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Adaptive Algorithm and Teaching Content Dynamic Adjustment Mechanism in the Innovative Optimization of Higher Education Theatre Performance Course

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Abstract In order to improve the inadequacy of the current college drama performance courses and teaching content, this paper firstly improves the scheduling method of drama performance through adaptive genetic algorithm, and then proposes a dynamic optimization mechanism of college drama performance teaching content for the teaching content. In order to test the effectiveness of the adaptive genetic algorithm in the scheduling of drama performance courses and the superiority of this paper's dynamic optimization mechanism of teaching content, the performance of the adaptive algorithm and the teaching effect of the dynamic optimization mechanism are verified respectively. In the algorithm performance experiments, this adaptive genetic algorithm achieves the optimal solution adaptation value (1595.7233) and convergence speed (57). The experimental group adopting the dynamic optimization mechanism of teaching content in this paper significantly improved the teaching effect on six dimensions: acting paradigm, drama theory, acting style, acting practice, character analysis, and plot comprehension ($p<0.05$), while the change in the control group was not significant ($p>0.05$). Before the experiment, the two groups were at the same level. After the experiment, the experimental group was significantly ahead of the control group in all dimensions ($p<0.05$).

Index Terms adaptive genetic algorithm, dynamic optimization mechanism, curriculum scheduling, curriculum innovation

I. Introduction

With the rapid development of social economy and the continuous improvement of residents' quality of life, people begin to pursue spiritual civilization, and this demand promotes the development of the drama business, and the market needs a large number of drama performance talents [1], [2]. In this context, in order to meet the market demand, colleges and universities have opened drama performance majors one after another. However, there are a lot of problems in the actual teaching of college drama performance majors, which require colleges and universities to do a good job of research and analysis, explore the reasons for the problems in teaching drama performance majors, and implement corresponding adjustment and optimization measures [3]-[5].

Colleges and universities theater performance courses are designed to provide comprehensive theater education, cultivate students' comprehensive quality and professional skills, and enable them to succeed in the field of theater or other fields [6]. Their course content usually covers multiple areas, including stage performance, voice, performance theory, stage design and technology, which enables students to acquire knowledge and skills in multiple areas [7]-[9]. However, the teaching methods of traditional drama performance courses are strongly traditional and professional in nature, with challenges such as limited teaching time and resources, difficulty in meeting individualized needs, and difficulty in evaluating teaching effectiveness [10]-[12]. In order to better meet the needs of students, modern theater education is increasingly inclined to use a combination of traditional methods and innovative teaching to more comprehensively develop students' theater skills and comprehensive quality [13], [14].

In this paper, we optimize the operations of coding design, population initialization and fitness function design on the basis of genetic algorithm to construct adaptive genetic-based course arrangement system, so as to deeply adjust and optimize the arrangement of college drama performance courses. In order to test the feasibility of adaptive genetic algorithm in college drama performance course arrangement, its performance is compared with other methods in terms of the value of the fitness of the optimal solution of the population and the optimal number of iterations of the population. Then the dynamic optimization mechanism of college drama performance teaching content is proposed, and the teaching effect of the experimental group and the control group is tested through the teaching experiment method to obtain whether the dynamic optimization mechanism of teaching content is effective in teaching practice.

II. Adaptive genetics-based course scheduling system for college theater performances

II. A. Principles of Genetic Algorithm

Genetic algorithm is an iterative process that simulates the process of biological evolution [15], [16], according to whether the value of the fitness function reaches the optimization criterion or not, the individuals of the population continuously carry out crossover and mutation operations until the optimal solution is found. The data theoretical basis of genetic algorithm is pattern theorem, block assumption and so on.

II. A. 1) Schema Theorem

In genetic algorithms need to use a lot of theorems, the pattern theorem is one of the most important, before elaborating the pattern theorem, first understand what is the pattern order, definition distance.

(1) Pattern and pattern order

Pattern is defined as the existence of many similar samples in individuals (i.e., genes) in a population, which is represented as a subset of a string by representing the same structure of eigenbits in the gene string as a subset of the string. In binary coding, a pattern is represented as a string of three character sets (0,1,*), where the symbol * represents any character, i.e., 0 or 1.

(2) Defining distance

Defining distance is the distance between the first defined position and the last defined position in the pattern. In genetic operations, patterns of the same order may have different properties, and this difference is represented by the definition distance of the pattern.

(3) Pattern theorem

Patterns in a population with low order, short definition distance and average fitness higher than the average fitness of the population will grow exponentially in the next generation, which is the pattern theorem.

The pattern theorem guarantees that the number of better patterns (i.e., the better solution of the genetic algorithm) in the population will grow exponentially in the next generation, thus providing a solid mathematical theoretical basis for explaining the mechanism of the genetic algorithm.

The mathematical representation of the pattern theorem in genetic algorithms takes the form:

$$m(H,d+1)\geq m(H,d)*\frac{f(H)}{\bar{f}}*[1-\frac{Pc*\delta(H)}{l-1}-o(H)*Pm] \tag{1}$$

where $m(H,d)$ indicates that a particular pattern H (determining order and defining distance) has $m(H,d)$ representative strings contained in the population at generation d. $f(H)$ represents the fitness of the pattern H, f is the average fitness of the population, and l is the chromosome length.

The pattern theorem shows that a pattern with a short definitional distance, a high average fitness, and a low order will obtain at least an exponentially increasing number of strings in successive generations, by the mechanism that the best patterns have a higher chance of replication through selection, and that the crossover operator is not prone to destroying short definitional-distance patterns that occur at a high frequency. At the same time the general mutation probability is very small, so the effect of mutation probability on such patterns is very small.

II. A. 2) Building block hypothesis problem

The building block hypothesis refers to the fact that patterns with low order, short definitional distance, and high average fitness are combined with each other under the operation of the genetic algorithm to ultimately approach a globally optimal solution. Thus, the pattern theorem enables the genetic algorithm to find the probabilistic existence of an optimal solution globally by enabling the number of samples with better patterns to grow exponentially. The building block hypothesis, on the other hand, enables genetic algorithms to generate globally optimal solutions by enabling them to operate under operators.

II. A. 3) Minimum Deception Problem

When determining whether a problem can be solved using a genetic algorithm, it depends on whether the problem can be encoded in a way that satisfies the assumptions of the building blocks, and if so, then a problem that satisfies the assumptions of the building blocks will have a higher efficiency when solved by a genetic algorithm, and of course the opposite will be less efficient, or even a more satisfactory solution cannot be found at all. However, lower-order blocks may introduce errors into the search process, resulting in the failure to find higher-order blocks, and ultimately causing the algorithm to lead to divergence, and ultimately failing to find an optimal solution, a phenomenon known as deception.

II. A. 4) Application of Genetic Algorithms in Combinatorial Optimization

Combinatorial optimization problem is to find the optimal solution from the feasible solution set of many combinatorial problems, usually combinatorial optimization problems are discontinuous, constrained, non-frivolous NP-complete problems, this is mainly because combinatorial optimization problems have a large number of local extrema, so it is a very difficult thing to find the optimal solution. Now, with the knowledge and research of genetic algorithm, it is understood that the application of genetic algorithm to solve combinatorial optimization problems is effective.

(1) Combinatorial optimization method based on genetic algorithm

The combinatorial optimization method of genetic algorithm can be generally described as follows:

$$P_i(k) = f(x_i) / \sum_{i=1}^{n} f(x_i) \tag{2}$$

① Determine the size of the population n, and generate n possible solutions $x_i(k)(1 \le i_n \le)$ to form the initial solution population using randomized methods or other methods.

② For each individual $x_i(k)$ variable k is called the number of "generations", and initially $k=1$, calculate its fitness $f(x_i(k))$.

③ For each individual $x_i(k)$, calculate the generation probability $P_i(k)$: and then design a random selector to generate mating individuals $P_i(k)$ based on $P_i(k)$ in a certain randomized method.

④ Generate the next generation solution group. Two mating individuals $x_1(k)$, $x_2(k)$ are selected and based on certain combination rules (e.g., crossover, mutation, reversal, etc.) $x_1(k)$, $x_2(k)$ are combined to form two new generation individuals $x_1(k+1)$, $x_2(k+1)$ until a new generation of n individuals is formed.

⑤ Repeat the steps from ① to ④ until the program end condition is satisfied.

The above algorithm will increase its objective function generation by generation and converge to some maximum value under suitable conditions.

(2) Determine the key parameters in the genetic algorithm

1) Determine the population size. The size of the population, generally represented by the variable n, will have a direct impact on the execution efficiency of the genetic algorithm and the final result of the problem solving. If the population size selected in the genetic algorithm is too large, it will increase the computational complexity of the algorithm, making the calculation speed slower; while if the population size is too small, the effect of using genetic algorithm to solve the problem will not be too good. So it is very important to determine the appropriate size of the population. After theoretical research and practical proof, the general population size is determined between 20 and 100.

2) Determine the crossover probability. The crossover probability is generally represented by the variable Pm, it can be said that the number of crossover operations is determined by the crossover probability, when the crossover probability of a larger selection, the search area of the genetic algorithm will increase, but the more complex the more prone to problems; and if the crossover probability of a lower, the search area of the genetic algorithm will be reduced, the iteration process will be too simple for the optimal solution to be generated. Therefore, the crossover probability is generally selected between 0.25 and 1.00.

3) Determine the mutation probability. The probability of mutation is generally represented by Pc, which is often used in genetic algorithms to change the characteristics of individuals through mutation operations to maintain the diversity of individuals in the population, in order to help genetic algorithms to improve the search ability. A high probability of mutation may cause the genetic algorithm to become a random search. A low probability of mutation may result in the loss of genes of individuals in the population. Generally the probability of variation is determined to be around 0.001.

II. B. Coding Design

Good or bad coding of genetic algorithm directly affects the computational complexity of the algorithm. Make the teacher's class schedule as the chromosome encoding of the genetic algorithm. The encoding ensures the uniqueness of each piece of scheduling information and facilitates the use of basic operations of the genetic algorithm to operate on the chromosome. Although the binary encoding makes scheduling more difficult, it facilitates the exponential growth of the portfolio due to future expansion of the curriculum or increase in teachers, classes, and classrooms. If all the schedules of a class are a solution to the scheduling problem, then all the schedules of all the classes in the school are the solution space of the scheduling problem, and the overall space is the composition of all the scheduling combinations. It can be seen that the complete schedule of a class is actually a two-dimensional array. The multi-objective optimization of the scheduling problem becomes a search for the solution space subject to constraints in the overall space.

II. C.Population initialization

The entire collection of individuals is the population, and each generation of the genetic algorithm contains all individuals, which really means the collection of chromosomal individuals. At the very beginning of the algorithm, the population is blank, i.e., there is no class generated. The representation inside B is that all the numbers in all the positions are 0, which is also the generation in the genetic algorithm. The initial lessons are not conflict-detected, as long as the number in the position does not exceed the set maximum value.

The initial population is generated using a simulated random Halton sequence based on the use of the Genetic Algorithm Toolbox in MATLAB, which produces individuals with low variability and high homogeneity. The initial size of the population was set to 89 according to the number of classes and the length of chromosomes was 30.

II. D.Adaptation function design

II. D. 1) Individual adaptations

For every two stained individuals, when more than two segments of the same number segment appear in the represented region, it means that there is a possibility of a hard conflict. For example, when both time and classroom are coded the same, there is a possibility that scheduling constraints have been violated. The more identical segments that appear, which of course cannot be identical chromosomes, the more likely a hard conflict is. In the case of a single individual, there is the possibility of scheduling a teacher or classroom at a time that is not class time, and so on.

In the scheduling problem, considering that each individual is generated without checking whether they satisfy the scheduling constraints, for an individual it is determined by several main aspects. First, whether it satisfies the class's section superiority. Second, whether it satisfies the uniformity of the daily distribution of the class. Third, whether there are any violations of scheduling constraints. Fourth, teacher satisfaction is prioritized. Fifth, student satisfaction; and sixth, school satisfaction.

II. D. 2) Adaptation function

The scheduling problem is a multi-objective optimization problem. Compared with other optimization methods, genetic algorithm has a great advantage. This paper proposes an improved adaptive genetic algorithm for solving the multi-objective optimization of the class scheduling problem on the basis of solving the basic genetic algorithm problem, and designing a suitable fitness function according to the optimization objective. After analyzing and studying the optimization objective of the scheduling problem, it is determined that the coordination curve method is more suitable for solving the multi-objective optimization problem of the scheduling problem. The genetic algorithm operates on a population and a single operation can find multiple Pareto solutions to the multi-objective optimization problem. The Pareto optimal solution [17], also known as the Pareto efficiency, is the set of solutions that consists of those solutions where an increase in the value of any of the objective functions has to be made at the expense of the values of the other objective functions, known as the Pareto optimal domain or the Pareto set. By Pareto-optimal individual, we mean an individual or individuals in the population, none of the other individuals are superior to it or them. However, a Pareto solution generated in a population does not imply that it is also a Pareto solution for the whole system.

Obviously, in the scheduling problem, to satisfy multiple optimization objectives, the fitness function is designed using the coordination curve method based on the Pareto concept. Accordingly, the formula for calculating individual fitness can be expressed as follows:

$$f(x)=\omega_1\tau_i+\omega_2 A+\omega_3\overline{g}+\omega_4\overline{\rho} \tag{3}$$

where $\omega_1,\omega_2,\omega_3,\omega_4$ are the weights of section superiority, uniformity of daily distribution, Cartesian product of classroom and time, and teacher satisfaction, respectively. Each weight can be set based on the experimental empirical values of other scheduling algorithms.

II. D. 3) Adaptation adjustments

The determination of the fitness directly affects the performance of the genetic algorithm, which needs to be adjusted appropriately according to different solution problems. Common adjustment methods include linear adjustment and nonlinear adjustment. Because linear adjustment in the late genetic algorithm may produce a problem is that some individuals fitness value is much smaller than the average fitness value and the maximum fitness value, and often the average fitness value and the maximum fitness value is very close. Therefore, a nonlinear adjustment method is used in this paper. The core idea of the fitness adjustment method designed in this paper is that the probability of an individual being selected is only related to the order. Therefore, the first step is to sort all the individuals according to the fitness from the largest to the smallest, set the adjustment parameter as f, set the new fitness function as F, then the mapping relationship between F and f is as follows:

$$F = \beta f(x_i)^{1-\beta} \tag{4}$$

where x_i is the well-ordered i th individual, and the value of β is generally between 0.01 and 0.03.

II. E. Selection operations

Following the individual's fitness value, the Boltzmann selection method is formulated as:

$$p_i = \frac{\exp(\frac{f_i}{T})}{\sum_{i=1}^{n} \exp(\frac{f_i}{T})} \tag{5}$$

Where T is a control parameter. When T takes a larger value, it has a smaller selection pressure, i.e., the relative proportion of the adaptation value is small; when T takes a smaller value, it has a larger selection pressure, i.e., the relative proportion of the adaptation value becomes larger. After calculating the selection probability of an individual with the above equation, then the gambling wheel method is used to select the parent. The specific steps are as follows:

(1) Random sampling mechanism selects p individuals, calculates their adaptation values and adjusts them accordingly.

(3) Finally, a simulated gambling board operation (i.e., a random number between 0 and 1) is then used to determine the probability of each individual being selected.

In order to select mating individuals, multiple rounds of selection are required, each generating a uniform random number between [0,1], which is used as a selection pointer to determine the selected individual. After individuals are selected, they can be randomly formed into mating pairs for later crossover operations.

III. Mechanism for dynamic optimization of the content of drama performance teaching in higher educational institutions

In order to be able to adapt to the rapid development of the theater performance industry and cultivate talents urgently needed by the industry, it is necessary to establish a dynamic adjustment mechanism for the teaching of theater performance majors to ensure that the training of talents is advanced and adapted to the industry's needs.

III. A. Conduct market demand analysis

Schools should establish a professional construction steering committee widely participated by industry and enterprise experts and front-line practitioners, conduct regular research and analysis of the industry market, understand the demand for talents in industry institutions, make relevant adjustments to the curriculum in time according to the demand for talents, and optimize the teaching content and form at the same time, so as to ensure that excellent talents in line with the market demand are cultivated.

III. B. Strengthening teacher training and professional guidance

The school regularly organizes teachers to participate in industry seminars, academic conferences, and visits to front-line performance sites to learn about the latest technology and development trends and to improve their teaching level and professionalism. At the same time, experts and enterprise technicians with rich practical experience and teaching experience are introduced to provide students with more comprehensive and in-depth teaching guidance.

III. C. Optimize the focus on practical teaching links

Based on the preliminary industry market research and analysis, as well as the industry development and students' needs, we have continuously optimized the practical teaching links, strengthened the cooperation with enterprises and institutions, and carried out school-enterprise cooperation projects, aiming at providing students with practical opportunities and enhancing their actual theatrical performance abilities.

III. D. Improvement of the evaluation system

Evaluation standards should be reflected in the talent training program, which requires the establishment of a scientific evaluation system to comprehensively assess students' learning achievements, practical performance ability and comprehensive quality. A variety of evaluation methods can be used to strengthen the process assessment, such as exams, reports, project work assessment, etc., to ensure that the evaluation results are objective and accurate. At the same time, timely adjustment of teaching methods and contents according to the evaluation results will improve the quality of teaching.

III. E. Establishment of institutional safeguards

It is recommended that a perfect management system and process be established at the school level to clarify the division of responsibilities and management requirements for all aspects of teaching, and to establish a mechanism for dynamic adjustment of the teaching content of drama performance. At the same time, corresponding rules and regulations and operation manuals should be formulated to ensure that the whole adjustment process is rule-based and evidence-based.

IV. Curriculum innovation and pedagogical analysis

IV. A. Algorithm Performance Analysis

In this paper, firstly, a mathematical model of the drama performance scheduling problem is implemented using Java language, secondly, the algorithm is applied to the mathematical model, and finally, experimental analysis is conducted. The experimental simulation in this section is divided into three parts to verify the performance of Adaptive Genetic Algorithm (AGA) on the drama performance scheduling problem by analyzing the experimental results.

(1) Experiment 1: Comparison of algorithm optimal solution adaptation values

The fitness values of the population optimal solutions of IGA, GA and AGA in this paper under the same data as well as parameters are shown in Fig. 1. The adaptation values are compared to measure the degree of superiority of the results obtained under different algorithms according to the magnitude of their values.

As can be seen from the experimental results graph, with the increase in the number of iterations, the optimal solution fitness values of the populations are increasing, indicating that the populations are evolving in a good direction. However, the optimal solution fitness values of 1577.2531 for GA and 1584.7989 for IGA are lower than the optimal solution fitness value of 1595.7233 for AGA proposed in this paper, and meanwhile, AGA has already reached the convergence in the 57th generation, while GA and IGA tend to be stabilized in the 65th and 70th generations. The decomposition results of the optimal solution adaptation values of the three algorithms are shown in Table 1.

By analyzing Table 1, in terms of course section optimization value, the solution result value of AGA reflects that teachers and students are more satisfied with the course section and class time. From the discrete value of course time, AGA is more scientific for the arrangement of 2 times per week, which ensures the rationality of teaching. In terms of teacher expectations, AGA better meets teacher expectations. From the viewpoint of classroom resource utilization, AGA solves for a higher value of the result, so it can ensure that the classroom resources are more fully utilized.

In summary, the reason for this phenomenon is that when the AGA performs crossover and mutation, the crossover probability and mutation probability are dynamically adjusted in an adaptive way, which enhances the population diversity, and the algorithm's global optimization ability is also enhanced. Therefore, the algorithm in this paper finally obtains a better quality of class schedule than the results of the other two algorithms.

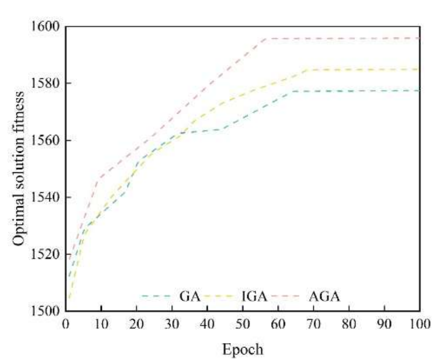

Figure 1: Comparison of optimal solution

Table 1: Decomposition results of optimal solution of 3 algorithms

Target function value	GA	IGA	AGA
Class optimization value	958.4	964.3	970.5
Class time discrete value	614	623	628
Teacher expectation value	15	18	22
Classroom resource utilization rate (%)	35.68	40.66	47.82

(2) Experiment 2: Comparison of average fitness values of algorithms

The average fitness values of the three algorithms for each generation of the population during the iteration process are shown in Figure 2. The advantages and disadvantages of the algorithms are compared by the average fitness value of the population. As can be seen from the experimental results Figure 2, with the increase in the number of iterations of the algorithms, it can be seen that the average fitness value of the population of all three algorithms is increasing. However, through the observation and comparison, it can be seen that the population average fitness value of AGA can finally reach about 1593.9389, while GA and IGA can only reach about 1571.8921 and 1582.9651, and at the same time, in the whole iteration of the algorithm, the population average fitness value of AGA is always higher than the population average fitness value of GA and IGA. Therefore, the improved algorithm in this paper is better than the other two algorithms in terms of population mean fitness value.

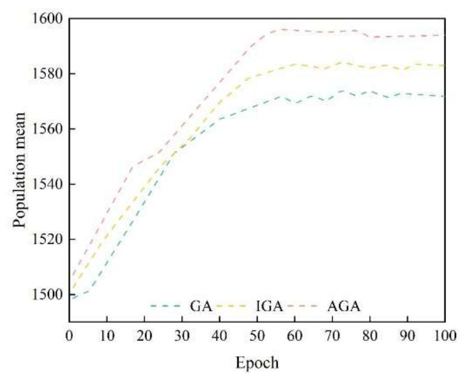

Figure 2: Comparison of average fitness value

(3) Experiment 3: Comparison of the average performance of the three algorithms

Experiment 1 and Experiment 2 are single experiments with a certain degree of chance and randomness, which cannot illustrate the advantages of the algorithm proposed in this paper. In order to better verify the superiority of the improved algorithm in solving the scheduling problem in this paper, GA, IGA, and AGA are executed 8 times respectively, and the optimal number of iterations, the running time (in seconds), and the value of the optimal solution adaptability are obtained for the three algorithms each time after the execution of each algorithm is completed and the average of the results of these 8 experiments is obtained as shown in Table 2. The results of these 8 experiments are averaged and the results are obtained as shown in Table 2.

According to the average of the 8 runs in Table 2, the average number of iterations of GA is 65.125, the running time is about 7.330 seconds, and the value of optimal solution adaptation is 1572.3689. The average number of iterations of IGA is 69.250, the running time is about 8.621 seconds, and the value of optimal solution adaptation is 1583.2291. The average number of iterations of AGA is 58.250, and the running time is 9.621 seconds. 58.250, the running time is 9.799 seconds and the optimal solution fitness value is 1593.8276.

From the above analysis, it is clear that the average number of best iterations and optimal solution value of AGA is higher than the other two algorithms but the running time of the algorithm is increased as compared to both the other algorithms.The average optimal solution fitness value of AGA is higher than that of GA by 21.4587 and higher than that of IGA by 10.5985. Therefore AGA achieves the goal of better fitness function values in the model in terms of both the solution efficiency of the algorithm and the quality of the solution when solving the class scheduling problem. This also proves that the improved algorithm is able to obtain a higher quality class schedule in solving the class scheduling problem, which is superior to the other two algorithms and has a better application value.

Table 2: Average performance comparison of three algorithms

	GA			IGA			AGA		
Calculation number	Epoch	Operation time (s)	Optimal solution	Epoch	Operation time (s)	Optimal solution	Epoch	Operation time (s)	Optimal solution
1	65	7.523	1572.4364	70	8.674	1583.4486	57	9.678	1593.7163
2	64	7.248	1572.3457	71	8.705	1583.3682	58	9.842	1593.7481
3	66	7.035	1573.2550	70	8.943	1583.5874	56	9.632	1593.7799
4	64	7.224	1572.1642	70	8.452	1583.2068	57	9.749	1593.8117
5	65	7.364	1572.0735	67	8.712	1583.3262	61	9.816	1593.8435
6	66	7.105	1572.9828	69	8.389	1583.0457	60	9.824	1593.8753
7	65	7.562	1571.8920	68	8.452	1582.9651	59	9.863	1593.9070
8	66	7.582	1571.8013	69	8.642	1582.8845	58	9.987	1593.9388
Average	65.125	7.330	1572.3689	69.250	8.621	1583.2291	58.250	9.799	1593.8276

IV. B. Analysis of Teaching Effectiveness

The teaching experiment method is used to verify the effect of the dynamic optimization mechanism of teaching content in this paper. Two classes of students majoring in drama performance in S school are selected as experimental subjects, divided into experimental group and control group. The dynamic optimization mechanism of this paper is adopted for the experimental group, while the teaching of the control group is maintained as normal. In this experiment, six dimensions of performance paradigm, drama theory, performance style, performance practice, character analysis, and plot comprehension were chosen as test indicators. The two groups are at the same level in the pre-test test of teaching effect, and no significant gap is produced between the groups.

IV. B. 1) Results of the post-instructional test for both groups

The teaching effects of the experimental and control groups after experimental teaching are shown in Table 3. From the post-test data of the experimental group and the control group, the two groups, which originally had no significant differences, showed very significant differences in various dimensions of the teaching effect ($p<0.05$). The experimental group achieved a comprehensive surpassing of the control group in all dimensions, and in the six dimensions of acting paradigm, drama theory, acting style, acting practice, character analysis, and plot comprehension, the experimental group outperformed the control group by 6.02, 4.56, 4.53, 5.66, 5.33, and 6.20 points, respectively.

Table 3: Teaching effect comparison after the experiment

Dimension	Experimental group		Control group		t	p
	M	SD	M	SD		
Performance paradigm	19.24	4.02	13.22	3.48	10.236	0.000
Drama theory	18.81	4.91	14.25	2.72	6.482	0.003
Performance style	18.89	6.77	14.36	2.04	5.514	0.002
Performance practice	19.87	5.74	14.21	3.79	9.154	0.001
Character analysis	19.56	4.42	14.23	3.22	7.954	0.001
Plot understanding	19.37	7.18	13.17	2.03	11.847	0.000

IV. B. 2) Analysis of the teaching effect of the experimental group

The test results of the experimental group before and after the experiment were compared to explore the actual effect of the teaching content dynamic optimization mechanism in this paper, and the results are shown in Table 4. As can be seen from Table 4, after the experimental group received the mechanism of dynamic optimization of teaching content of drama performance, its performance paradigm, drama theory, performance style, performance practice, character analysis, and plot comprehension improved by 6.19, 6.27, 4.91, 5.72, 5.23, and 6.94 points, respectively, and the improvement of the six dimensions was significant ($p<0.05$).

Table 4: Comparison of teaching effect of experimental group before and after the experiment

Dimension	Before		After		t	p
	M	SD	M	SD		
Performance paradigm	13.05	4.16	19.24	4.02	-10.623	0.000
Drama theory	12.54	2.36	18.81	4.91	-11.574	0.000
Performance style	13.98	3.22	18.89	6.77	-3.849	0.004
Performance practice	14.15	2.26	19.87	5.74	-8.415	0.001
Character analysis	14.33	3.95	19.56	4.42	-6.481	0.002
Plot understanding	12.43	4.11	19.37	7.18	-14.622	0.000

IV. B. 3) Analysis of the effectiveness of teaching the control group

In the same way as the experimental group, the pre- and post-test teaching effect data of the control group were compared, and the comparison results are shown in Table 5. Through the analysis of the teaching effect of the control group before and after the experiment, it was found that although the control group improved in six aspects of acting paradigm, drama theory, acting style, acting practice, character analysis, and plot comprehension after the experiment, the increase in each dimension was no more than 1.5 points and was not significant ($p>0.05$).

In conclusion, the dynamic optimization mechanism of drama performance teaching content proposed in this paper can indeed promote the improvement of students in the aspects of acting paradigm, drama theory, acting style, acting practice, character analysis and plot understanding.

Table 5: Comparison of teaching effect of control group before and after the experiment

Dimension	Before		After		t	p
	M	SD	M	SD		
Performance paradigm	12.66	3.41	13.22	3.48	-0.326	0.698
Drama theory	13.01	3.79	14.25	2.72	-0.963	0.526
Performance style	13.41	3.96	14.36	2.04	-0.758	0.647
Performance practice	13.21	2.88	14.21	3.79	-0.892	0.589
Character analysis	13.83	2.25	14.23	3.22	-0.211	0.856
Plot understanding	12.69	3.28	13.17	2.03	-0.305	0.734

V. Conclusion

The author will use the adaptive legacy algorithm in the scheduling optimization of drama performance courses to improve the scheduling efficiency of the courses. Then the dynamic optimization mechanism of teaching content of college drama performance will be proposed to improve the teaching effect of college drama performance.

(1) The optimal solution adaptation value of the adaptive genetic algorithm in this paper is 1595.7233, while the AGA has reached convergence in the 57th generation. Its optimal solution adaptation value is larger than other comparative methods, and the convergence speed is faster than other methods. The average optimal number of iterations and optimal solution value of the adaptive genetic algorithm are the best performance.

(2) The experimental group that adopts the dynamic optimization mechanism of teaching content in this paper significantly improves its teaching effect in the areas including acting paradigm, drama theory, acting style, acting practice, character analysis, and plot comprehension ($p<0.05$), while the control group's enhancement is very limited, and no significant difference is seen ($p>0.05$). The experimental group was 6.02, 4.56, 4.53, 5.66, 5.33, and 6.20 points higher than the control group. This shows the effectiveness of the dynamic optimization mechanism proposed in this paper.

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References

[1] Myeni, S. (2023). Talent development in the digital age: implications for self-employability in films and television industry. International Journal of Research in Business and Social Science, 12(8), 188-196.

[2] Wang, W., & Huang, X. (2018). Study of application-oriented film and television art talent practice platform. In International conference on education, psychology, and management science, ICEPMS.

[3] Li, H. (2022). Research on Talent Training Method Based on" Operability" in the Teaching of Drama Film and Television Performance. Frontiers in Art Research.

[4] Ran, Y. (2023, October). Formulation and Path Research of Talent Training Program for Drama, Film and TV Discipline. In 2023 2nd International Conference on Sport Science, Education and Social Development (SSESD 2023) (pp. 194-199). Atlantis Press.

[5] Li, C., Gu, H., & Zhang, Q. (2021). Research on the training mode of film and television cultural talents under the background of barrier free information development. Art and Design Review, 10(1), 136-143.

[6] Zhen, C. (2018, May). Research on the teaching reform and talent cultivation methods of drama and film major in colleges and universities. In 2018 8th international conference on social science and education research (SSER 2018) (pp. 136-139). Atlantis Press.

[7] Zakopoulos, V., Makri, A., Ntanos, S., & Tampakis, S. (2023). Drama/theatre performance in education through the use of digital technologies for enhancing students' sustainability awareness: A literature review. Sustainability, 15(18), 13387.

[8] Lehtonen, A., Österlind, E., & Viirret, T. L. (2020). Drama in education for sustainability: Becoming connected through embodiment. International Journal of Education & the Arts, 21(19).

[9] Mokoena, M. T., & Van Vuuren, P. J. (2023). Lessons learnt from teaching an Applied Drama and Theatre pedagogy online in a digitally divided South Africa. Perspectives in Education, 41(1), 103-118.

[10] Zhigang, J. (2022, June). Research on Theater, Film and Television Performance Teaching in Art Colleges and Universities Under the Background of New Liberal Arts. In 2022 8th International Conference on Humanities and Social Science Research (ICHSSR 2022) (pp. 286-290). Atlantis Press.

[11] Karaosmanoglu, G., Metinnam, İ., Özen, Z., & Adigüzel, Ö. (2022). Can Drama Lessons Be Given Online? Perspectives of Drama Teachers during the COVID-19. International Online Journal of Education and Teaching, 9(3), 1249-1272.

[12] Yang, J., Chen, S. T., Dai, Y., & Li, X. W. (2025). Research on teacher learning in the practice of educational drama in China. Research in Drama Education: The Journal of Applied Theatre and Performance, 30(1), 161-166.

[13] Xing, H. (2023). The Practical Application of New Media Technology in Higher Education Drama Performance Teaching. Frontiers in Educational Research, 6(28).

[14] Feng, M. (2024). Innovative and Practical Research on the Teaching Mode of New Media Operation Course in Drama, Film and Television Art Design Major. New Explorations in Education and Teaching, 2(4).

[15] Jie Liang,Fang Ye,Qiang Song,Yuchen Cao,Caixiang Xiao,Yiming Qin... & Chen Li. (2025). Genetic algorithm designed multilayered Si3N4 nanowire membranes hybridized by dielectric wide-range tunable CVD graphene skin for broadband microwave absorption. Composites Part B,297,112298-112298.

[16] Michelle Setiyanti,Genrawan Hoendarto & Jimmy Tjen. (2025). Enhancing Water Potability Identification through Random Forest Regression and Genetic Algorithm Optimization. Engineering Headway,18,101-110.

[17] Hongyu Zhang,Qingfang Ruan,Yong Jin & Shuaian Wang. (2025). Bi-Objective Optimization for Transportation: Generating Near-Optimal Subsets of Pareto Optimal Solutions. Applied Sciences,15(5),2519-2519.