital transformation of Civic and Political Education, the allocation of curriculum resources faces the problem of multi-dimensional goal conflict and dynamic adaptation. Traditional resource allocation methods are difficult to balance the relationship between the breadth of knowledge coverage, ideological depth and teaching effectiveness, and there is an urgent need to introduce intelligent optimization technology.

II. A.Analytical Framework Model for Curriculum Resourcing

Curriculum resource allocation is based on the construction of the curriculum objectives of the various curriculum resources in the quality and other attributes of the demand for the equipment, while the nature of these curriculum resources based on the characteristics of the nature of the resources and their interrelationships between the arrangement, so as to build the maximum degree of realization of the objectives of the curriculum curriculum resources system.

Combined with the actual situation of China's ideological education and teaching, and grasping the principles of analytical framework construction, this paper determines the following analytical framework for the allocation of curriculum resources, and the framework model is shown in Figure 1.

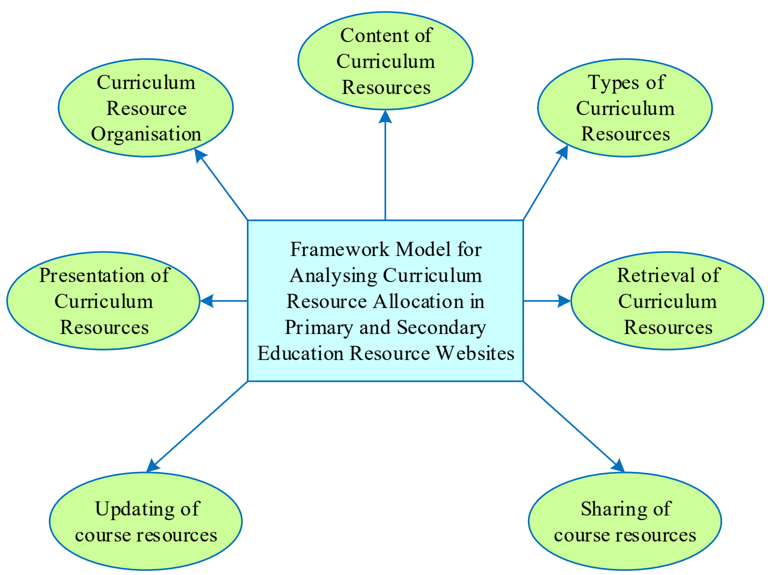


Figure 1: Analysis framework model for Course Resource allocation

(1) Content composition of curriculum resources

The so-called content composition of curriculum resources refers to the specific resources that constitute the ideological and material aspects of curriculum resources. It is specifically manifested as the knowledge of various aspects of the disciplines related to education and teaching as well as the resources of a particular aspect of a specific discipline, which includes not only the content of the curriculum resources, but also the intrinsic structural nature of the content of the curriculum resources. The specific variables of this dimension can include whether the curriculum content carried by the provided curriculum resources is comprehensive, whether the content of the subject range of the included disciplines is extensive and whether it has depth. Therefore, this paper argues that the content of curriculum resources includes three dimensions: curriculum resources involving disciplines, resource breadth, and resource depth. In the dimension of resource depth, the value-oriented intensity of Civic and Political Education is strengthened to quantify the extent to which the resources embody socialist core values.

(2) Types of curriculum resources

A good classification mechanism of curriculum resources can efficiently realize its organization, management and use of curriculum resources. The type of curriculum resources is to distinguish many curriculum resources according to certain criteria, principles and characteristics of the curriculum resources themselves, so as to make better use of them. The specific variable of the curriculum resource type dimension can be described as whether the classification of the presented curriculum resources is scientific and reasonable. Therefore, this paper will analyze the division dimension and the basis of classification respectively. The bases for the division of curriculum resources can be the following: object-oriented, data processing characteristics of the resource, linguistic form, disciplinary attributes and knowledge categories with the paid nature of the resource. Highlighting the dimension of ideological carrier type, distinguishing the categories unique to ideological education such as theoretical texts, practical cases, role models and demonstrations.

(3) Organization of curriculum resources

The so-called organization of curriculum resources refers to the process of reasonably organizing all the collected curriculum resources according to certain principles and order and forming a certain organizational structure according to the needs of the theme. The organization of curriculum resources will reflect certain educational concepts and greatly affect the utilization effect of curriculum resources. Specific variables of the organizational dimension of curriculum resources can include whether the organizational template is single or diverse. Based on the needs of civic education and following the law of civic education of “cognition-identification-practice”, this paper designs the organization of curriculum resources including three measurement dimensions: organization principle, organization structure and organization order.

(4) Sharing of course resources

The sharing of course resources on the website consists of two dimensions: on the one hand, it supports users to upload resources to enrich the resource library and allows users to make evaluation and feedback on the resources, and on the other hand, the website is available for users to download the resources. The dimensions of course resource sharing include whether the resources can be downloaded, whether they have download privileges, and whether they are downloaded frequently. Therefore, course resource sharing in this paper includes four dimensions: download permission, download speed, upload permission and upload speed.

II. B.Improved HGGA algorithm based on greedy strategy

II. B. 1) Basic Overview of Genetic Algorithms

Genetic algorithm (GA) as a kind of intelligent optimization algorithm, genetic algorithm models the problem as a chromosome form, according to the genetic selection, genetic crossover, genetic variation and other forms of evolution, the cycle of iteration ultimately produces the most optimal chromosome, i.e., optimal solution of the genetic problem that meets the conditions. Compared with the general traditional optimization algorithms, genetic algorithms have outstanding advantages, especially for the optimization of cumbersome, nonlinear problem solving is more convenient, fast and efficient.

Genetic algorithm has the following advantages: First, it has the group search characteristics, the algorithm solving efficiency is faster. Second, the feasible solution expression form is more extensive. Third, it has a wide range of application space, only need to one-to-one correspondence between the feasible solution space and genetic code. Fourth, it is characterized by strong scalability, and it is easier to mix or cross use with other algorithms.

II. B. 2) Genetic Algorithm Basic Algorithm Flow

The process of solving the genetic algorithm is a very typical iterative process of finding the best, and the basic flow is shown in Figure 2.

Step 1: Select the appropriate genetic coding rules, the production operation process for the corresponding transformation, the formation of the corresponding code form.

Step 2: Randomly generate the initial population, which is assumed to have N individual.

Step 3: The chromosome fitness value is obtained by defining the individuals of the initial population starting from the fitness function.

Step 4: Carry out the determination of whether the termination criterion is met, if so, end the operation to output the results of the operation. Otherwise, screen individuals from the existing population according to the corresponding rules to generate a new population.

Step 5: According to the genetic crossover probability, genetic crossover is performed on the new population to generate a new genetic crossover population.

Step 6: Form a new genetic population from the genetic mutation rate and return to step 4 to continue the operation.

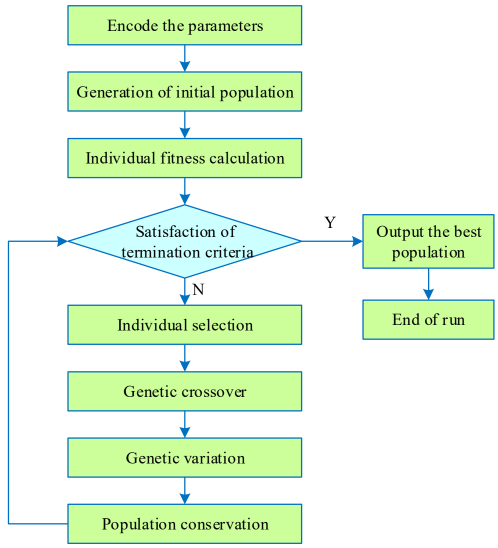


Figure 2: Basic Processing flow of genetic algorithm

II. B. 3) Greedy strategies for improving genetic algorithms

The greedy strategy is a step-by-step optimization approach that starts with an initial solution to the problem and approaches the true optimal solution by choosing the local solution that seems best at the moment at each subsequent step. This strategy is centered on locally optimal decisions rather than based on global considerations, so its output is often not the global optimal solution. However, a greedy strategy may sometimes produce a globally optimal solution for problems with a particular structure, rules, or constraints that are characterized by the following:

First of all, the problem can be refined to a step-by-step execution according to the same or consistent rules, so that at each step the best possible local solution can be chosen, which is based on the choices made in the previous step and the previous ones, and the decision at each step cannot be changed iteratively.

Second, the problem at the current stage can only be focused locally, i.e., the optimal solution can be solved as much as possible in the execution steps that are refined into one step. Although this may result in a non-optimal overall solution, in many cases the greedy strategy still provides a satisfactory solution, and has significant advantages over dynamic programming in terms of time efficiency, memory footprint, and programming convenience.

According to the core idea of greedy strategy and its characteristics, the core of the greedy algorithm lies in how to judge that a certain individual is a local optimal criterion. In the common methods of test case set parsimony techniques, ensuring the completeness of the test is the cornerstone of all optimization, and the most critical index to ensure such completeness is the coverage. In most cases, greedy algorithms tend to select the test cases that cover the most requirements. However, since the original set of test cases tends to have a large amount of excess coverage, simply adding cases with greater absolute coverage to the approximation set is not enough to ensure that the number of requirements covered will definitely increase for this purpose, and this can be optimized here by committing to selecting those cases that can bring about the largest incremental increase in test coverage to be added to the subset of test cases.

Based on this principle, the execution process of the genetic algorithm is optimized using the idea of greedy, and after initializing the population, the randomly generated individuals are classified into perfect and imperfect solutions based on the coverage in the fitness, and these two solutions are corrected to different degrees using the idea of the greedy algorithm, respectively.

The greedy correction algorithm for imperfect solutions can be described as follows:

(1) Find the uncovered requirement $\{r_1, r_2, \ldots, r_m\}$ in individual $G\{g_1, g_2, \ldots, g_n\}$;

(2) Calculate the change in coverage $Cov(RS)$ after each test case in test case set $T = \{t_1, t_2, \ldots, t_n\}$ is added to the approximation set RS separately as shown in equation (1):

$$\Delta Cov(t_i) = Cov(RS \cup \{t_i\}) - Cov(RS) \tag{1}$$

(3) Find the optimal use case t_i, i.e., $\Delta Cov(t_i)$ the largest test case, and add it to the approximation set RS;

(4) If at this point $Cov(RS) > C$, where C is the set lower limit of coverage, stop the correction operation, otherwise go to (2) for the next round of correction of imperfect solutions.

The core value of the above algorithm lies in the fact that in the process of selecting test cases, it not only takes into account the duplicate coverage problem that may result from the crossover between individuals, but also essentially prioritizes the use cases, and when constructing the set of regression test cases, they are added to the set in order of their size in terms of their contribution to the test coverage, thus ensuring that the final set of test cases is both streamlined and efficient, and that in the event of a time-consuming condition, the The correction of imperfect solutions is realized in order to achieve an increase in coverage at minimal cost (number of test cases). For perfect solutions, the idea of correction is the opposite.

The correction algorithm for the perfect solution can be described as follows:

(1) Find the covered requirement set $\{r_1, r_2, \ldots, r_m\}$ in individual $G\{g_1, g_2, \ldots, g_n\}$;

(2) Calculate the change in coverage $Cov(RS)$ for each test case in test case set $T = \{t_1, t_2, \ldots, t_n\}$ after removing it from approximate set RS , respectively, as in equation (2):

$$\Delta Cov(t_i) = Cov(\{t_i\} \subset RS) - Cov(RS) \tag{2}$$

(3) Identify the optimal use case t_i , i.e., the $\Delta Cov(t_i)$ -invariant test case, and remove it from the approximation set RS ;

(4) If, during the correction process, the coverage $Cov(RS) < K$, where K is the lower limit of coverage, stop the correction operation immediately and that correction operation is not performed again to ensure the coverage, otherwise go to (2) for the next round of correction of the perfect solution.

If the greedy strategy is applied directly to the perfect and imperfect solutions after the initialization of the population, it will largely interfere with the diversity of the population in the early stage. At the beginning of the algorithm start iteration, select part of the solution based on lower probability, apply the greedy strategy for optimization to enhance the local search ability of the genetic algorithm; and at the later stage of the iteration, as the population gradually converges to the optimal solution, correspondingly increase the correction probability of the solution in order to accelerate the convergence process of the genetic algorithm, and the mathematical expression of the correction probability used is shown in equation (3):

$$p_d = p_d + (1 - p_d)\frac{d}{D} \tag{3}$$

where p_d is the initially set correction probability; d is the current number of iterations; and D is the total number of iterations. This formula allows the algorithm to correct the solutions in the population with a small probability in the early stages, and increases the correction probability in the later stages, accelerating the algorithm to find the optimal solution.

III. Application of HGGA algorithm in path planning of resource allocation for Civic and Political Education courses

III. A. Simulation experiment analysis

III. A. 1) Experimental environment and setup

In this paper, MATLAB 2021b is used for simulation. In order to verify the superiority of the algorithm improvement, the traditional stochastic method and Logistic chaotic mapping method are selected as the control. In order to verify the solving ability of HGGA algorithm in function optimization problems, four classical test functions, numbered f1~f4, are selected as test objects, and SGA, AGAI, IAGA, NIAGA and HGGA are run independently for 250 times for the simulation experiments under the same environment, and the five genetic algorithms are encoded in binary code with the maximum number of evolutionary generations of 200.

III. A. 2) Population initialization

In order to verify the improvement effect of greedy strategy on the nature of the initial population distribution, taking the initial population number of 100 and the variable value space -100≤x,y≤100 as an example, the traditional stochastic method, Logistic chaotic mapping method, and greedy strategy are selected to carry out the population initialization operation respectively. The initial population distribution obtained by the three methods is shown in Fig. 3.

As can be seen from Figure 3, the traditional stochastic method, Logistic chaotic mapping method have randomness, the initial population distribution obtained will appear a certain band of optimization space did not produce the initial individual and the initial individual concentration phenomenon. Assuming that the global optimal solution is distributed in the space of blank area and the local optimal solution is distributed in the space of individual concentrated area, and the operation of crossover and mutation does not jump out of the local optimal well, and it is easy to converge to the local optimal solution in the process of evolution, therefore, the two methods do not improve the nature of the distribution of the initial population. On the other hand, the distribution of the initial population under the greedy strategy is very uniform and stable, so that the population maintains a high degree of richness, which greatly enhances the possibility of the algorithm to converge to the global optimal solution.

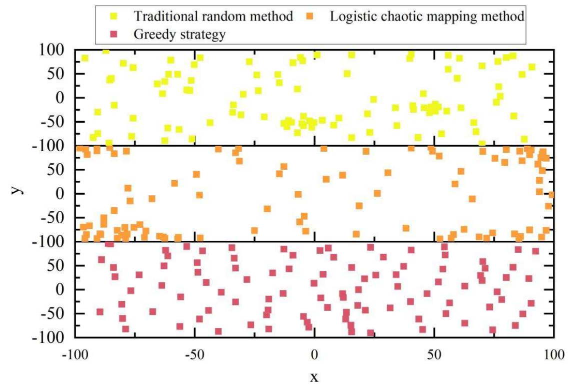


Figure 3: Initial population distributions obtained by the three methods

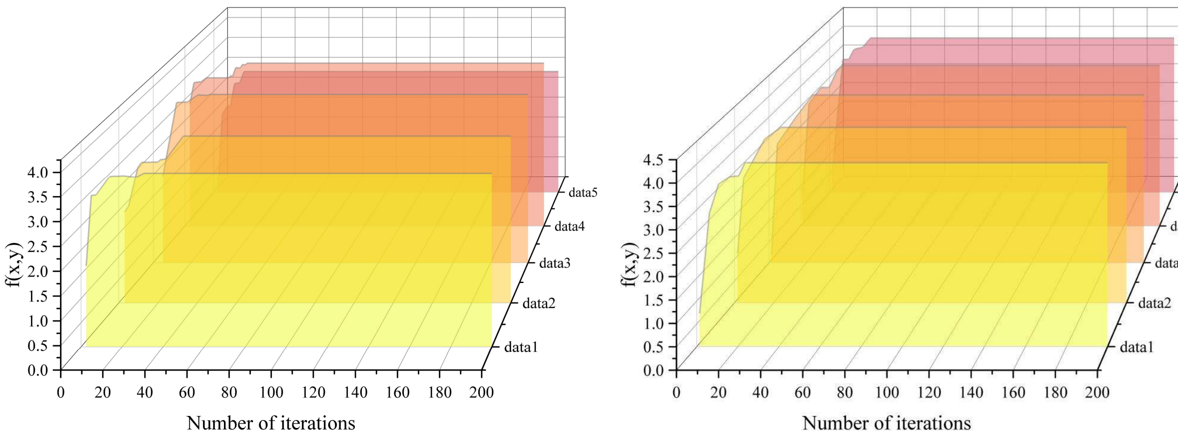
III. A. 3) Analysis of experimental results

The solution results of the five genetic algorithms are shown in Table 1. HGGA has the largest convergence probability in the test function compared with the comparison algorithm, and the convergence probability reaches 1.0 in the test function f1, which is the same as NIAGA and better than SGA, AGA, and IAGA, and shows strong stability. In terms of convergence speed, the average number of convergence generations of HGGA is around 25, which is smaller than that of the comparison genetic algorithms, and the convergence speed has a certain advantage. In addition, HGGA is better than other algorithms in terms of optimal convergence extremes and average convergence extremes, with better solution accuracy, showing strong robustness and global optimization performance.

Table 1: Experimental results

Test function	Algorithm	OS	AOS	CR	AOI
f1	SGA	3.96242	3.96235	0.69	61
	AGA	3.96882	3.96876	0.82	52
	IAGA	3.97028	3.97019	0.95	43
	NIAGA	3.97467	3.97452	1.00	35
	HGGA	4.02786	4.02762	1.00	23
f2	SGA	12.37435	12.03875	0.22	47
	AGA	12.56836	12.20371	0.51	36
	IAGA	12.80382	12.42564	0.63	32
	NIAGA	12.93821	12.51753	0.92	28
	HGGA	13.17352	13.07451	0.98	23
f3	SGA	0.99134	0.98736	0.47	72
	AGA	0.99475	0.98937	0.55	65
	IAGA	0.99733	0.99283	0.62	53
	NIAGA	0.99816	0.99456	0.78	42
	HGGA	0.99999	0.99937	0.97	28
f4	SGA	0.99197	0.98835	0.61	93
	AGA	0.99502	0.98992	0.77	86
	IAGA	0.99765	0.99351	0.85	69
	NIAGA	0.99878	0.99534	0.98	57
	HGGA	1.00378	1.00139	0.99	25

Taking the function f1 as an example, the traditional genetic algorithm and the optimized HGGA algorithm in this paper are respectively applied to perform the optimization search calculation to further verify the effectiveness of the improvement strategy in this paper. The two algorithms are run five times in the same environment, and their iteration process is shown in Fig. 4 (a~b). From Fig. 4, it can be seen that the HGGA algorithm improves the speed of optimization searching, and the traditional genetic algorithm has to be iterated to about 30 generations to find the optimal solution under the calculation of the algorithm, while the HGGA algorithm only needs to be iterated to about 23 generations to find the optimal solution under the calculation of its algorithm. In addition, the stability of the HGGA algorithm is also improved, the two algorithms were run independently and randomly for five times in the same environment, and the traditional genetic algorithm appeared four different optimal solutions, while the HGGA algorithm had the same result after running for five times. The results show that the HGGA algorithm is more stable and faster in finding the optimal speed, and the improvement scheme based on greedy strategy in this paper is effective.



(a) GA (b) HGGA

Figure 4: Comparison of iterative process

III. B. Examples of Application of Curriculum Resource Allocation and Analysis of Effectiveness

Students in some classes of 2023 in a middle school in Province C were selected as experimental subjects. According to the purpose of the study and the actual situation, in order to reduce the influence of irrelevant variables such as teachers' teaching style, teaching ability, teaching experience and so on on the experiment, the experimental and control group classes in this paper were selected from the classes taught by the same teacher, and the sample size totaled 80, and the experimental and control groups were both 40 students. In the process of teaching implementation, in order to minimize the differences in teaching conditions, the teaching progress and homework assignments of each class were kept uniform. All the classes in the control group were taught using conventional teaching methods, and the classes in the experimental group were taught using the curriculum resource allocation optimized by the HGGA algorithm to carry out the 12-week experimental teaching, which lasted from September to December 2024.

At the end of the experiment, the students in the experimental group classes and the control group classes filled in the Civics Course Learning Interest Scale for Secondary School Students according to their actual situation. This scale has 15 questions, which consists of three dimensions, namely, behavioral attitude, value orientation, and affective tendency, and the maximum score for each question is 5 points. A total of 40 copies were distributed and 40 copies were recovered in the experimental group classes, with an effective rate of 100%, while 40 copies were distributed and 40 copies were recovered in the control group classes, with an effective rate of 100%.

III. B. 1) Analysis of academic performance

The results of the final exam in July 2024, the midterm test in November 2024, the final exam in January 2025 after the end of the experiment, and the opening test in February two months after the end of the experiment were compiled. The passing and excellence rates of the students in the classes of the experimental and control groups were compared, and the comparison results are shown in Figure 5. As can be seen from the four test scores of the experimental and control groups, the passing rate of the classes in the experimental group was 5% higher than that of the control group and the excellence rate was 5% lower than that of the control group before the teaching experiment was carried out. From the situation of the midterm test after a period of time, the gap between the passing rate of the experimental group class and the control group became larger, and the excellence rate increased, exceeding the control group class by 2.5%. In the final test at the end of the experiment, the passing rate of the experimental group class was 7.5% higher than that of the control group class, and the excellence rate was 2.5% higher compared to the control group class. After a period of time after the experiment, the pass rate and the excellence rate of the experimental group class remained high compared to the control group class.

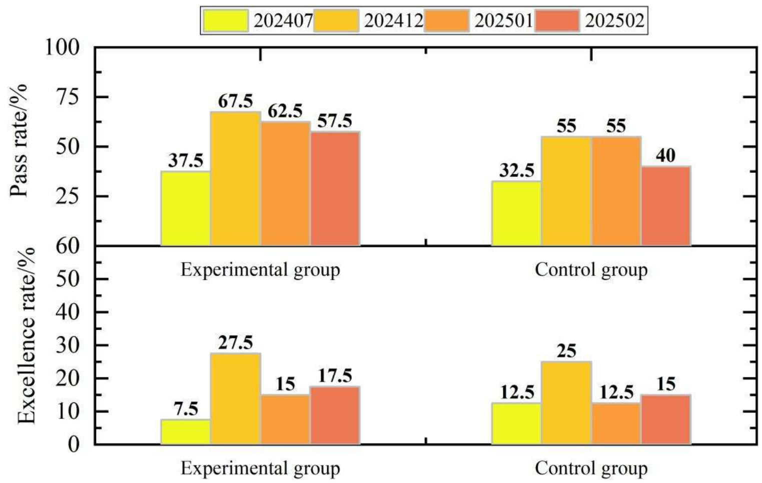


Figure 5: Comparison of pass rate and excellent rate

The mean scores of the classes in the experimental and control groups were compared by independent samples t-test, and the results of the comparison are shown in Figure 6. After a period of experimentation, there was a gap between the mean score values of the two groups in the midterm test, and the experimental group was higher than the control group class by 5.21 points, but there was no significant difference. At the end of the experiment, comparing the students' final exam results, it was found that the gap between the scores of the experimental group and the control group class increased further, with the average score 7.97 points higher than that of the control group class, and there was a significant difference in the students' Civics and Political Science scores ($p=0.019$, $p<0.05$), and the significance of the difference in the students' academic scores declined in the opening test of the February school year, which was two months after the end of the experiment ($p=0.163$), and the students' scores in the Civics and Political Science scores declined. However, the experimental group still scored 7.27 points higher than the control class.

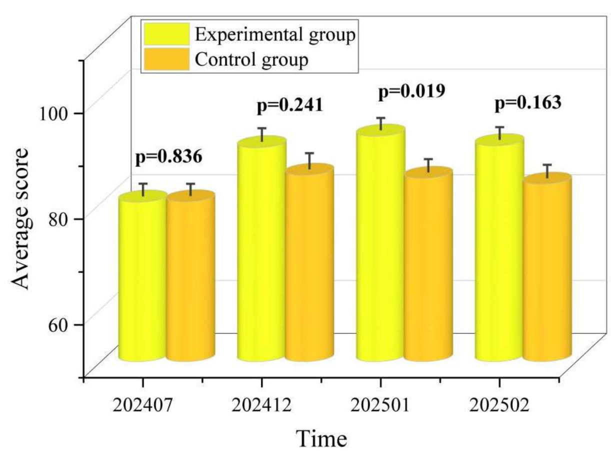


Figure 6: Comparison of average scores

In summary, after using the HGGA algorithm to optimize the allocation of course resources, the pass rate of the experimental group increased significantly, and the academic performance of the class with the control group appeared to be significantly different, and after a period of time at the end of the experiment the overall level of the overall academic performance of the experimental group was still higher than that of the control group, which indicates the feasibility and validity of the application of HGGA algorithm in the planning of pathway for allocation of course resources for the ideology and political education.

III. B. 2) Analysis of learning interests

In order to clarify the reasons for the differences between the experimental group and the control group, at the end of the experiment, students in both the experimental group and the control group conducted self-assessment using the Civics Course Learning Interest Scale for Secondary School Students. From the students' self-assessment scale, the differences between the experimental and control group classes are mainly reflected in the following aspects: in terms of behavioral attitudes, students in the experimental group like to talk about Civics and politics with other people, often ask questions to the Civics teacher, and when they encounter Civics and politics problems, they will try to solve them. In terms of affective tendency the experimental group classes prefer to take Civics and Politics classes, hope that the teacher expands on certain contents during lectures, and are eager to read more books outside Civics and Politics classes. In terms of value tendency, the experimental group classes pay more attention in class, don't want to get out of class quickly in Civics and Political Science class, and are more concerned about Civics and Political Science test scores.

After collecting the data and processing the data, in which the questions in the value orientation part were reverse scored and analyzed by SPSS, the results of the comparison of learning interest in the Civics course are shown in Figure 7. The average scores of students in the experimental group classes in the three dimensions of behavioral attitudes, affective tendencies, and value orientation were higher than those of the control group classes, and significant differences ($p<0.05$) appeared in the dimensions of affective tendencies ($p=0.013$) and value orientation ($p=0.035$).

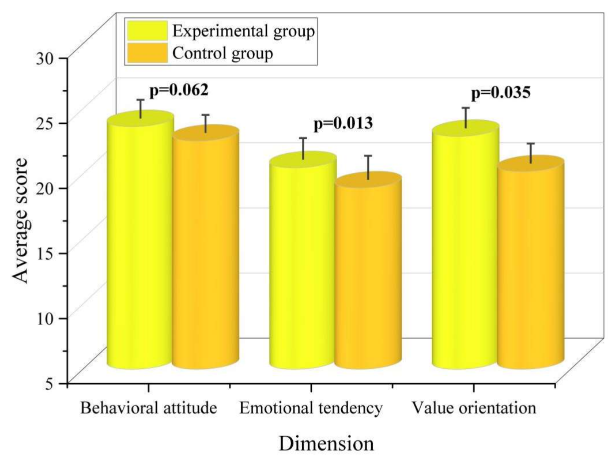


Figure 7: Comparison of learning interests in ideological and political courses

IV. Conclusion

In this paper, we designed the HGGA algorithm improved based on greedy strategy, explored its performance level through controlled experiments, and set up teaching experiments to analyze the feasibility of applying the HGGA algorithm in the path planning of resource allocation for Civic and Political Education courses.

Traditional stochastic method, Logistic chaotic mapping method have randomness, the initial population distribution obtained will appear a certain band optimization space did not produce the phenomenon of initial individual and initial individual concentration. The distribution of the initial population under the greedy strategy is very uniform and stable, which greatly enhances the possibility of the algorithm to converge to the global optimal solution.HGGA has the largest convergence probability in the test function compared with the comparison algorithms, and the convergence probability reaches 1.0 in the test function f1, which is the same as that of NIAGA and better than that of SGA, AGA and IAGA.In terms of the convergence speed, the average number of generations of convergence of HGGA is around 25, which is smaller than that of the comparison genetic algorithms. Which are smaller than the comparison genetic algorithms. In terms of optimal convergence extremes and average convergence extremes, HGGA is better than other algorithms, and the solution accuracy is better. The traditional genetic algorithm has to be iterated to about 30 generations to find the optimal solution under the calculation of the algorithm, while the HGGA algorithm can find the optimal solution under the calculation of its algorithm as long as it is iterated to about 23 generations. The traditional genetic algorithm showed four different optimal solutions, while the HGGA algorithm showed the same results after five runs. The results show that the HGGA algorithm is more stable and faster in terms of finding the optimal speed, and the improvement scheme in this paper is effective.

Before conducting the teaching experiment, the passing rate of the experimental group class was 5% higher and the excellence rate was 5% lower than that of the control group. In the midterm test after a period of time, the gap between the passing rate of the experimental group class and the control group became larger, and the excellence rate increased, exceeding the control group class by 2.5%. In the final test at the end of the experiment, the passing rate of the experimental group class was 7.5% higher than that of the control group class, and the excellence rate was 2.5% higher compared to the control group class. After a period of time at the end of the experiment, the pass rate and the excellence rate of the experimental group class remained at a high level compared to the control group class. The results of the mean score t-test show that the mean score of the experimental group is 7.97 points higher than that of the control group at the end of the experiment, and there is a significant difference in the students' performance in Civics and Political Science ($p=0.019$, $p<0.05$). The mean scores of students in the experimental group classes were higher than those in the control group classes in the dimensions of behavioral attitudes, affective tendencies, and value orientations, and significant differences emerged in the dimensions of affective tendencies ($p=0.013$) and value orientations ($p=0.035$) ($p<0.05$).

References

[1] Zhang, C., & Wei, Z. (2021, January). Research on strategies for improving the effectiveness of moral education in ideological and political courses in universities. In 2021 10th International Conference on Educational and Information Technology (ICEIT) (pp. 190-194). IEEE.

[2] Li, L. (2017). Teaching of ideological and political education for college students from the perspective of culture. DEStech Transactions on Social Science Education and Human Science, 1, 656-661.

[3] Wang, C. (2023). Exploration on the Path of Ideological and Political Education Practice in Colleges and Universities under the New Situation. Curriculum and Teaching Methodology, 6(10), 33-37.

[4] Gong, G. (2017). The integration of ideological and political education in colleges and universities and employment of college students. International technology management, 5, 30-32.

[5] Wang, J. (2021). Analysis of challenges and countermeasures of ideological and political education in colleges and universities in the new era. J. High. Educ. Res, 2(6), 35.

[6] Tian, J. (2024). Exploring the Implementation and Practice of Ideological and Political Education Concepts in Human Resource Management Teaching. International Journal of New Developments in Education, 6(8).

[7] Han, W., & Li, S. (2022). The method of allocating resources for ideological and political education in universities based on iot technology. Journal of Information & Knowledge Management, 21(Supp02), 2240011.

[8] Henderson, D. J., Simar, L., & Wang, L. (2017). The three I s of public schools: irrelevant inputs, insufficient resources and inefficiency. Applied Economics, 49(12), 1164-1184.

[9] Wang, X. (2021, July). The teaching reform exploration and practice of the curriculum ideological and political education in practical training course based on internet cloud platform. In 2021 International Conference on Education, Information Management and Service Science (EIMSS) (pp. 305-308). IEEE.

[10] Liu, Y. (2024). Resource Sharing of Ideological and Political Education in Universities Based on the Development of the Internet of Things. Revista Ibérica de Sistemas e Tecnologias de Informação, (E67), 351-361.

[11] Cui, L. (2020, November). Research on the application of social network service in resource sharing of ideological and political education in colleges. In 2020 International Conference on Robots & Intelligent System (ICRIS) (pp. 210-213). IEEE.

[12] Qiao, L. (2021, March). Design and Implementation of A Mobile Learning Resource Sharing System for Ideological and Political Education. In 2021 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS) (pp. 509-512). IEEE.

[13] Liu, W. (2025). Balanced scheduling method of ideological and political teaching resources based on cluster analysis algorithm. International Journal of Reasoning-based Intelligent Systems, 17(1), 1-8.

[14] Sun, M., & Wang, J. (2024). Online allocation of teaching resources for ideological and political courses in colleges and universities based on differential search algorithm. International Journal of Information Technology and Management, 23(3-4), 278-290.