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Article

Research on the Integration of Automation Technology Teaching Strategy and Intelligent Manufacturing Model Based on Differential Evolutionary Algorithm

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Abstract: This paper combines test paper quality indicators to construct a test paper assembly mathematical model and uses an improved differential evolution algorithm to solve the model. It generates an initial population through uniform search of the question bank and dynamically adjusts the mutation rate and crossover rate based on the fitness values of the population. Building on this, the paper adopts a backward design approach based on the OBE philosophy, focusing on three aspects—curriculum content, instructional organization, and instructional feedback—to construct an educational reform strategy and intelligent manufacturing-oriented teaching model that integrates automation technology, characterized by "two increases, two decreases, and one improvement." Finally, the model was tested on students from a certain school, leading to the conclusion that among the experimental data on difficulty level score distributions of test papers generated by different algorithms, the algorithm proposed in this paper had the smallest distribution at the difficult level, with a minimum of 7.89, indicating that the paper's test paper generation strategy is more effective. Through empirical research, it was found that after applying the teaching model proposed in this paper, students in the experimental class achieved higher average scores on each question in the test compared to the control class. Additionally, as teaching progressed, students in the experimental class demonstrated a gradually superior trend in their mastery of computational concepts compared to students in the control class.

Keywords: differential evolution algorithm; intelligent test paper generation; automation technology; intelligent manufacturing model

1. Introduction

With the rapid development of technology, the global manufacturing industry is undergoing an unprecedented transformation [1]. The development of smart manufacturing has become a key driving force for the transformation and upgrading of the manufacturing industry [2]. Smart manufacturing refers to a manufacturing development model based on modern information technology, which combines traditional manufacturing with internet technology to achieve automation, informatization, and intelligence in the production process [3-5]. Smart manufacturing offers advantages such as high efficiency, flexibility, and sustainability, enabling it to meet the ever-changing demands of the market while enhancing production efficiency and product quality [6-7]. Against this backdrop, exploring the integration of automation technology curriculum reform strategies with smart manufacturing models holds significant practical and historical importance [8-9].

As the smart manufacturing model continues to evolve, traditional course content no longer meets the demands of the times, necessitating updates to include new knowledge areas such as artificial intelligence, big data analysis, and cloud computing to align with industry needs [10-13]. In the smart manufacturing context, course instruction should place greater emphasis on practical components, utilizing laboratory courses, internships, and graduation projects to enable students to master professional knowledge and skills and apply them in real-world work scenarios [14-16]. By collaborating with enterprises to organize internships, students can gain firsthand exposure to real-world work environments and enhance their practical skills [17-18]. Additionally, interdisciplinary courses can be introduced to allow students to explore related disciplines alongside their automation studies, thereby enhancing their comprehensive capabilities and cultivating professionals with the expertise required for smart manufacturing [19-22].

Literature [23] examines the significance of intelligent manufacturing for mechanical design courses and analyzes the current needs and challenges of mechanical design course instruction, aiming to provide practical support for mechanical design course reforms, improve teaching quality, and cultivate professionals capable of adapting to intelligent manufacturing models. Literature [24] examines how schools and teachers utilize technology-driven electrical engineering and automation education curriculum reforms to adapt to changes in the times, emphasizing the importance of leveraging modern information technology in electrical engineering and automation education to promote the development of high-quality educational programs and enhance student quality. Literature [25] emphasizes the importance of comprehensively understanding artificial intelligence technology and proposes reform strategies for integrating artificial intelligence literacy into mechanical automation education, including integrating course content, innovating teaching methods, and fostering interdisciplinary collaboration, with the aim of cultivating professional talent in the field of intelligent manufacturing. Literature [26] proposes a reform plan for the cultivation of intelligent manufacturing talent in higher education institutions to address the demand for talent in the steel manufacturing industry and the need for green intelligent steel technology. It demonstrates that innovative talent cultivation models can reconstruct the steel intelligent manufacturing engineering education system, contributing to the creation of positive social benefits. Literature [27] discusses the development opportunities for talent cultivation and education in the field of electrical engineering and automation, and proposes educational reform strategies such as innovative curriculum systems and automated practical teaching to provide professional talent support for intelligent manufacturing. The above studies examined talent cultivation in automation technology teaching specialties such as mechanical design courses and mechanical automation education under the backdrop of intelligent manufacturing, pointing out that various automation technology teaching specialties should adapt to the development needs of intelligent manufacturing and reform in terms of teaching content, strategies, and methods to cultivate high-quality professional talent. Literature [28] noted that intelligent manufacturing has become a trend in manufacturing development, widely applied in countries such as China, the EU, and the US, and has become an important driving force for enhancing competitiveness, while providing a review of current related research. Literature [29] proposes the concept of human-centered intelligent manufacturing (HCIM) in the context of intelligent manufacturing development, discussing HCIM from its background, human factors, and practical applications, and offering suggestions from multiple levels such as policy decision-making and corporate development, providing references for promoting the development and application of HCIM in China. Literature [30] points out that intelligent manufacturing (IM), which integrates multiple disruptive information technologies and advanced manufacturing technologies, is widely applied. It empirically examines the impact of IM on operational performance from the perspective of labor productivity and identifies the conditions for achieving greater benefits. Literature [31] explains that over the past three decades, the manufacturing sector has been described using various terms, ranging from flexible units, flexible manufacturing systems, to computer integration and intelligent manufacturing. The above studies describe the development process, application, and impact of intelligent manufacturing, whose utilization is of significant importance for enhancing market competitiveness.

The article first clarifies the factors influencing the quality indicators of examination papers, then constructs a mathematical model for the paper-setting algorithm. Subsequently, it proposes an improved SDE algorithm based on the differential evolution algorithm to enhance the quality and efficiency of intelligent paper-setting. Based on the paper-setting algorithm and the differential evolution algorithm model, a flowchart of the intelligent paper-setting program using the differential evolution algorithm is drawn, with explanations provided for the main steps. The application of the differential evolution algorithm-based paper assembly strategy is demonstrated, and simulation experiments are conducted using MATLAB tools to compare other paper assembly algorithms. The superiority of the algorithm is validated through comparisons of various paper quality metrics. Furthermore, guided by the OBE philosophy, the objectives were set as cultivating problem-solving thinking ability, framework design thinking ability, associative ability, and algorithm design thinking ability. A teaching reform strategy integrating automation technology and a smart manufacturing mode teaching model were constructed based on the principle of "two increases, two decreases, and one improvement." Finally, 80 students from a certain school were selected as the empirical research subjects, and teaching practices were conducted to validate the effectiveness of the teaching model proposed in this paper.

2. Intelligent test paper composition method for automated technical examinations based on differential evolution algorithms

2.1. Mathematical model of the test paper compilation algorithm

The process of intelligent test paper generation involves identifying the relationships between variables in questions to convert real-world problems into mathematical models that can be solved using computers. The quality of test paper generation depends on the mathematical models. Therefore, establishing mathematical models is the fundamental task of intelligent test paper generation.

2.1.1. Indicators Affecting Test Paper Quality

According to Classical Test Theory (CTT), a question bank is a collection of subject-specific questions constructed based on certain educational measurement theories and utilizing computer technology. The questions in an intelligent test generation system are sourced from the question bank, and the quality of the questions in the question bank directly affects the quality of the test generation. Referring to the question quantification indicators of CTT, the attribute indicators that affect test quality are summarized as follows:

(1) Reliability: Reflects the stability of test results, i.e., the credibility of test outcomes. High reliability indicates that test scores are less susceptible to random factors, and scores can more accurately reflect a test-taker's actual proficiency level. Factors influencing reliability include question difficulty, number of questions, and the accuracy of question wording.

(2) Validity: Reflects the effectiveness of the exam paper, i.e., the extent to which exam results align with the intended exam objectives. A high-validity exam paper can accurately assess candidates' actual mastery or application of learned knowledge and skills. To enhance validity, ensure consistency between questions, exam objectives, and curriculum standards.

(3) Difficulty: This reflects the extent to which the questions or exam assess students' knowledge and ability levels appropriately. When the difficulty is moderate, scores follow a normal distribution. When the difficulty is high, scores follow a negatively skewed distribution. When the difficulty is low, scores follow a positively skewed distribution. Since difficulty values are determined through statistical analysis after the exam, it is essential to make a relatively accurate estimate of difficulty when compiling the exam.

(4) Discrimination: This reflects the ability of a question to distinguish between students of different levels. A test with high discrimination can differentiate between students with different knowledge levels and abilities, allowing high-performing students to score high and low-performing students to score low. Discrimination is closely related to difficulty; only appropriate difficulty can achieve good discrimination.

2.1.2. Description of the Test Paper Compilation Mathematical Model

When organizing an exam paper, it is necessary to determine key parameters such as the total score, question difficulty, number of questions, distribution of knowledge points, and the level of abilities being assessed. Based on the actual circumstances of the exam, a smart test paper generation mathematical model is established using nine core attributes. The parameters of a test paper are represented as a nine-dimensional vector space, namely: questions (question number, score, difficulty coefficient, ability level, knowledge points, question type, discrimination index, answering time, and usage frequency). A single question is determined by 9 parameter indicators (attributes), i.e., by the characteristics of a 9-dimensional vector space $\left(a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9\right)$.

Let a test paper with n questions be represented by a matrix of size $\left(n \times 9\right)$:

$$S = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} & a_{18} & a_{19} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} & a_{27} & a_{28} & a_{29} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & a_{n3} & a_{n4} & a_{n5} & a_{n6} & a_{n7} & a_{n8} & a_{n9} \end{bmatrix} \tag{1}$$

The attributes in the formula are described as follows:

(1) Question number. The question number $\left(a_{11}, a_{21}, \ldots, a_{n1}\right)$ is the unique identifier of the question,

which is extremely important for computer processing.

(2) Score. The question scores $\left(a_{12}, a_{22}, \ldots, a_{n2}\right)$ represent the points for each question. Let the total score for the exam be P, then $\sum_{i=1}^{n} a_{i2} = P$. The default value of P is 100, which can be set by the exam compiler during exam compilation.

(3) Difficulty coefficient. $\left(a_{13}, a_{23}, \ldots, a_{n3}\right)$ represent the difficulty coefficient of each question, which is directly read from the question bank. The overall difficulty coefficient TD of the exam paper is a weighted value, i.e., $TD = \sum_{i=1}^{n} a_{i2} a_{i3}$. The average difficulty coefficient ND of the test paper is typically expressed as the difficulty coefficient per point, i.e., $ND = \sum_{i=1}^{n} a_{i2} a_{i3} / P$.

(4) Ability levels. There are three ability levels: general requirements, higher requirements, and higher requirements, each with its corresponding code. a_{i4} represents the ability level code of the i th question, and the selected questions should meet the specified ability level requirements.

(5) Knowledge Points. Knowledge points are the basic units of knowledge, taught as a whole during instruction and are indivisible. When constructing a test, the score for each knowledge point is set by the user according to their needs. Let the score for the j th knowledge point be P_j. When constructing a test, the following constraint must be satisfied: $\sum_{i=1}^{n} C_{i5} a_{i5} = P_j$. When $a_{i5} = j$, $C_{i5} = 1$. When $a_{i5} \neq j$, $C_{i5} = 0$.

(6) Question type. Similar to knowledge point attributes, the score for each question type must be set when compiling the test. Let the score for the j th question type be M_j. When compiling the test, the constraint condition for question types must be satisfied: $\sum_{i=1}^{n} C_{i6} a_{i6} = M_j$. When $a_{i6} = j$, $C_{i6} = 1$. When $a_{i6} \neq j$, $C_{i6} = 0$.

(7) Discrimination. Let P be the total score of the exam paper. The formula for calculating the discrimination of the exam paper is $\sum_{i=1}^{n} a_{i2} a_{i7} / P$. Sort the scores obtained by candidates on each question from high to low, dividing them into high-score groups and low-score groups. Based on the score rates of the high-score and low-score groups, the discrimination of each question is obtained. The discrimination of the exam paper is the weighted average of the discrimination of each question.

(8) Answering time. Answering time refers to the exam time, where a_{i8} represents the answering time for the i th question. The sum of the answering times for all questions is the total answering time, with a default value of 120 minutes, set by the test paper compiler. Let T be the total answering time, then the following constraint exists between the total answering time and the answering time for each question: $\sum_{i=1}^{n} a_{i8} = T$.

(9) Usage frequency. a_{i9} represents the number of times the i th question is used per unit of time, where the unit of time can be a year or a semester. If the usage frequency is high, it indicates that students are more likely to have encountered the question before. Therefore, after the initial completion of the test paper compilation, the usage frequency should be examined, and questions with high usage frequencies should be replaced.

2.2. Paper assembly process based on improved differential algorithm

2.2.1. Improvements to the Differential Evolution Algorithm

The Differential Evolution (DE) algorithm can solve extreme value optimization problems with multiple constraints. It is an algorithm with fewer control parameters and a higher convergence rate. Based on the standard DE algorithm, this paper proposes an optimized DE algorithm—the SDE algorithm. First, the initial population is uniformly and randomly generated from the question bank according to the distribution of question types. Compared to the traditional direct random sampling method, the initial population has a broader coverage and more uniform distribution, making the algorithm's search space more reasonable and significantly improving its global optimization capability [32]. Additionally, based on fitness changes, the algorithm parameters mutation rate and crossover rate are adjusted through feedback-based adaptive regulation. This enables fine-tuning of the mutation direction for individuals in the next generation based on search information from the previous generation, ensuring both efficiency and high precision in the search process.

2.2.2. Paper assembly process

According to the improved differential evolution algorithm steps, an initial population of a certain size should first be generated. There are a total of m questions in the question bank, which are divided into several areas according to question types. Then, according to the qualitative indicators for question selection, a random initial solution is generated in each area to form the initial population. The rules are as follows:

$$\begin{gathered} x_{i,j} = \left(x_{i,\min} + (i-1)\cdot d\right) + rand(\ )\cdot d \\ d = \left(x_{i,\max} - x_{i,\min}\right)/N \end{gathered} \tag{2}$$

In this context, $x_{i,j}$ denotes the j th component of the initial population individual x_i , N represents the number of individuals in the population, and d denotes the length of each interval. $x_{i,\max}$, and $x_{i,\min}$ respectively denote the upper and lower bounds of its values. The population matrix is expressed as follows:

$$P(t) = \begin{bmatrix} x_{11}(t) & x_{12}(t) & \cdots & x_{1n}(t) \\ x_{21}(t) & x_{22}(t) & \cdots & x_{2n}(t) \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1}(t) & x_{N2}(t) & \cdots & x_{Nn}(t) \end{bmatrix} \tag{3}$$

Where t is set to 0, representing the 0th generation, i.e., the initial population. Each row of $P(0)$ represents a feasible solution to the problem of forming groups, which can be expressed as $x_i(0) = (x_{i1}(0), x_{i2}(0), \cdots, x_{in}(0))^T (i = 1, 2, \cdots, N)$, Therefore, the ultimate goal of the scheduling problem is to evolve through t generations so that a row vector satisfying the termination condition is generated in $P(t)$.

The second step is to perform mutation operations. According to the improvement measures, calculate the fitness, let F_t be the current mutation rate, and let $f_{i\_\max}$ and f_{i_avg} be the maximum fitness and average fitness in the population, respectively. Then, the update formula for the mutation rate F is:

$$F = F_t + f_{i\_\max} \cdot \left(f_{i\_\max} - f_i(i)\right) / \hat{e}\left(f_{i\_\max} - f_{i\_avg}\right) \tag{4}$$

The mutation rate for each generation is calculated using the above formula, with values ranging from $F \in [0.5, 1]$. The mutation rate is updated to perform mutation operations on the feasible solutions $x_i(0) = (x_{i1}(0), x_{i2}(0), \cdots, x_{in}(0))^T (i = 1, 2, \cdots, N)$ in the t th generation population $P(t)$ using the mutation operation, the generated new individuals are $x_i'(t) = (x_{i1}'(t), x_{i2}'(t), \cdots, x_{in}'(t))$, and each new individual is calculated as follows:

$$x_{ij}'(t) = x_{ij}(t) + F(x_{rj}(t) - x_{sj}(t)) \tag{5}$$

Among them, $i, r, s \in \{1, 2, \cdots, N\}$. $i \neq r \neq s$, $x_{rj}(t)$ and $x_{sj}(t)$ are the j th components of two individuals in the evolutionary population that are different from $x_i(t)$.

Step 3: Perform the crossover operation. The update formula for the crossover rate Cr is as follows, where $f_{i\_\max}$ and f_{i_avg} are the maximum fitness and average fitness in the population, respectively, and Cr is in the range $Cr \in [0.8,1]$.

$$Cr = \left(f_{i\_\max} - f_i(i)\right) \big/ \hat{e}\left(f_{i\_\max} - f_{i\_avg}\right) \tag{6}$$

For the parent-generation individual $x_i(t) = (x_{i1}(t), x_{i2}(t), \cdots, x_{in}(t)), (i = 1, 2, \cdots, N)$, each component $x_{ij}(t)$ generates a random number β_i within the interval $[0,1]$ and then, based on the relationship between β_i and Cr, it is determined whether to replace the j th component $x_i'(t)$ of $x_{ij}'(t)$ in the mutation step with $x_{ij}(t)$. The specific rules are as follows:

$$x_{ij}'(t) = \begin{cases} x_{ij}(t) & if\, \beta_i \geq Cr \\ x_{ij}'(t) & otherwise \end{cases} \tag{7}$$

The fourth step is to select individuals in the population based on fitness. First, each individual in the population is ranked, and then a roulette wheel method is used for selection, with individuals with higher fitness having a greater probability of being selected for evolution [33].

The fifth step is to reach the termination condition, which is set as a fixed number of evolutionary generations or fitness requirements. When this condition is met, the algorithm terminates.

2.3. Intelligent Test Paper Generation Program Flowchart

Under multiple constraints, the test paper compilation problem is essentially an optimization problem, and there is more than one optimal solution that satisfies the conditions. Computer-based intelligent test paper compilation is based on software development using mathematical models. The process of applying the differential evolution algorithm in intelligent test paper compilation is shown in Figure 1.

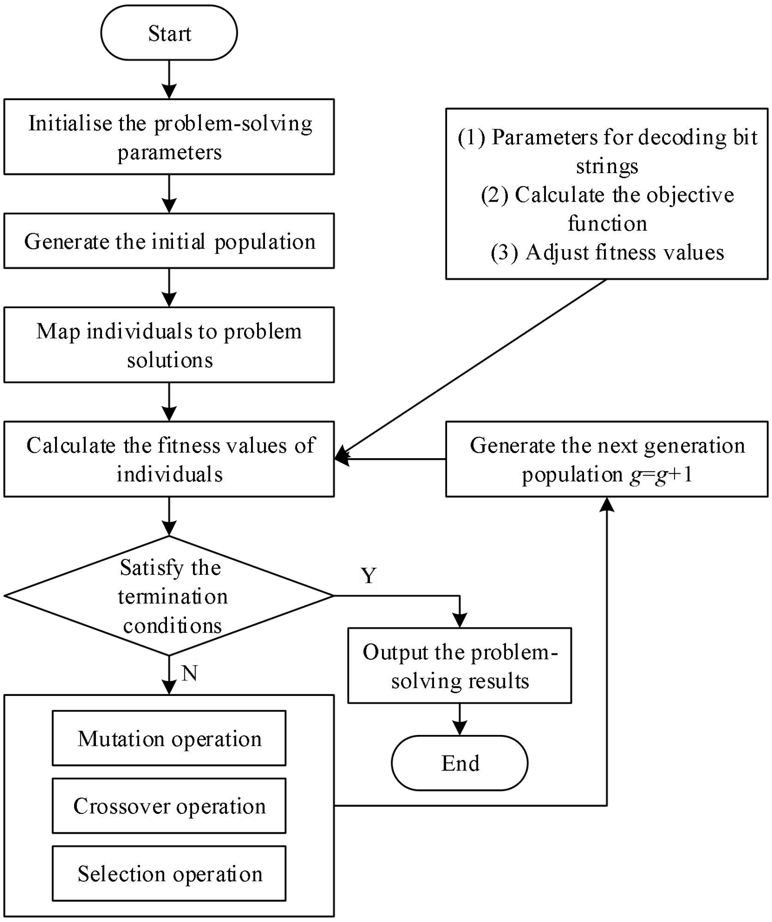

Figure 1. Intelligent group volume process.

a. Initialize the test paper composition parameters, including the parameters of the test paper composition algorithm mathematical model (including equal difficulty coefficients, knowledge points, question types, discrimination, answering time, usage frequency, ability levels, etc.) and the parameters of the differential evolution algorithm (including population size, maximum iteration times, mutation operators, crossover operators, etc.).

b. Generate the initial population. The population is initialized to establish the starting point for optimization search. Values are randomly selected from within the given boundary constraints, where the boundary values are $x_k^{(s)} < x_k < x_k^{(L)}$, $x_{ki}^0 = x_k^{(s)} + rand[0,1] * \left(x_k^{(L)} - x_k^{(s)}\right)$, where $rand[0,1]$ represents a uniform random number within the specified interval.

c. Mapping of individuals to problem solutions. Intelligent test paper generation is essentially a combinatorial optimization problem. Traditional DE algorithms have continuous population encoding characteristics and need to complete the mapping between population individuals and problem solutions. Let $\xi = (c_1, c_2, \cdots, c_k, \cdots, c_n)$ represent the solution to the problem, i.e., the generated set of test papers. The mapping formula from x_k^g (population individual) to the problem solution is: $C_k = \begin{cases} 1, & If\ x_k^g \geq 0.5 \\ 0, & Other \end{cases}$ C_k represents the test question, and k represents the test question number.

d. Calculate the fitness values of individual vectors. Fitness is represented numerically and serves as an indicator of the quality of an individual vector relative to the entire population. Calculating fitness values requires a fitness function (evaluation function). In the DE algorithm, the fitness function can be arbitrarily defined within a region and does not require the constraint of being continuously differentiable. The fitness function takes non-negative values, which increases the probability of selecting individuals with better fitness, simplifies the design, and reduces computational complexity.

e. Determine whether the algorithm termination conditions are met. The maximum number of evolutionary generations serves as the algorithm termination condition, but additional criteria are also required. Typically, the program terminates when the objective function value is less than a threshold (often set to 10). Alternatively, if it is determined that the optimal value in the population has not changed significantly over several consecutive generations, the program terminates.

f. Perform differential evolution operations. Conduct mutation, crossover, and selection operations according to the algorithm model.

By utilizing different-sized real question banks, the algorithm is simulated and tested. The test results indicate that compared to the basic genetic algorithm, this algorithm demonstrates superior performance in terms of test paper generation success rate and quality.

3. Simulation experiments and analysis of results

Using "Automated Technology Programming" as a simulation experiment example, the performance of the test paper generation strategy based on the differential evolution algorithm is validated using the obtained simulation data. To simplify the test paper generation process, various test paper information must be input during generation, such as test paper code, full marks, and required number of copies. In the simulation experiments, four algorithms—Hybrid Particle Swarm Optimization (HPSO), Improved Genetic Algorithm (IGA), Random Algorithm (RA), and Particle Swarm Optimization (PSO)—were used for automatic question selection and paper assembly comparison to assess their performance in an automatic question selection and paper assembly system. Additionally, four question types were employed in the experiments: multiple-choice, procedural questions, procedural fill-in-the-blank, and procedural design.

3.1. Setting algorithm parameters

The exam paper is composed of randomly selected questions, with the following constraints: the total score of the exam paper is 100 points, the total exam time is 120 minutes, and the simulation parameters for the four algorithms being compared are as follows: Random algorithm for paper composition, with a population size of 50. Improved genetic algorithm for paper composition, with 300 iterations, a population size of 50, a crossover rate of 0.76, and a mutation rate of 0.02. Hybrid particle swarm algorithm for paper composition, with a population size of 50 particles and 200 iterations. Particle swarm algorithm for paper composition, with a population size of 50 particles and 300 iterations, acceleration factors $c1 = c2 = 1.52641$.

3.2. Analysis of Results

To validate the effectiveness of the algorithms, five sets of 50 test paper generation experiments were conducted under identical experimental conditions for the four algorithms—RA, IGA, HPSO, and PSO—using the parameter values set for each algorithm. The experimental data obtained were then analyzed.

(1) Experimental data on the difficulty level score distribution of test papers generated by different algorithms

Using the difficulty level scores of the questions in the test papers obtained from the 50 experiments, the average values of the difficulty level scores were calculated using the formula. The comparison of the difficulty level distributions of the test papers generated by each algorithm is shown in Table 1. As shown in the table, the minimum difficulty level distribution of the algorithm in this paper is 7.89, indicating that the test paper generation strategy based on the algorithm in this paper is more effective.

Table 1. The comparison of the difficulty distribution of the test paper is generated

Difficulty level	Easy	Easier	General	Harder	Difficulty
User expectation score	13	32	35	18	7
RA	6.6	10.98	50.65	23.93	9.55
IGA	9.65	18.65	42.79	22.45	8.41
Ours	12.65	23.24	35.95	21.78	7.89
PSO	7.06	5.46	55.69	15.74	10.55

(2) Experimental data on the distribution of knowledge points (chapters) in test papers generated by different algorithms

The distribution of chapters in test papers generated by each algorithm is shown in Table 2. From the matching situation of knowledge points in each chapter of test papers composed of questions selected according to the four strategies, the method in this paper is superior.

Table 2. Each algorithm generates the distribution of the examination paper in the section

Chapters	Chapter 1	Chapter 2	Chapter 3	Chapter 4	Chapter 5	Chapter 6	Chapter 7	Chapter 8
Expectancy Score	6	11	20	25	8	14	6	12
RA	5.81	12.49	22.3	20.36	8.36	11.26	9.66	10.96
IGA	5.12	10	19.85	23.11	8.88	12.96	8.74	11.26
Ours	5	10.06	19.75	25.06	9.63	13.06	8.65	10.05
PSO	8.79	19.06	17.32	11.65	13.65	8.32	10.9	9.65

(3) Experimental data on the discrimination attribute of test papers under four algorithms

The scores for each difficulty level of the test questions obtained from 50 experiments are shown in Table 3, which compares the discrimination distribution of the test papers generated by the algorithms. The discrimination score distribution of the test paper composition strategy based on the method in this paper is the smallest, indicating that the test papers composed by this algorithm better meet the test paper requirements of users.

Table 3. The comparison of the distribution of the test paper in the distribution.

Differentiating attribute	worse	medium	good	excellence
Group volume expectation score	10	23	40	22
RA	13.65	39.26	36.95	14.96
IGA	8.56	27.55	44.65	21.25
Ours	8.12	23.65	45.82	24.69
PSO	19.32	33.51	32.23	15.03

(4) Comparative experiment of the four algorithms in terms of cognitive level

After selecting questions and compiling test papers using the four algorithms, the scores for the cognitive level of the test papers can be obtained based on the formula. The comparison of the cognitive level of the test papers generated by the algorithms is shown in Table 4. With an expected score of 15 for the knowledge application level, the RA algorithm scored 15.06, the IGA algorithm scored 15.32, and the test papers generated by the algorithm in this paper scored 15.75 in knowledge application. This demonstrates the superiority of the algorithm in this paper in terms of cognitive level.

Table 4. The algorithm generates the comparison of the cognitive level.

Cognitive hierarchy	Applied	Master	Understand	Remember
Group volume expectation score	15	20	40	25
RA	15.06	44.65	33.2	8.02
IGA	15.32	35.96	35.6	13.6
Ours	15.75	29.43	37.99	13.25
PSO	5.82	33.26	42.69	18.69

3.3. Performance comparison experiments between algorithms of the same type

To demonstrate the advantages of the algorithm proposed in this paper for solving the test paper composition problem, it is compared with several other population-based algorithms. APSO stands for Adaptive Particle Swarm Optimization, LinWPSO for Linear Weight Decreasing Particle Swarm Optimization, LnCPSO for Learning Factor Synchronous Particle Swarm Optimization, and SecPSO for Second-Order Oscillating Particle Swarm Optimization. To compare the effects of different parameters—Popsize (population size) and Maxgen (number of iterations)—on the performance of each algorithm, 50 experiments were conducted using PSO, APSO, LinWPSO, LnCPSO, SecPSO, and the proposed algorithm to solve the scheduling problem. The fitness function values obtained were then compared. PSO, APSO, LinWPSO, LnCPSO, SecPSO, and HPSO algorithms are shown in Tables 5 and 6, respectively. The proposed algorithm performed well in all five experiments. When searching for the optimal combination of test questions, the proposed algorithm can find the minimum value of the intelligent test paper generation objective function and achieves the best average performance. Additionally, as the population size increases and the number of iterations increases, the objective function value decreases, and the resulting questions better meet the constraints of each paper-setting group. However, as shown in the fifth group of SecPSO and the sixth group of HPSO in the table, increasing the number of iterations (Maxgen) does not always reduce the objective function value. The experiments demonstrate that compared to other population-based optimization algorithms, the algorithm proposed in this paper has superior performance and is a more effective method for solving the intelligent paper-setting problem.

Table 5. Algorithm optimal value.

Parameter		Algorithm					
Popsize	Maxgen	PSO	APSO	LinWPSO	LnCPSO	SecPSO	Ours
50	50	3.1664	3.1072	3.2189	3.2816	3.2433	0.4717
50	100	3.1695	3.0524	3.2011	3.1938	3.3106	0.2605
50	200	3.1593	3.0382	3.1486	3.1886	3.3585	0.1694
100	100	3.1456	3.0593	3.1272	3.2051	3.3742	0.1869
100	200	3.1422	2.9594	3.1227	3.2229	3.3157	0.1588

Table 6. Algorithm mean.

Parameter		Algorithm					
Popsize	Maxgen	PSO	APSO	LinWPSO	LnCPSO	SecPSO	Ours
50	50	3.349	3.3142	3.3726	3.4091	3.4528	0.8357
50	100	3.3414	3.2734	3.3221	3.3568	3.4869	0.5963
50	200	3.3192	3.2584	3.3265	3.3814	3.5024	0.4828
100	100	3.3128	3.1982	3.3248	3.3777	3.4506	0.5203
100	200	3.3058	3.1823	3.2538	3.3117	3.4493	0.3737

4. Intelligent manufacturing teaching model integrating automation technology teaching reform strategies

4.1. Construction of Teaching Models

This paper proposes an OBE-oriented “two increases, two decreases, and improvement” intelligent manufacturing teaching model. The “two increases, two decreases, and improvement” theory-practice integrated teaching model is shown in Figure 2.

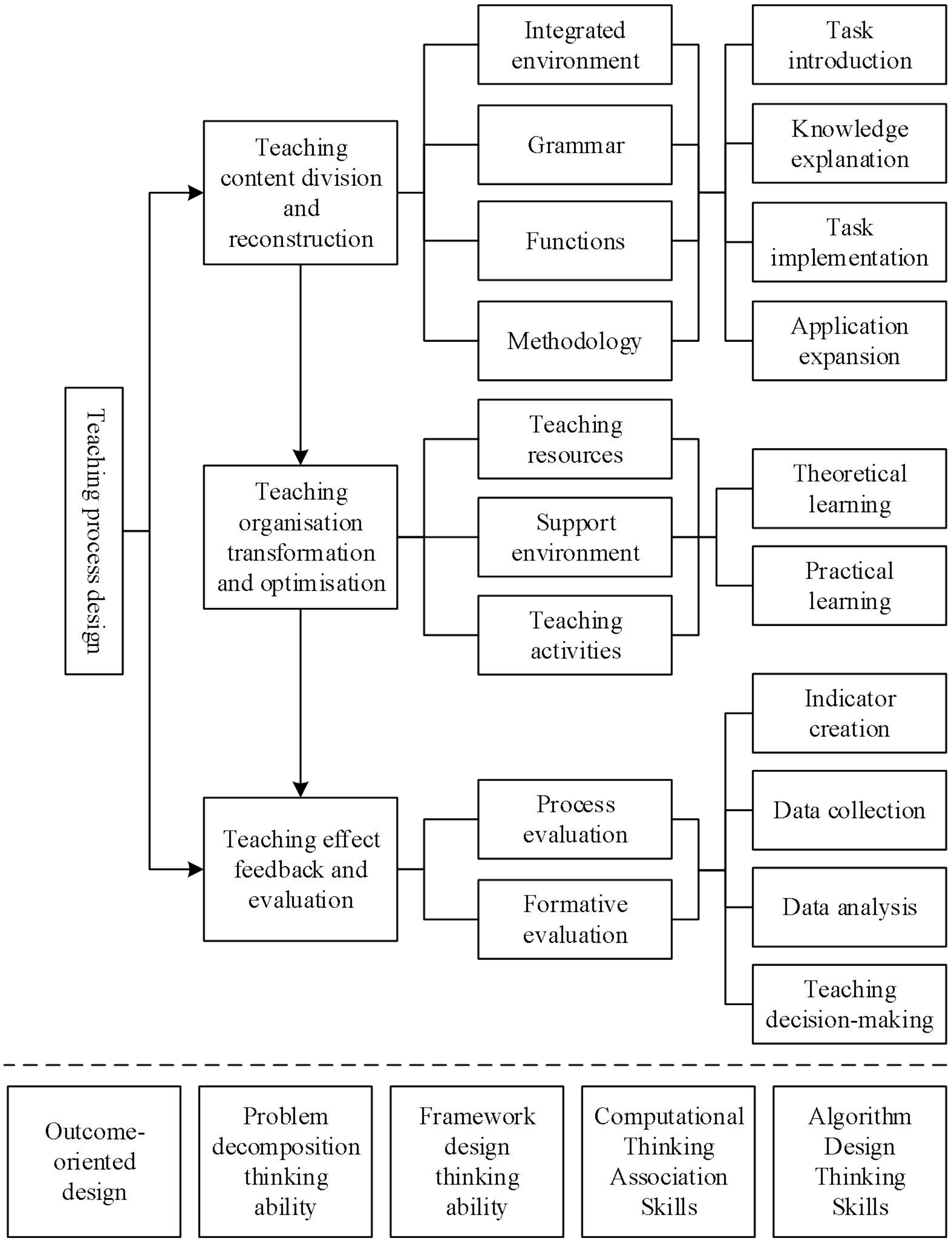

Figure 2. Integrated teaching mode.

4.2. Teaching Practice

4.2.1. Teaching Content

In the course, the teaching content is restructured. First, the system is broken down into 10 teaching projects. Then, the implementation sequence of the teaching projects is determined based on the main thread of the program design. Next, the course content is linked and integrated with the teaching projects according to the syllabus. Finally, different sub-tasks are set under each teaching project, and the teaching is conducted in the order of “task introduction—knowledge explanation—task implementation—application expansion.” Under this system, the learning tasks students encounter are practical and design-oriented, clearly defining the application pathways and contexts for knowledge and skills, thereby addressing the shortfall in skill training in traditional teaching methods.

4.2.2. Teaching Organization

(1) SPOC online learning.

SPOC online open courses are developed on the “Learning Pass” platform, and relevant teaching resources are uploaded to the teaching platform for students to study on their own. The teaching resources mainly consist of explanatory videos recorded by teachers, which are organized into a series. Each teaching task includes 3-5 videos, with each video lasting less than 5 minutes, making it easy for students to study during their spare time. To broaden students' horizons, instructors use knowledge-enhancing tools to guide students in extracting knowledge and skills from fragmented online information. Through assessments, students are encouraged to integrate and utilize these fragmented resources, fostering a more comprehensive, innovative, and enriched understanding.

(2) Group-based interactive teaching.

During classroom instruction, to actively engage students, instructors organize activities such as quick-response quizzes, tests, and voting. Students participate in classroom interaction by completing tasks. Additionally, teachers randomly select students to present their code and its execution results. Classroom instruction requires not only teacher-student interaction but also student-to-student interaction. Therefore, during task implementation, students are divided into several groups for practical exercises. When forming groups, it is important to consider students' personalities and complementary strengths to enhance internal group interaction and communication. During group collaboration, teachers provide timely guidance and corrections to ensure smooth task execution.

(3) Post-class extension exercises.

Teachers post post-class test questions on the “Learning Pass” platform. The tests are designed with a focus on practical application, reflecting the extensibility of classroom content and featuring a certain degree of openness. Students complete the test exercises by reviewing classroom content, consulting extracurricular materials, and discussing with peers. Teachers promptly evaluate students' extension exercise outcomes and address their questions and concerns.

4.2.3. Teaching Feedback

Formative assessment consists of factors such as the number of visits, the duration of course video learning, and post-class test scores. Summative assessment consists of chapter test scores and final exam scores. The “Learning Pass” platform provides powerful data monitoring and statistical functions, comprehensively recording students' learning activities before, during, and after class.

5. Practical application of teaching models based on OBE concepts

5.1. Study Design

5.1.1. Object Design

The subjects of this study were 80 students from two classes at a certain school. One class served as the experimental class, where teaching was conducted using an intelligent manufacturing teaching model based on the OBE concept, while the other class served as the control class, where traditional content was taught. The experimental class consisted of 40 students, and the control class also had 40 students. By administering the “Smart Manufacturing Thinking Survey Questionnaire (Pre-test),” the levels of thinking across various dimensions were observed in both the experimental and control classes to ensure that the samples in both groups were homogeneous.

5.1.2. Survey Tool Design

"Intelligent Manufacturing Thinking Questionnaire (Pre-test)" is a questionnaire designed to understand the current situation of intelligent manufacturing thinking ability of two classes in the school. Each question is set up with five options: very consistent, somewhat consistent, average, somewhat disagreeable, and very disagreeable, with 5 points for selecting very much agreeing, 1 point for choosing more consistent, 3 points for choosing general, 2 points for choosing more disagreeing, and 1 point for choosing very disagreeing. In this way, the level of intelligent manufacturing thinking ability can be judged. A total of 80 copies of the "Intelligent Manufacturing Thinking Survey Questionnaire (Pre-test)" were distributed, 80 were recovered, and 80 valid questionnaires were collected.

5.2. Application Effect Analysis

5.2.1. Cultivating the Concept of Smart Manufacturing Models

To objectively assess students' understanding and application of the basic concepts of smart manufacturing, the author developed a preliminary draft of test questions covering the following topics: basic definitions, smart manufacturing system architecture and components, industrial Internet of Things (IoT) and data acquisition technology, digital twin technology applications, smart production planning and scheduling, industrial robot applications and programming, quality intelligent detection technology, predictive maintenance technology, and smart logistics and warehousing systems. The test knowledge points for smart manufacturing are shown in Table 7.

Table 7. Test knowledge point.

	1	2	3	4	5	6	7	8	9
Survey	Basic definition	Intelligent manufacturing system architecture and composition	Technology of industrial Internet and data acquisition	Digital twin technology application	Intelligent production planning and scheduling	Industrial robot application and programming	Quality intelligent detection technology	Predictive maintenance technology	Intelligent logistics and warehousing system

Then, an independent samples t-test was conducted to examine the significant difference in test scores between the two classes. The results of the independent samples t-test for the basic concept questions on the smart manufacturing model are shown in Table 8. As can be seen from the table, the average score for the experimental class was 25.69 points, while the average score for the control group was 16.86 points. The results of the independent samples t-test for the test data of the control group and the experimental group are $t = -3.652$, with a corresponding significance level of $p = 0.001$. Since $p < 0.05$, the null hypothesis is rejected, indicating that there is a significant difference in test results. The students in the experimental group achieved more effective learning outcomes than those in the control group who received traditional instruction.

Table 8. Independent sample T test.

Test class	N	Mean value	Standard deviation	t	df	p
Cross-reference class	40	16.86	11.006	-3.652	75	0.001
Laboratory class	40	25.69	8.652			

To understand the specific differences between the experimental class and the control class, the author conducted a further analysis of the test questions, using an independent samples t-test to examine questions 1–8 separately. The results of the independent samples t-tests for each question are shown in Table 9. As shown in the table, the average scores of the experimental class were higher than those of the control class for questions 1–8. For question 2, the independent samples t-test results for the two classes were: $t = -2.127$, with a corresponding significance p-value of 0.036 (less than 0.05). This indicates that there is a significant difference between the two classes primarily in terms of “basic definitions.” This demonstrates that the teaching model designed in this study has a significant promotional effect on students' mastery and application of concepts. Furthermore, as the teaching progresses, students in the experimental class exhibit a gradually superior trend in their mastery of concepts compared to those in the control class.

Table 9. Test the independent sample T test.

		N	Mean value	Standard deviation	t	df	p
Basic definition	Cross-reference class	40	4.03	1.997	-1.809	58.559	0.075
	Laboratory class	40	4.65	1.158			
Intelligent manufacturing system architecture and composition	Cross-reference class	40	1.9	2.475	-2.127	70	0.036
	Laboratory class	40	2.98	2.43			
Technology of industrial Internet and data acquisition	Cross-reference class	40	2.43	2.528	-0.905	70	0.351
	Laboratory class	40	3	2.481			
Digital twin technology application	Cross-reference class	40	1.72	2.427	-2.908	70	0.015
	Laboratory class	40	3.55	2.385			
Intelligent production planning and scheduling	Cross-reference class	40	2	2.468	-1.169	70	0.25
	Laboratory class	40	2.48	2.537			
Industrial robot application and programming	Cross-reference class	40	2.23	2.515	-1.637	70	0.107
	Laboratory class	40	3.12	2.47			
Quality intelligent detection technology	Cross-reference class	40	1.74	2.48	-1.641	70	0.109
	Laboratory class	40	3.15	2.494			
Predictive maintenance technology	Cross-reference class	40	0.71	1.188	-2.397	70	0.028
	Laboratory class	40	1.55	1.254			
Intelligent logistics and warehousing system	Cross-reference class	40	0.84	1.157	-2.92	70	0.005
	Laboratory class	40	1.43	1.224			

5.2.2. Cultivating Awareness of Smart Manufacturing Models

The author designed a survey questionnaire titled “Post-Test Questionnaire on Smart Manufacturing Mode Thinking.” This questionnaire consists of two parts. The first part investigates the acceptance levels and improvement suggestions of the experimental class and the control class regarding different teaching strategies. The second part is the main body of the questionnaire, designed based on the practice and concept dimensions of the three-dimensional framework of smart manufacturing mode thinking for measurement. Each question has five response options: “Strongly Disagree,” “Disagree,” “Neutral,” “Agree,” and “Strongly Agree.” There were 40 students in the experimental class and 40 in the control class, with a total of 80 questionnaires distributed and a 100% response rate.

(1) Basic Situation Analysis

To understand the experimental class students' views on the teaching process of the OBE-based intelligent manufacturing teaching model, we compared the responses of the experimental class with those of the control class and explored and analyzed the students' acceptance of the teaching model proposed in this study from the perspectives of student attention, the effectiveness of teaching tasks, and their understanding of the intelligent manufacturing model. The evaluation of concentration in class is shown in Table 10. Through the comparison of the two classes, it can be seen that students in both the control class and the experimental class can generally concentrate on learning, and the activities in the task-based teaching process are closely related to real life. As shown in Table 11, students in the experimental class are more interested in the classroom. Most students in the experimental class are willing to continue learning, while although half of the students in the control class are also willing to continue learning, the proportion of students who are very unwilling to continue learning accounts for 14.1%, indicating that students in the control class are beginning to show signs of polarization.

Table 10. Study in the middle of the classroom(%).

	Very fit	Fit	General	Inconsistent	Very inconsistent
Laboratory class	24.05	21.82	36.94	11.82	5.37
Cross-reference class	21.82	28.15	36.74	4.13	9.17

Table 11. Be more interested in the classroom(%).

	Very fit	Fit	General	Inconsistent	Very inconsistent
Laboratory class	33.94	26.09	20.98	16.19	2.8
Cross-reference class	17.97	31.73	34.77	1.43	14.1

The statistical values for the two independent sample t-tests are shown in Table 12. The results of the independent samples t-test are shown in Table 13. From the data, it can be seen that the Sig. of the F value is 0.306 (greater than 0.05). Therefore, data can be obtained from the homogeneity of variances between the two classes, with t = 3.162 and Sig. (two-tailed) = 0.001, which is less than 0.05. Thus, it is concluded that there is a significant difference between the two classes.

Table 12. The statistical quantity of the two separate samples of the test group.

Class type	N	Mean	Standard deviation	Standard error of mean
Laboratory class	40	39.71	7.396	1.195
Cross-reference class	40	33.95	8.221	1.362

Table 13. Two separate sample T tests.

		Levene test of the variance equation		T test of the mean equation						
		F	Sig.	t	df	Sig.(Double side)	Mean difference	Standard error value	95% confidence interval of the difference	
									Lower limit	Upper limit
thinking	Let's say the variance is equal	1.089	0.306	3.162	75	0.001	5.862	1.85	2.112	9.632

(2) The effectiveness of cultivating smart manufacturing mode thinking

The post-test results for smart manufacturing mode thinking for the two classes are shown in Table 14. The independent sample t-test results for the two classes are shown in Table 15. The data in the table shows that the experimental class had higher average scores than the control class in all aspects of thinking. Except for “problem-oriented thinking” and “sustainable thinking,” there were significant differences in all other aspects.

Table 14. The statistics of the two classes.

		N	Mean value	Standard deviation	Standard error of mean
System thinking	Cross-reference class	40	3.98	1.073	0.164
	Laboratory class	40	3.19	1.06	0.17

Data driven thinking	Cross-reference class	40	3.55	1.173	0.196
	Laboratory class	40	3.42	0.892	0.166
Iterative optimization thinking	Cross-reference class	40	3.96	0.996	0.161
	Laboratory class	40	3.39	1.092	0.176
Interdisciplinary thinking	Cross-reference class	40	4.19	1.074	0.17
	Laboratory class	40	3.21	1.246	0.207
Automatic optimization thinking	Cross-reference class	40	3.93	0.928	0.161
	Laboratory class	40	3.5	1.274	0.215
Problem oriented thinking	Cross-reference class	40	4.2	1.076	0.167
	Laboratory class	40	3.7	1.176	0.183
Agile response thinking	Cross-reference class	40	3.85	0.925	0.176
	Laboratory class	40	3.55	1.003	0.161
Man-machine collaborative thinking	Cross-reference class	40	4.38	0.917	0.151
	Laboratory class	40	3.21	1.112	0.17
Sustainable thinking	Cross-reference class	40	3.96	0.945	0.154
	Laboratory class	40	3.44	1.183	0.186

Table 15. Separate sample t test of the two classes.

	Levene test of the variance equation		T test of the mean equation						
	F	Sig.	t	df	Sig.(Double side)	Mean difference	Standard error value	95% confidence interval of the difference	
								Lower limit	Upper limit
System thinking	0	0.989	2.313	75	0.027	0.568	0.229	0.098	1.063
Data driven thinking	4.405	0.058	2.469	69.192	0.03	0.602	0.239	0.13	1.079
Iterative optimization thinking	0.198	0.672	2.807	75	-0.01	0.675	0.246	0.193	1.151
Interdisciplinary thinking	1.754	0.187	2.617	75	0.009	0.703	0.271	0.149	1.238
Automatic optimization thinking	5.995	0.014	2.217	66.273	0.027	0.59	0.251	0.06	1.086
Problem oriented	1.078	0.306	1.773	75	0.076	0.473	0.263	-0.067	0.972

thinking									
Agile response thinking	0.806	0.372	2.79	75	0.018	0.617	0.23	0.175	1.058
Man-machine collaborative thinking	3.995	0.036	2.572	70.206	-0.001	0.599	0.236	0.129	1.075
Sustainable thinking	5.412	0.028	1.536	68.422	0.119	0.357	0.249	-0.115	0.899

6. Conclusion

To promote the integration of automation technology educational reform strategies with intelligent manufacturing models, this paper proposes an intelligent test paper generation method for automation technology examinations based on the differential evolution algorithm, and introduces an intelligent manufacturing teaching model that integrates automation technology educational reform strategies. The conclusions drawn in this paper are as follows:

In a comparative experiment of four algorithm-based paper-setting methods at the cognitive level, the scores under the RA algorithm and IGA algorithm were 15.06 and 15.32, respectively, while the algorithm proposed in this paper achieved a score of 15.75 in knowledge application. This demonstrates the superiority of the algorithm proposed in this paper.

Using 80 students from a certain school as the empirical research subjects for teaching tests, it was found that after adopting the teaching model proposed in this paper, the experimental class outperformed the control class in terms of thinking, with significant differences. The average scores in all computational thinking categories were higher than those of the control class, except for "problem-oriented thinking" and "sustainable thinking," where significant differences were observed in all other categories.

In summary, the improved differential algorithm demonstrates excellent global optimization capabilities when addressing exam questions, achieving high test paper quality and efficiency. The intelligent manufacturing teaching model proposed in this paper, which integrates automated technology reform strategies, enhances teaching effectiveness and promotes the integration of automated technology reform strategies with intelligent manufacturing models.

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