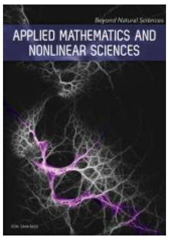
sciendo Applied Mathematics and Nonlinear Sciences, 9(1) (2024) 1-19



Applied Mathematics and Nonlinear Sciences

https://www.sciendo.com

Construction of an Innovative System for Examination Management and Education Based on Artificial Intelligence Technology

Qian Chen[1,†]

1. Information Division, Tianjin Municipal Educational Admission and Examinations Authority, Tianjin, 300387, China.

Submission Info

Communicated by Z. Sabir
Received April 13, 2024
Accepted April 27, 2024
Available online May 3, 2024

Abstract

Leveraging artificial intelligence (AI), this study revolutionizes examination management and education in universities by developing an intelligent system encompassing comprehensive management, pre-examination activities, scheduling, and preparation. The system also features a quality management component for educational outcomes. An enhanced genetic algorithm introduces an adaptation function to optimize intelligent grouping, facilitating effective exam paper distribution. Applied at Y University, our innovative approach significantly refines exam paper difficulty (ranging between 0.5016 and 0.5581) and differentiation (0.3845 to 0.4596), showcasing the intelligent algorithm's effectiveness in exam management and contributing valuable insights to educational research.

Keywords: Artificial intelligence; Genetic algorithm; Intelligent paper grouping; Constraints; Examination management system.
AMS 2010 codes: 97M50

†Corresponding author.
Email address: mvp131@126.com

ISSN 2444-8656
https://doi.org/10.2478/amns-2024-0996

1 Introduction

Artificial Intelligence (AI) is a new technical science that simulates, extends, and expands the information process of human consciousness and thinking [1]. At present, artificial intelligence is deeply integrated with various fields of college education management and constantly promotes the transformation of college management to scientific, precise, and personalized aspects [2-3]. Among them, college examination management is an important link in the construction of information technology in college education, and college examination management information technology involves achievement management, examination management, examination site command, etc., which is the organization and management of the whole process of examination management of various majors in colleges and universities [4-6]. Its management regulations, management level, management order, and management methods are the objective embodiment of the level of examination management work in colleges and universities [7]. The integration of artificial intelligence technology into examination management can not only solve the scientific and personalized education management of colleges and universities but also provide a new solution for examination management in colleges and universities.

Scholars such as Nigussie, B. noted that effective administration of university entrance examinations is crucial for a country, and their assessment of examination administration methods in Ethiopia provides strong evidence for short-term improvements and policy actions for examination administration in the country [8]. Mgbeafulike, I and Chekwube, E noted that the development of information technology and artificial intelligence technology had made the development of information technology and artificial intelligence technology has made it possible to improve the Efficiency of examination management and, at the same time, compared with the traditional examination method, the method of combining information technology examination has the characteristics of confidentiality and rationality of evaluation, etc. [9]. Scholars such as Al-Hawari, F and other scholars pointed out that the examination management system based on network technology and artificial intelligence technology can flexibly define and set up the examination based on the tree examination structure, and at the same time, it can provide a variety of security programs, which can effectively prevent the examination cheating. Effectively prevented cheating on the exam [10].

Hui, D found in the study of nurturing Efficiency of medical teacher qualification examination in China and pointed out that there are still many problems in the licensed medical practitioner qualification examination, such as the examination level is not professionalized enough, the examination management is not standardized enough, and the scope of the examination is not scientific enough [11]. Tashu, T. M and other scholars pointed out that the examination as an educational evaluation plays a central role in the process of teaching and learning and combined with computer technology to construct an examination management system, which adopts a pairwise approach and semantically realizes the automatic grading of essays [12]. Mahdi, O. R., and other scholars pointed out that the essence of examination management is the knowledge management process (KMP) and that innovating KMP based on the viewpoint of knowledge (KBV) and the viewpoint of resources (RBV) can significantly improve the advantages of human education in universities and colleges [13].

This paper firstly proposes an intelligent and scientific examination system covering the establishment of a scientific and efficient management system, the rational design of assessment methods and standards, paperless examinations and unproctored examinations, and four examination management and education. On this basis, an examination management system is designed based on the examination quality management system of eight single processes: course examination outline development, propositioning, paper making, transportation, storage, distribution, group examination, and paper evaluation. Based on the grouping function in the examination management system, an improved genetic algorithm NCAGA is proposed under the constraints of intelligent grouping, and its optimal value is solved using its fitness function. Finally, taking A university as the research object, we carry out the empirical analysis of the innovative system of exam management and education in terms of the performance of the improved genetic algorithm, the Quality of the test paper, and the Efficiency of the grouping of the paper, and verify its practical value for exam management and education.

2 Construction of an innovative system of examination management for educating people

2.1 Innovative Ideas for Exam Management Parenting

The examination is an important part of the educational and teaching activities in colleges and universities, is an important way to test the learning achievements of students and assess their learning results, and is also an important part of the teaching quality monitoring system in colleges and universities. Establishing a perfect teaching quality monitoring system requires scientific and effective examination management. With the deepening of China's higher education reform and development, the traditional examination mode and examination management system has been unable to adapt to the needs of the reform of the university talent cultivation objectives and talent cultivation mode and has not been able to play a good role in the detection of the Quality of teaching, diagnosis, orientation. This paper covers the scientific construction of the examination system, the establishment of a scientific and efficient management system, the rational design of the assessment methods and standards, paperless exams, and unproctored four aspects of the examination management and education system for reform and innovation.

2.2 Design and realization of the examination management system

2.2.1 Overall system design objectives

The system design goal is to develop an examination management system with high security and applicability that can satisfy the teaching management needs of multi-campus under the credit system. The system adopts a distributed architecture to implement the functions of the teaching information management system, which is a three-tier or multi-tier C/S and B/S application system. Figure 1 shows the application system architecture, which seals the enterprise application logic code capable of executing a specific enterprise function into an application enterprise object and releases it to the application server for invocation by the Web server and the C/S client.

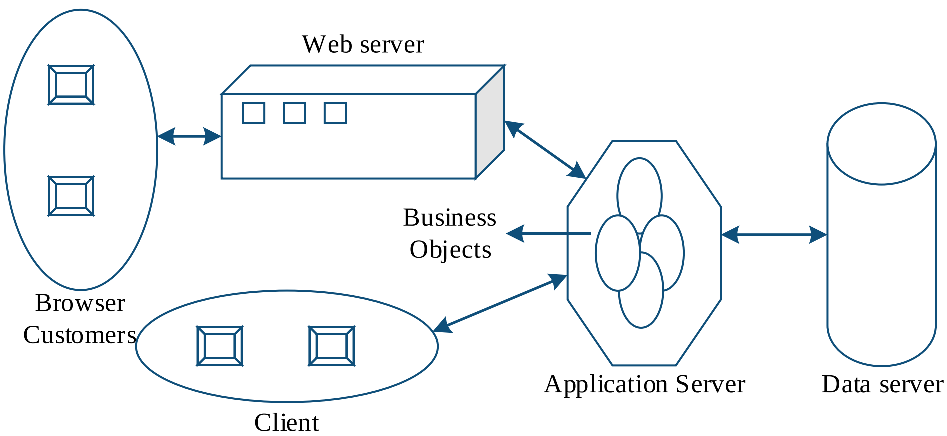


Figure 1. Three or more multi-layer distributed applications

2.2.2 Overall functional design of the system

Figure 2 shows the overall functional modules of the examination management system for higher education, which consists of 11 modules in four subsystems, namely, system management, pre-test management, test scheduling management, and test preparation management, and the modules are relatively independent of each other for the expansion and maintenance of the system.

1) The system management subsystem contains the following sub-modules

(1) System User Management

This includes adding/deleting users at all levels, managing user rights, managing user passwords, managing operation logs, and performing other functions.

(2) System basic data maintenance

This includes adding/deleting examination locations, adding/deleting invigilator teachers, maintaining course library information, maintaining basic candidate information, and performing other functions.

2) The pre-test management sub-system contains the following sub-modules

(1) Generation of final examination subject list

The semester course schedule dictates how the final examination subject list is generated.

(2) Maintenance of examination course information

Mainly maintains the information of the course, such as the course unit, examination form, examination organization unit, examination group, examination time period, the composition of the teaching class, starting and ending weeks, and the person responsible for proposing the examination paper.

(3) Maintenance of basic data for scheduling examinations

This mainly includes examination time period settings, course paper number generation, and examination-specific time settings.

3) Exam scheduling management sub-system contains the following sub-modules

(1) Examination time arrangement

Staff must first ensure the completion of the teaching program by scheduling exams and adopting relevant conflict-checking measures to avoid time conflicts.

(2) Examination place arrangement

After the examination time is scheduled, the examination place should be arranged by considering the situation of spare classrooms in the current time period and the number of candidates for each course in the current time period.

(3) Arrangement of Invigilators

The invigilators shall be arranged by both the college where the course is held and the college where the students are enrolled. The main invigilator is usually the teacher of the course, and when there are not enough teachers, the college should be responsible for making up for the shortage, and the deputy invigilator is arranged by the student's college.

4) The examination preparation management sub-system contains the following sub-modules

(1) Examination arrangement information output and printing

It realizes the comprehensive inquiry and printing of information, such as the output of the examination arrangement table, the printing of the list of examination candidates, and the printing of the distribution map of the examination room in each time period.

(2) Statistics of Invigilator Teacher Information

Create summary statistics of the invigilation task information for teachers by setting limiting conditions to facilitate the implementation of the task by each college.

(3) Examination paper management

According to the courses and examination centers participating in the examination, the statistics related to examination papers can be provided, and the statistics and printing functions such as the printing of the mother paper pocket, the statistics of the number of bags of examination papers, and the handing over sheet of examination papers can be provided.

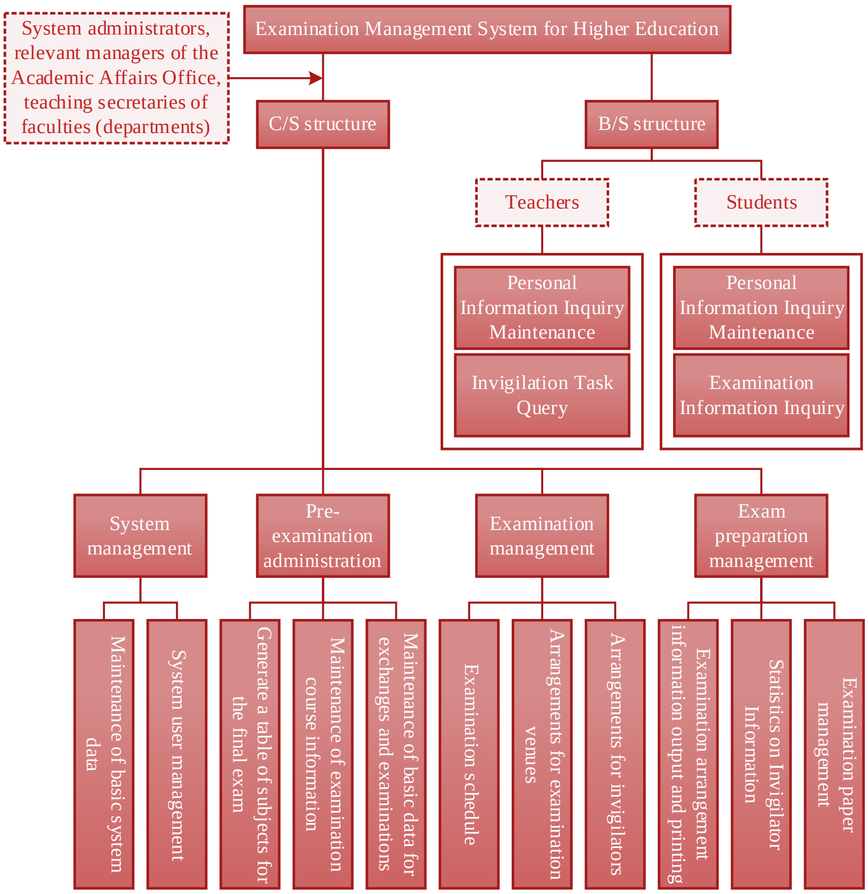


Figure 2. System general function module

2.3 Construction of examination quality management system

Taking the examination quality management as a whole, the quality management model is constructed on the basis of eight single processes: syllabus development, propositioning, volume production, transportation, storage, distribution, group examination, and marking of examination scripts, as shown in Fig. 3, in which the individual single processes are closely related to each other, and the next process is the value-added to the previous one. At the same time, the next process is also a check on the previous process, while the proposition management staff, examination management staff, examination institutions engaged in self-study examination staff, and proposition teachers are inspectors. In quality management, the proposition management staff and examination management staff are not isolated individuals but rather an organic unit that constantly adjusts the primary and secondary processes according to the management process. The relevant managers understand the disposition of the previous link by adopting reasonable improvement suggestions when faced with existing problems. In the quality management model, the examination outline is an important part of quality management, which is related to the application of the results of the marking but also reflects the disposition of the propositioning process to the examination outline.

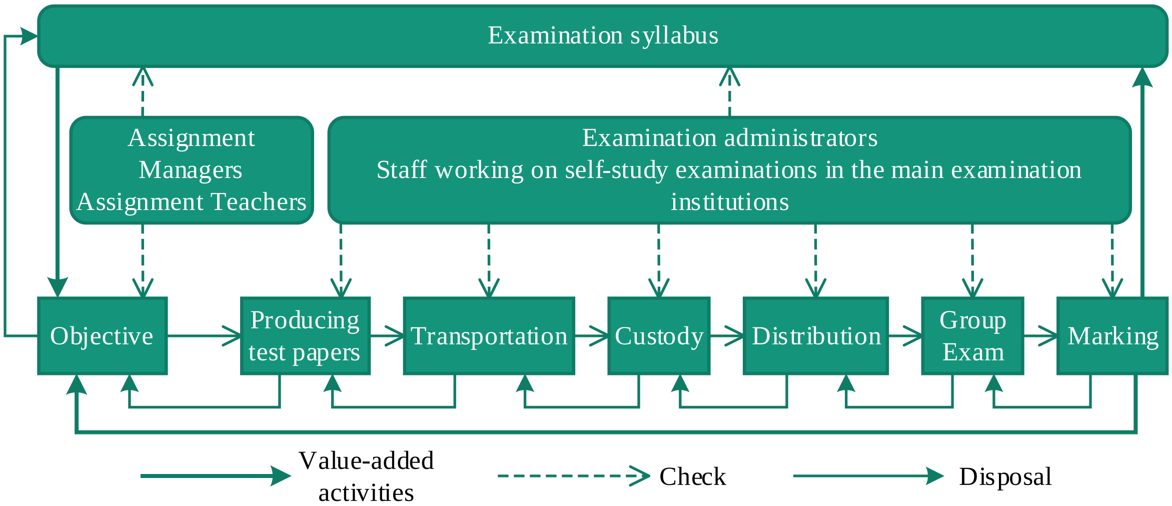


Figure 3. Quality management model

3 Design of grouping function based on artificial intelligence technology

The automatic paper-forming function is based on artificial intelligence technology, combining the knowledge and experience of paper-forming with those of human education experts and using the search and optimization techniques of artificial intelligence to automatically select test questions from a test bank to form a test paper, and the computer completes the design of the content of the test paper, and makes the computer-generated test paper reach the level of experts. This chapter introduces the theory of intelligent paper formation in the above examination management system and provides the basis for setting the conditions for paper formation, designing the attributes contained in the test question table in the database, and designing the fitness function in the genetic algorithm.

3.1 The fitness function of the genetic algorithm

Genetic algorithms are global optimization search algorithms that draw on the genetic mechanism and evolutionary process of organisms in the natural environment. Different practical problems corresponding to the requirements of the fitness function are also different in the design of the fitness function. Usually, the fitness function should have a simple design, strong versatility, monotonous continuity, non-negative, and other characteristics.

The fitness function is transformed from the objective function of the actual problem. The genetic algorithm requires that the fitness value should be non-negative, but the value of the objective function in the actual problem may be positive or negative, so the objective function and the fitness function should be transformed and adjusted accordingly. The commonly used transformation methods are as follows:

1) Direct method

The objective function is denoted by $f(x)$ and the fitness function is denoted by $F(x)$. The relationship between them is:

$$F(x) = f(x) \tag{1}$$

This method is simple and easy to use, but its value can be positive or negative. If the value of the adaptation function is negative, it will affect the overall performance of the algorithm.

2) Boundary method

For the optimization problem of finding a great value, the fitness function and the objective function of the solution can be transformed as follows, where $C_{\min}$ is used to indicate the minimum value of the objective function estimate.

$$F_{\max}(x) = \begin{cases} f(x) - C_{\min}, & f(x) > C_{\min} \\ 0, & \text{Other} \end{cases} \tag{2}$$

In Equation (2), $C_{\min}$ can be the objective value of the minimum function of the population evolved to the current generation or the value of the external input.

For the optimization problem of finding the minimum value, the fitness function and the objective function of the solution can be transformed as follows, where $C_{\max}$ is used to denote the maximum value of the objective function estimate.

$$F_{\min}(x) = \begin{cases} C_{\max} - f(x), & f(x) < C_{\max} \\ 0, & \text{Other} \end{cases} \tag{3}$$

Although this method is better than the direct method, it can still be challenging to find the correct value at times.

3) Bounding method for optimization

For the optimization problem of finding a great value, the fitness function and objective function of the solution can be transformed as follows:

$$F_{\max}(x) = \frac{1}{A - f(x)} \tag{4}$$

For the optimization problem of finding the minimum value, the fitness function and the objective function of the solution can be transformed as follows:

$$F_{\min}(x)=\frac{1}{A+f(x)} \tag{5}$$

In Eqs. (4) and (5), A denotes the pre-estimate of the bounds of the objective function to be solved, which ensures that the denominator is positive in both equations.

3.2 Constraints for Intelligent Grouping

Setting parameters for intelligent grouping is often necessary to accurately express and comprehensively reflect the test taker's mastery of knowledge in online test questions. Subject, chapter, knowledge point, score, difficulty, question type, expected response time, exposure time, differentiation, and other parameters are the general parameters. Solving the multidimensional global optimal solution problem is the mathematical essence of the intelligent paper grouping problem. We can represent the complete parameter matrix D of a question paper as:

$$D=\begin{pmatrix} a_{11},a_{12} & \cdots & a_{19} \\ \vdots & \vdots & \vdots \\ a_{n1},a_{n2} & \cdots & a_{n9} \end{pmatrix} \tag{6}$$

In Matrix D, a_{i1}, a_{i2}, a_{i3}, a_{i4}, a_{i5}, a_{i6}, a_{i7}, a_{18} and a_{i9} $(1\le i\le n, n$ is the number of questions in this paper) denote the subject, chapter, knowledge point, score, difficulty, question type, expected response time, exposure time, and differentiation of the ith question, respectively, and the values of the elements satisfying the different parameters of this Matrix denote the grouping of papers user's requirements for different aspects of the paper or for different exams. In this complete paper organizing model, the constraint relationships of each parameter are as follows. Finally, the objective function of solving the intelligent paper organizing problem is given.

1) Subject constraints

All questions in grouping papers tend to be on the same subject. Therefore, the following constraints are satisfied:

$$f_1=\begin{cases}1, & \forall a_{i1}=s \\ 0, & \exists a_{i1}\neq s\end{cases} \tag{7}$$

Where s indicates the subject number to which the paper belongs, and questions from subjects that are not part of this group will be constrained.

2) Chapter constraints

In the group paper, usually, all the questions limit the scope of the examination of the subject. Limit the examination section. Thus, the constraints listed below have been met:

$$f_2=\begin{cases}1, & \forall a_{i2}\in C \\ 0, & \exists a_{i2}\notin C\end{cases} \tag{8}$$

Where, C denotes the numbered set of chapters examined in the paper, and questions from chapters that do not belong to this group of papers will be constrained.

3) Knowledge constraints

In the group paper, the test questions are usually restricted to examining the scope of the chapter in question. Restrictions on examining knowledge points. Therefore, the following constraints are satisfied:

$$f_3 = \begin{cases} 1, & \forall a_{i3} \in K \\ 0, & \exists a_{i3} \notin K \end{cases} \tag{9}$$

Where, K denotes the numbered set of knowledge points examined in the paper, and questions that do not belong to the knowledge points of this group of papers will be constrained.

4) Marks constraint

In the group paper, the sum of the marks of the test questions should satisfy the preset mark value of the test paper. The best case is that the total marks of the test questions in the group paper are equal to the preset mark value of the test paper, and in general, when the difference between the two is not too big (the ratio is defined here as δ), it is considered to be acceptable. The score limit is:

$$f_4 = \frac{\sum_{i=1}^{n} a_{i4}}{S^*} \tag{10}$$

Where, S^* denotes the pre-determined score value of the paper, the constraint f_4 has an acceptable range and the range of values is limited by δ so that the f_4 corrected value is:

$$f_4 = \begin{cases} f_4, 1-\delta \le f_4 \le 1+\delta \\ 0, others \end{cases} \tag{11}$$

5) Difficulty constraint

In this group paper model, a_{i5} denotes the difficulty value of a particular question, so the actual difficulty of this set of papers is averaged:

$$H = \frac{\sum_{i=1}^{n} a_{i5}}{n} \tag{12}$$

The difficulty constraint can be expressed as:

$$f_5 = \frac{|H-h|}{H} \tag{13}$$

Where h denotes the average difficulty of the preset. As with the score constraint, a reasonable range of difficulty errors is acceptable. The specific error value is determined based on the actual exam requirements.

6) Question type constraint

In general, the structure of the questions on the exam paper is fixed and enumerable. Commonly used question types include single-choice questions, multiple-choice questions, fixed-value fill-in-the-blank questions, fill-in-the-blank questions, judgment questions, subjective questions, and so on. The mark constraints in each question type are governed by the distributional rationality constraints of the question type constraints. The marks for each question type in the question paper can be summed up as:

$$QT_j = \sum C_{\mu 1} a_{i4}, \text{ where } C_{\mu 1} = \begin{cases} 1, & a_{i6} \text{ is the type of question } j \\ 0, & a_{i6} \text{ is not the type of question } j \end{cases} \tag{14}$$

Where QT_j denotes the distribution of scores for question type j in the test paper and C_{ji} refers to whether test question i belongs to question type j. So the question type constraint can be expressed as:

$$f_6 = \sum_j \frac{\left|QT_j - qt_j\right|}{QT_j} \tag{15}$$

Where qt_j denotes the mark value of question type j pre-determined in the test paper. A reasonable range of question-type constraint errors is acceptable, and specific error thresholds are determined based on actual exam requirements.

7) Answering time constraints

The expected response time attribute of the test questions is generally given an initial value by the teacher who produces the questions based on the amount of calculations and experience in producing the questions, and adjustments are made as appropriate according to the actual answer situation. The total answering time T of the group paper shall not exceed the preset exam time t, nor shall it be less than 90% of the preset exam time, so the answering time constraint is:

$$f_7 = \frac{T - t}{T}, \text{ where } 0.9t \le T \le t \tag{16}$$

8) Exposure time constraint

The time interval between the questions in the question bank and the last time the question was asked in the paper is known as exposure time. In the actual online test situation, if a test question appears frequently in a short period of time, it is easy to cause a similar “out of the original question” unfair phenomenon, so the a need for exposure time constraints. The following is how it is expressed:

$$f_8 = \begin{cases} 1, & \forall a_{i8} \ge e \\ 0, & \exists a_{i8} < e \end{cases} \tag{17}$$

Where, e denotes a preset value of exposure time, and trials below the value of e will be constrained.

9) Distinctiveness constraint

The differentiation degree is a statistical value that is derived from the examination results and can indicate the Quality of the test questions. Test questions below the preset differentiation are not allowed in principle, and the restriction is expressed as follows:

$$f_9 = \begin{cases} 1, & \forall a_{i9} \geq d \\ 0, & \exists a_{f9} < d \end{cases} \tag{18}$$

Where, d denotes the preset differentiation value and test questions below the value of d will be restricted.

10) Objective function

The objective function of the group paper is not a difficult representation based on the constraints obtained above:

$$f = \sum \omega_i f_i \tag{19}$$

Where ω_i denotes the weights. In this way, a generalized grouping model and constraints are represented. In reality, there are some constraints that can be unrestricted, and weights that are set to zero are sufficient.

3.3 Intelligent grouping based on improved genetic algorithm

In this section, an improved genetic algorithm NCAGA is proposed to optimize the algorithm in terms of global convergence speed and prevent the phenomenon of early convergence, which is based on the idea that by introducing a chaotic selection method according to the given constraints, chaotic individual variables are generated to satisfy the constraints of the solution and form the initial populations, which are roughly selected individuals and thus are able to accelerate the convergence of the genetic algorithm. The genetic algorithm's convergence speed is accelerated by roughly selecting the initial population. At the same time, the small habitat technology is introduced to eliminate the individuals in the population according to the characteristics of the small habitat, to avoid the occurrence of early convergence phenomenon, and to optimize the calculation function of the crossover and mutation probability, which ensures the diversity of the population and a better convergence speed.

3.3.1 Chaotic initial population

Chaos theory is employed in this section to select individuals in the initial population by utilizing its initial-value-sensitive property and to accelerate the search for individuals in the population through the dynamic traversal nature of chaos.

Logistic mapping is a form of chaotic mapping that is frequently employed to produce chaotic sequences, which is formulated as follows:

$$x_{i+1} = \eta x_i \left(1 - x_i\right), i \in \{0,1,2,3\cdots,n\} \tag{20}$$

Where η is a control constant taking the value of $(0,4]$, x_i is in the range [0,1], and n is the maximum value of i. When $0<\eta\le 1$, x_i the sequence exists a fixed solution, and the sequence will eventually converge to order after many iterations regardless of the value of the initial value.

The chaotic selection method is introduced during population initialization of the genetic algorithm, and full mapping is used to generate chaotic individual variables, which are calculated by the formula:

$$p_{i+1}(R(m)) = 1 - p_i^2(R(m)) \tag{21}$$

Where m is the number of constraints and $R(m)$ denotes the sum of the values taken by each constraint.

The process of generating the initial population using the chaotic selection method:

1) Setting the chaotic initial value. Determine the number of constraints of the desired problem m, and calculate the value of each constraint r_j, where the value range of j is $[1,m]$. Sum the values of each constraint to get $R(m)$, and use it as the initial value of chaos $p_0(R(m)) = R(m)$.

2) Generate a chaotic individual, set $t=1$, substitute the chaotic initial value into Eq. (21) to generate a chaotic individual p_i, and judge whether p_i satisfies the set constraints; if it does, it is retained, and vice versa, it is eliminated.

3) Set $t=t+1$, go to process (2) to get a new chaotic variable.

4) Until a chaotic sequence is generated that meets the initial population size, the length of the chaotic sequence is the initial population size.

3.3.2 Dynamic cross-variance probability optimization

The performance of genetic algorithms' global convergence optimization is influenced by the appropriateness of control parameter settings. Among them, crossover probability and mutation probability are two more important parameters, which may cause early convergence phenomena in the late stage of the algorithm if they are not set properly. In this paper, the optimized dynamic crossover probability P_c and mutation probability P_m are proposed based on such reasons, and their calculation formulas are:

$$P_c = \begin{cases} P_{c2} + \left(P_{c1} - P_{c2}\right)\cos\left(\dfrac{f_{\max} - f'}{f_{\max} - f'_{avg}}\right)\dfrac{\pi}{2}, & f' \ge f'_{avg} \\ P_{c1}, & f' < f'_{avg} \end{cases} \tag{22}$$

$$P_m = \begin{cases} P_{m2} + \left(P_{m1} - P_{m2}\right)\cos\left(\dfrac{f_{\max} - f}{f_{\max} - f'_{avg}}\right)\dfrac{\pi}{2}, & f \ge f'_{avg} \\ P_{m1}, & f < f'_{avg} \end{cases} \tag{23}$$

In equations (22) and (23), P_{c1} and P_{c2} denote the maximum and minimum crossover probability of crossover individuals, and P_{m1} and P_{m2} denote the maximum and minimum mutation probability of mutated individuals, respectively. $f_{\max}$ denotes the maximum fitness value of individuals in the population, f' denotes the fitness value of the larger of the two individuals to be crossed, f denotes the fitness value of the variant individuals, and f'_{avg} denotes the average fitness of the part of individuals whose fitness is greater than the average fitness.

By analyzing equations (22) and (23), it can be seen that the optimized probability formula has the following main characteristics:

1) Adaptive changes in crossover variance probabilities based on differences in individual fitness can better preserve the good individuals in a population.

2) When the value of fitness f' or f is closer to $f_{\max}$, the crossover probability P_c and mutation probability P_m are smaller, thus protecting the good individuals in the population, and vice versa, the crossover probability P_c and mutation probability P_m are larger, thus increasing the diversity of the population.

3.3.3 Microhabitat culling strategies

In the course of population evolution, there will always be individuals who are not well-adapted, and these individuals will eventually be eliminated to improve the population's development. To eliminate these individuals, this paper describes a "culling" strategy based on the small habitat technique. The method for implementing a habitat culling strategy is as follows:

1) Calculate the distance between individual I_i, I_j, i.e., calculate the Heming distance according to the length of individual code, and its calculation formula is:

$$d\left(I_i, I_j\right) = \sqrt{\sum_{x}^{L}\left(I_{ix} - I_{jx}\right)^2} \tag{24}$$

Where L denotes the length of the individual code and $i \in [1, M-1], j \in [i+1, M], M$ denotes the size of the population.

2) If $d\left(I_i, I_j\right) < \Lambda$, where Λ is a predetermined distance, compare the fitness of individual I_i, I_j and take the lower fitness $\min\left[f\left(I_i\right), f\left(I_j\right)\right]$.

3) Based on the lower fitness individuals obtained from the process (2), apply a culling factor α. For computational convenience, the culling factor $\alpha = f_{\min}, f_{\min}$ is the lowest fitness of the individuals in the population.

4) Generate a new generation of the population by using an optimal conservation strategy to retain the better individuals and eliminate the individuals who are penalized in the process (3).

4 Empirical analysis of examination management education innovation system

In order to verify the validity and feasibility of the innovative system of examination management and education constructed above, this section takes University Y as an example to analyze the data on the performance of the proposed improved genetic algorithm, the Quality of examination papers, and the Efficiency of grouping papers.

4.1 Simulation analysis of improved genetic algorithm

To verify the feasibility and effectiveness of the proposed improved genetic algorithm, this section compares the improved algorithm with the traditional genetic algorithm. Taking the test bank in the constructed examination management system as an example, the test bank contains a total of 46,511 test questions, and the question types include four kinds: multiple-choice, judgment, fill-in-the-blank, and short-answer questions. The difficulty level of the test questions has five kinds: 5, 4, 3, 2, and 1, respectively, which means more difficult, difficult, general, easier, and easy. First, set the group paper constraints: the total score of the test paper is 100 points by default, the average difficulty coefficient of the test paper is 0.55, the last hit time of the test questions is 2023-12.15, the total score of the test questions of 1-5 difficulty levels accounted for the proportion of the total score of the test paper 0.1, 0.2, 0.4, 0.2, 0.1, respectively. Multiple choice questions (2 points), judgmental questions (1 point), fill in the blanks (2 points), and short answer questions (3 points). The number of questions for the four types of questions are 15, 20, 10, 10. Set the maximum number of iterations for the group paper as 200, the minimum number of iterations as 30, and the iteration can be ended when the fitness value of the optimal individual in the population is less than 0.2. Variation probability $P_m = 0.05$, crossover probability $P_c = 0.75$.

4.1.1 Effect of Intelligent Assignment of Grouped Volumes

In order to verify the effect of intelligent allocation of grouped papers, this paper compares the attribute values of the grouped papers with those of the traditional genetic algorithm (shipping time, knowledge point coverage, and average difficulty coefficient). In order to have comparability, the fitness function of the traditional genetic algorithm and the fitness function of the improved algorithm are chosen to be the same, but the traditional genetic algorithm is not adjusted by using the method of exponential proportional change. The selected population n=50. Table 1 shows the comparison results of running time, knowledge point coverage, and average difficulty coefficient. From the results of the comparison of the running time of the optimal solution, the running time of the improved algorithm (Avg=15.60) is significantly better than the running time of the traditional genetic algorithm (Avg=21.74). In terms of the coverage of the knowledge points that make up the test paper as a whole, the average number of knowledge points included in the improved genetic algorithm in the six experiments (9.17) is 2.5 more than that of the traditional genetic algorithm (6.67), and the knowledge points of the grouped papers utilizing the present method are richer. In the comparison results of the average difficulty coefficient of the test papers formed by the two algorithms, the average difficulty coefficient of the six experiments of the improved genetic algorithm is 0.545, and the average difficulty coefficient of the six experiments of the traditional genetic algorithm is 0.54, and the average difficulty coefficient of the test papers formed by the improved genetic algorithm is much closer to the requirements of the test papers, and it also proves that the optimization of the initialized population in this paper plays a certain role in controlling the average difficulty coefficient of the test papers. It also proves that the optimization of the initialization population in this paper plays a certain role in controlling the average difficulty coefficient of the test paper. In conclusion, the improved genetic algorithm proposed in this paper can shorten the running time of the algorithm, quickly distinguish between different types of questions, ensure that the number of individual questions under each type of question meets the requirements of the group paper, and obtain the optimal solution for a single type of questions to form the initialization population, improve the Quality of the initial population, and accelerate the convergence speed of the algorithm.

Table 1. The comparison of the difficulty coefficient of the time and the knowledge point coverage

Group volume mode \ Experimental frequency		1	2	3	4	5	6
Performance period(s)	Traditional genetic algorithm	20.256	23.165	22.652	18.741	23.145	22.485
	Improved genetic algorithm	14.041	16.355	15.123	16.049	15.568	16.468
Knowledge point coverage	Group volume requirement	10	10	10	10	10	10
	Traditional genetic algorithm	8	6	6	5	7	8
	Improved genetic algorithm	10	9	8	9	9	10
Mean difficulty coefficient	Group volume requirement	0.55	0.55	0.55	0.55	0.55	0.55
	Traditional genetic algorithm	0.43	0.62	0.51	0.48	0.59	0.61
	Improved genetic algorithm	0.53	0.56	0.55	0.57	0.52	0.54

4.1.2 Adaptation analysis

Comparison is made between the optimal fitness of the population after the same number of iterations of the improved genetic algorithm and the traditional genetic algorithm. Here, the fitness value is the value before the exponential change. Fig. 4 shows the results of the comparison of the fitness of the improved algorithm and the traditional algorithm in different generations, where the horizontal scale represents the number of iterations and the vertical coordinate represents the optimal fitness in the current population. The fitness value of the initialized population of the improved genetic algorithm (Avg=0.33469) is 0.26 lower than the fitness value of the traditional genetic algorithm (Avg=0.59865), and the number of iterations needed to get the same target fitness value is less than that required by the traditional genetic algorithm. This is closely connected to the reduction in running time mentioned earlier. It is also proven that the improved genetic algorithm proposed in this paper is capable of both reducing the running time of the algorithm and improving the Quality of the initial population. After using the method of exponential change in the fitness value, the improved genetic algorithm ensures the diversity of the population in the early part of the iteration and accelerates the convergence speed in the later part of the iteration, thus improving the Quality of the assembled test papers even further.

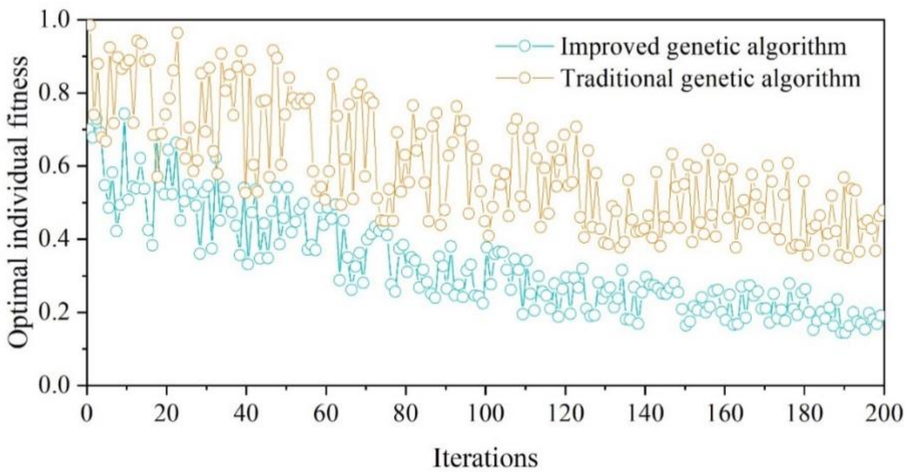


Figure 4. The two algorithms are compared to different algebraic indications

4.2 Intelligent Grouping Function Analysis

Taking University Y's application of the examination management system proposed in this paper as an example, the intelligent paper forming function of its examination management system is tested, and the intelligent paper forming algorithm based on the improved genetic algorithm proposed above is used to carry out simulation experiments. The simulation experiment is based on the test question attributes (test question number, question type number, test question difficulty, test question differentiation, test question time, test question score), test paper evaluation indexes and mathematical models, constraints, and the objective function to form the test paper. Among them, the difficulty of the test questions is divided into easy [0,0.2], easier (0.2,0.4], moderate (0.4,0.6], more difficult (0.6,0.8], difficult (0.8,1], and the level of differentiation of the test questions is divided into unqualified (<=0.2), more qualified (0.2,0.29], qualified (0.3,0.39], and excellent (>=0.4). Assuming that the exam is a testing exam, set the desired paper difficulty as moderate and the paper differentiation as excellent. Analyze the Quality and Efficiency of the assembled papers.

4.2.1 Quality of examination papers

Five group paper tests were conducted using the intelligent algorithm based on the improved genetic algorithm, and the Quality of the test papers was evaluated using evaluation indexes. Since the test paper scores, the number of test questions, and the time of the test paper are the same, the analysis of the Quality of the test paper mainly focuses on the difficulty and differentiation of the test paper. The test papers formed in the five experiments are shown in Table 2. According to the evaluation criteria of the Quality of the test paper, it can be seen that the difficulty of the test paper of the five experiments is within the moderate range, the differentiation of the test paper is within the excellent range, and the following analysis of the distribution of reagent scores for the difficulty and differentiation of the test questions of each group of experiments. Among the five experiments, the 1st experiment has the highest difficulty level, and the distribution of the difficulty level of the test questions is unreasonable. The more difficult and difficult level accounted for 0.3, while the test questions with moderate difficulty level only accounted for 0.2. The score of the test questions with a differentiation level of qualified and excellent is larger and accounted for 0.64, but the differentiation level of the unqualified test questions accounted for 0.22, and the distribution of the differentiation level of the test questions showed polarization. The difficulty of the 5th experiment meets the requirements. Easy and easier test questions accounted for a total of 0.32, the proportion of more difficult and difficult test questions is the same as 0.32, and the difficulty of the moderate test questions accounted for 0.36, the distribution of test question difficulty is uniform and more ideal. The differentiation of test questions showed an upward trend. The qualified and excellent differentiation of the test questions accounted for 0.68. A larger proportion of the test paper can effectively differentiate the ability of the candidates.

In summary, it can be seen that the 5th experimental formation of the test paper test question difficulty and differentiation distribution is more reasonable. The formation of the test paper meets the specified requirements for the formation of the test paper, the test paper is more satisfactory.

Table 2. The best exam for five experiments

Experimental frequency		1	2	3	4	5
Test difficulty		0.5581	0.5345	0.5016	0.5548	0.5249
Test distinction		0.3845	0.4318	0.4596	0.4187	0.4041
Actual score of difficulty	Easy	10	14	18	12	14
	Easier	15	18	24	18	18
	Moderation	22	40	47	32	36
	Harder	28	17	7	20	16
	Hard	25	11	4	18	16
The distinction is the actual score	Disqualification	22	11	18	20	12
	Better	14	27	23	12	20
	Qualified	39	33	24	44	32
	Excellence	25	29	35	24	36

4.2.2 Efficiency in Organizing Volumes

The improved genetic algorithm is applied for automatic scrolling and compared to the traditional method. The improved genetic algorithm and the traditional method were respectively grouped to test and analyze their convergence accuracy, convergence time, and grouping success rate in the order of comparison. Grouping efficiency comparison results are shown in Table 3, Table 4, and Table 5. From Table 3 and Table 4, it can be seen that the convergence accuracy of the improved genetic algorithm is better than that of the traditional method, while the convergence time of this algorithm (35-43s) is half of that of the traditional algorithm (78-88s), and it can converge to the optimal solution faster. As can be seen from Table 5, compared with the traditional method (0.36~0.55), the success rate of this paper's algorithm for grouping (0.90~1.00) is higher, where the success rate = number of successful groupings/total number of experiments. This is because the intelligent grouping algorithm based on the improved genetic algorithm adopts integer coding without decoding, and the initial population has already satisfied the three constraints of S_p, N_p, and T_p, so the algorithm effectively reduces the redundancy of grouping and improves the convergence speed of the algorithm. The algorithm's global optimization-seeking ability and local optimization-seeking ability are enhanced by the improved tour step size and migration probability, which prevents the problem of falling into local extreme points. In conclusion, applying an intelligent paper-forming algorithm based on an improved genetic algorithm to the examination management and education system has certain theoretical and practical significance.

Table 3. Improving the convergence accuracy of genetic algorithms and traditional methods

Experimental frequency	This algorithm			Traditional algorithm		
	Maximum value	Mean value	Standard deviation	Maximum value	Mean value	Standard deviation
1	9.4745E-02	9.4725E-02	2.1215E-03	9.3616E-02	9.3529E-02	8.1564E-03
2	9.4651E-02	9.4633E-02	2.0874E-03	9.3541E-02	9.3418E-02	8.4711E-03
3	9.4584E-02	9.4525E-02	2.0659E-03	9.3396E-02	9.3259E-02	8.5650E-03
4	9.4478E-02	9.4466E-02	2.0415E-03	9.3218E-02	9.3187E-02	8.2561E-03
5	9.4354E-02	9.4334E-02	2.0156E-03	9.3185E-02	9.3048E-02	8.0885E-03

Table 4. Improve the average time of genetic algorithms and traditional methods

Experimental frequency	This algorithm		Traditional algorithm	
	Evolutionary algebra	Time spent (s)	Evolutionary algebra	Time spent (s)
1	27	41	42	88
2	33	43	40	85
3	31	39	37	81
4	28	37	35	78
5	26	35	33	79

Table 5. Improve the success rate of genetic algorithm and traditional method

Experimental frequency	This algorithm		Traditional algorithm	
	Success number	Success rate	Success number	Success rate
1	20	0.90	9	0.41
2	21	0.95	11	0.5
3	22	1.00	12	0.55
4	22	1.00	11	0.5
5	22	1.00	8	0.36

5 Conclusion

The objective of this study is to develop an intelligent paper-grouping management system that effectively constructs an innovative system for exam management and education based on artificial intelligence technology. The study takes University A as an example and carries out in-depth research on three aspects: the performance of the improved genetic algorithm, the Quality of test papers, and the Efficiency of grouping papers.

The simulation analysis of the improved genetic algorithm shows that the improved genetic algorithm proposed in this paper can shorten the running time of the algorithm (6.14s), the number of knowledge points covered in the overall composition of the test paper is 2.5 more than that of the traditional algorithm, differentiate between different types of questions quickly, and ensure that the number of individual questions under each type of question meets the requirements of the grouping of papers. At the same time, the fitness value of the initialized population of the improved genetic algorithm (Avg=0.33469) is much lower than that of the traditional genetic algorithm (Avg=0.59865), which further proves that the improved genetic algorithm proposed in this paper is able to reduce the running time of the algorithm as well as improve the Quality of the initial population.

In the intelligent paper formation function, the Quality and Efficiency of the formed papers are analyzed by setting the desired difficulty of the papers as moderate and the differentiation of the papers as excellent. The results show that, compared with the traditional method, the difficulty and differentiation distribution of test papers formed by the intelligent algorithm based on the improved genetic algorithm proposed in this paper is more reasonable, which meets the specified grouping requirements, and the test papers are more ideal, and the convergence time of the algorithm in this paper (35~43s) is half shorter than that of the traditional algorithm (78~88s), which greatly improves the Efficiency of grouping test papers.

This study makes full use of the achievements of artificial intelligence technology, actively explores the methods and approaches of “intelligent technology” in the application of examination management and education, and strives to use modern information technology to avoid examination risks in an all-round and effective way, improve work efficiency, ensure examination fairness, impartiality, and security, and continuously improve the Quality of the examination.

Funding:

This research was supported by the 2021 National Education Science Planning- Ministry of Education Youth Project: Research on the Application of Cloud-Network Convergence in Online Large-Scale National Examinations (ECA210409).

References

[1] Hamid, R. H. A., Yusof, M. M., & Warland, A. (2020). Electronic records management in schools: the case study of school examination analysis system. Penerbit Universiti Kebangsaan Malaysia.

[2] Azeta, A. A., Misra, S., Azeta, V. I., & Osamor, V. C. (2019). Determining suitability of speech-enabled examination result management system. Wireless Networks, 25(6), 3657-3664.

[3] Enis, E., & Christopher, B. (2022). Experiential examination of higher education partnerships in the uk: a knowledge management perspective. Journal of knowledge management(1), 26.

[4] Lagrosen, S., Seyyed-Hashemi, R., & Leitner, M. (2004). Examination of the dimensions of Quality in higher education. Quality assurance in education, 12(2), 61-69.

[5] Brown, G. T. (2010). The validity of examination essays in higher education: Issues and responses. Higher Education Quarterly, 64(3), 276-291.

[6] Shraim, K. (2019). Online examination practices in higher education institutions: learners' perspectives. Turkish Online Journal of Distance Education, 20(4), 185-196.

[7] Umbricht, M. R., Fernandez, F., & Ortagus, J. C. (2017). An examination of the (un) intended consequences of performance funding in higher education. Educational Policy, 31(5), 643-673.

[8] Nigussie, B., Getachew, K., Mikre, F., Amsale, F., Belay, A., Workeneh, N.,.. & Tilahun, G. (2023). A Move towards Choosing a Workable National Examination Management Approach for Ethiopia. The Ethiopian Journal of Social Sciences and Language Studies (EJSSLS), 10(1), 3-12.

[9] Mgbeafulike, I., & Chekwube, E. (2021). An integrated system for continuous assessment and examination management in schools and colleges. International Journal of Computer Applications Technology and Research(04).

[10] Al-Hawari, F., Alshawabkeh, M., Althawbih, H., & Nawas, O. A. (2019). Integrated and secure web-based examination management system. Computer Applications in Engineering Education(1).

[11] Hui, D. (2018). Analysis on the present situation and countermeasures of the examination management of chinese medical students' qualification examination. Journal of Clinical and Experimental Medicine, 2(4), 13-20.

[12] Tashu, T. M., Esclamado, J. P., & Horvath, T. (2019, May). Intelligent on-line exam management and evaluation system. In International Conference on Intelligent Tutoring Systems (pp. 105-111). Cham: Springer International Publishing.

[13] Mahdi, O. R., Nassar, I. A., & Almsafir, M. K. (2019). Knowledge management processes and sustainable competitive advantage: An empirical examination in private universities. Journal of business research, 94, 320-334.