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Article

Optimization of environmental engineering practical teaching system based on cellular mechanics principles and construction of multi-dimensional evaluation model

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Abstract: In the realm of emerging engineering education, the practical teaching of environmental engineering majors cries out for reform and optimization, which can be analogized to the regulatory mechanisms within cellular molecular biomechanics. Cells maintain their functionality and adaptability through a complex network of molecular interactions and signaling pathways. Similarly, an effective practical teaching system must have a well-structured and optimized framework. This study aims to explore the reform of the practical teaching system for environmental engineering majors in the context of emerging engineering education. A multi-dimensional evaluation model was constructed based on the Analytic Hierarchy Process (AHP), and the heuristic algorithm was integrated for weight optimization. The results show that the Improved Genetic Particle Swarm Optimization (IG-PSO) exhibits significant advantages in optimizing the weights of various indicators. After optimization, its Consistency Ratio (CR) decreased to 0.07, representing a 53% and 46% improvement over Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), respectively. Additionally, the fitness value of IG-PSO after 800 iterations reached 0.046, significantly outperforming other comparative algorithms. Furthermore, the assessment of teaching effects in dimensions like experimental performance and innovation ability parallels the overall functionality and responsiveness of a cell. The IG-PSO-optimized evaluation system achieved an excellent score of over 90 in the assessment of actual teaching effectiveness across dimensions such as experimental performance and innovation ability. It shows that the teaching system is a healthy, well-regulated cell that can effectively perform its functions and adapt to different educational needs. Through the analogy with cellular molecular biomechanics, we can gain a deeper understanding of the improvement and optimization of the practical teaching system of environmental engineering, which is crucial for the cultivation of skilled professionals in this field.

Keywords: environmental engineering; practical teaching; reform exploration; genetic algorithm; cellular molecular biomechanics

1. Introduction

With the rapid advancement of global industrialization and urbanization, environmental issues have become increasingly prominent, underscoring the crucial role of environmental engineering majors in addressing environmental pollution and rational utilization of resources. In recent years, amidst technological advancements and industrial structural adjustments, the demand for environmental engineering talents has transcended mere theoretical knowledge and now necessitates robust practical operation skills and innovative thinking [1–3]. Consequently, the traditional teaching model has become inadequate in fulfilling the needs of modern environmental engineering talent cultivation, necessitating urgent reforms [4].

Against the backdrop of emerging engineering education, universities have gradually propelled reforms in the practical teaching of engineering disciplines, emphasizing the integration of practice and theory to enhance students' comprehensive qualities. The emerging engineering education concept aims to cultivate innovative engineering and technical talents for the industry by integrating interdisciplinary knowledge, industry-university collaboration, and project-based learning [5,6]. The teaching mode based on project learning (PBL) and industry-university-research cooperation has gradually become the mainstream. These reforms emphasize the deep integration of theory and practice, which not only improves students' hands-on skills, but also promotes the application of interdisciplinary knowledge. In addition, some universities have introduced virtual simulation technology to make up for the deficiency of actual experimental conditions by constructing virtual laboratories, thus improving the teaching effect. These measures provide a new path for the personnel training of environmental engineering major, and also provide a practical basis and theoretical basis for the evaluation system reform proposed in this study. Nevertheless, environmental engineering majors still confront numerous challenges in practical teaching. For instance, the practical teaching system's structure remains incomplete, and the evaluation index system lacks scientific basis, making it difficult to accurately gauge teaching effectiveness. Additionally, limited resources for industry-university collaboration leads to inadequate practical opportunities for students and suboptimal innovation capabilities cultivation.

Current research on practical teaching systems primarily focuses on teaching model innovations and individual curriculum reforms, yet there are still deficiencies in constructing multi-dimensional evaluation systems. Specifically, in terms of weight allocation and optimization of evaluation indicators, traditional methods fail to fully consider the complex teaching environment and lack effective optimization tools [7–9]. Therefore, it is imperative to explore optimization methods for evaluation systems based on advanced algorithms to enhance the scientificity and applicability of practical teaching, thereby driving comprehensive reforms and innovations in the practical teaching of environmental engineering majors.

2. Algorithm development: Construction of practical teaching evaluation system

2.1. Multi-dimensional evaluation model based on analytic hierarchy process (AHP)

The multi-dimensional evaluation model based on AHP provides a scientific basis for constructing the practical teaching evaluation system. In the practical teaching system of environmental engineering majors, the evaluation system should encompass multiple dimensions, ranging from teaching effectiveness, experimental facilities, to student competency development. By decomposing complex issues into multiple levels and indicators, AHP constructs a clearly structured and hierarchical evaluation system, thereby assisting decision-makers in systematically assessing the relative importance of various factors [10]. In evaluating practical teaching, the first step is to establish a reasonable indicator system. Based on the characteristics of environmental engineering practical teaching, the multi-dimensional evaluation indicator system developed in this study is divided into three tiers: the objective level, the criterion level, and the indicator level.

The objective level is set as “Practical Teaching Effectiveness of Environmental Engineering Majors” aiming to provide a comprehensive evaluation of the entire practical teaching system. The criterion level is further expanded into five dimensions: scientificity of teaching content (B1); advancement of experimental facilities (B2); cultivation of students’ practical abilities (B3); industry-university collaboration and resource sharing (B4); and transformation of teaching achievements and cultivation of innovation abilities (B5). When choosing the five dimensions of the criterion layer, the requirements of the practice teaching of environmental engineering are considered comprehensively. First of all, the scientific content of teaching (B1) and the advanced nature of experimental equipment (B2) are essential to ensure the teaching effect. Secondly, the cultivation of students’ practical ability (B3) is the core goal of talent training under the background of new engineering. School-enterprise cooperation and resource sharing (B4) can enhance the docking of teaching and industry needs and improve the utilization efficiency of teaching resources. Finally, the transformation of teaching results and the cultivation of innovative ability (B5) is not only an important evaluation index of practical teaching, but also a key aspect of measuring students’ innovative ability. Other potential dimensions such as management mechanisms and curriculum coordination were also considered, but after weight analysis and actual teaching needs assessment, they were not included in the final system due to their low impact.

The indicator level is refined into 13 specific evaluation indicators, covering aspects such as curriculum design, experimental teaching, resource allocation, and achievement application, as detailed in **Table 1**. The evaluation indicator system is structured around the five criterion levels. The scientificity of teaching content reflects the integration of theory and practice and the alignment of course content with practical needs, ensuring that teaching content closely matches professional requirements [11]. The advancement of experimental facilities assesses the quantity and applicability of experimental equipment to ensure the smooth implementation of the teaching process. The cultivation of students’ practical abilities focuses on enhancing students’ abilities in experimental operations and problem-solving. The dimension of industry-university collaboration and resource sharing evaluates the frequency of collaboration and resource utilization, highlighting the importance of integrating teaching with industry [12,13]. Lastly, the transformation of teaching achievements and cultivation of innovation abilities measures teaching effectiveness and students’ innovation capabilities through indicators such as the rate of scientific research achievement transformation and participation in innovative projects.

Table 1. Construction of the indicator level.

Criterion Level	Indicator Level
B1 Scientificity of Teaching Content	C1 Degree of Integration Between Theory and Practice
	C2 Alignment of Course Content with Actual Needs
B2 Advancement of Experimental Facilities	C3 Quantity of Experimental Equipment
	C4 Advancement and Applicability of Experimental Equipment
B3 Cultivation of Students' Practical Abilities	C5 Students' Experimental Operation Ability
	C6 Students' Problem-Solving Ability
B4 Industry-University Collaboration and Resource Sharing	C7 Frequency of Industry-University Collaboration
	C8 Efficiency of Utilizing Enterprise Resources
B5 Transformation of Teaching Achievements and Cultivation of Innovation Abilities	C9 Conversion Rate of Students' Scientific Research Achievements
	C10 Participation in Innovative Projects
	C11 Presentation and Evaluation of Innovation and Entrepreneurship Project Outcomes

After defining the evaluation index system, it is imperative to determine the weight of each index through the Analytic Hierarchy Process (AHP). The pivotal step in AHP involves constructing a judgment matrix, which serves to quantify the relative importance between different indicators. Assuming there are n indicators, denoted as A_n, then each element $A = (a_{ij})$ in the judgment matrix a_{ij} represents the relative importance of indicator A_i compared to A_j. These values are assigned using the 1–9 scale method, as exemplified in **Table 2**.

Table 2. Scale method for assigning values.

Ratio Value	Explanation
1	Two factors are equally important
3	One factor is slightly more important than the other
5	One factor is noticeably more important than the other
7	One factor is considerably more important than the other
9	One factor is extremely more important than the other
2, 4, 6, 8	Intermediate values between the above pairs

Subsequently, the weight calculation is performed, where the weight vector can be derived by normalizing the eigenvector of the judgment matrix. The judgment matrix A is normalized, and the sum of the ratios of each element is calculated to obtain the weight vector w. This is shown in Equation (1).

$$w_i = \frac{\sum_{j=1}^{n} a_{ij}}{n} \tag{1}$$

Then, a consistency check is conducted by calculating the consistency index CI and the consistency ratio CR, where CI is computed according to Equation (2).

$$CI = \frac{\lambda_{max}}{n-1} \tag{2}$$

where $\lambda_{\max}$ is the maximum eigenvalue of the judgment matrix, and n is the order of the matrix. Following this, the consistency ratio is calculated.

$$CR = \frac{CI}{RI} \tag{3}$$

where RI represents the random consistency index. When $CR < 0.1$, the judgment matrix is considered to have acceptable consistency. If this condition is not met, the judgment matrix needs to be adjusted accordingly.

In the process of constructing a multi-level indicator system, the dependency relationships between indicators at different levels are expressed through a hierarchical model. The construction of a practical teaching evaluation system can be divided into three layers: the goal layer, the criterion layer, and the indicator layer. In the Analytic Hierarchy Process (AHP), the goal layer is set as the overall evaluation objective for practical teaching in environmental engineering. The criterion layer is subdivided into multiple dimensions (e.g., teaching content, experimental equipment, student ability cultivation, etc.), and each criterion is further refined into multiple specific evaluation indicators (i.e., the indicator layer) [14,15]. Goal Layer: The overall evaluation objective, which is a comprehensive evaluation of the effectiveness of practical teaching in environmental engineering. Criterion Layer: Under the goal layer, the criterion layer defines multiple key factors that influence teaching effectiveness, including five dimensions: scientificity of teaching content, advancement of experimental equipment, cultivation of students' practical abilities, industry-university collaboration and resource sharing, and transformation of teaching achievements [16].

Indicator Layer: Each criterion is further refined into specific evaluation indicators. For example, the scientificity of teaching content includes the degree of integration between theory and practice and the alignment of course content with actual needs. The advancement of experimental equipment encompasses specific indicators such as the quantity, advancement, and applicability of experimental equipment. For each criterion layer and indicator layer, the determination of weights will be conducted through the previously mentioned construction of judgment matrices and weight calculations, ultimately yielding weight values for different dimensions and indicators [17].

2.2. Optimization model based on heuristic algorithm

Particle Swarm Optimization (PSO), as a global search algorithm rooted in swarm intelligence, is frequently employed to tackle optimization problems within multi-criteria decision-making systems. In the context of the practical teaching evaluation system, PSO can optimize the weights of evaluation indicators by simulating the information exchange and collaboration among swarm individuals, ultimately finding the optimal weight allocation scheme. The fundamental idea of PSO revolves around the search conducted by a swarm of particles in the solution space, gradually converging the weights of the evaluation system towards the global optimal solution.

Each particle in the solution space represents a potential solution, and the state of a particle is determined by its position $x_i$and velocity v_i. The update formulas of PSO are shown in Equation (4).

$$\begin{cases} v_i(t+1) = \omega \cdot v_i(t) + c_1 \cdot rand_1 \cdot (p_{best_i} - x_i(t)) + c_2 \cdot rand_2 \cdot (g_{best} - x_i(t)) \\ x_i(t+1) = x_i(t) + v_i(t+1) \end{cases} \quad (4)$$

where $v_i(t)$ represents the velocity of particle i at time t, $x_i(t)$ denotes the current position of particle i, p_{best_i} is the best historical position of particle i, g_{best} is the global best position, $rand_1$ and $rand_2$ are two random numbers, c_1 and c_2 are the cognitive and social learning factors respectively, and ω is the inertia weight, which controls the magnitude of velocity updates. Consequently, the process of applying PSO to optimize indicator weights is as follows:

(1) Initialize the particle swarm: Generate a set of particles with random weights and initialize the velocity of each particle.

(2) Iterative search: Update the velocity and position of each particle, and sequentially calculate the fitness of each particle.

(3) Update the optimal solutions: For each particle, compare the current solution with its historical best solution and update the historical best solution accordingly. Then, compare the historical best solutions of all particles to update the global best solution.

(4) Determine the termination condition: If the maximum number of iterations is reached or the precision requirement is met, stop the iteration; otherwise, continue updating the positions and velocities of the particles.

In this algorithm, the definition of the fitness function is the result of the consistency check of the indicator weights, with the objective of minimizing the Consistency Ratio $CR < 0.1$ to ensure that the optimized judgment matrix meets the consistency requirements.

Genetic Algorithm (GA), on the other hand, is an optimization algorithm based on natural selection and genetic mechanisms, commonly used to tackle complex optimization problems. The combination of GA and Analytic Hierarchy Process (AHP) can effectively address the issues of subjectivity and difficulty in consistency checking encountered in AHP. GA optimizes the weights of the initial judgment matrix through operations such as encoding, selection, crossover, and mutation, ultimately yielding a weight distribution scheme that meets the consistency requirements.

The steps for applying GA to optimize AHP are as follows:

(1) Encoding: Encode the upper triangular elements of the judgment matrix using real numbers, representing the initial value of each weight as a chromosome. For a matrix such as (5):

$$A = \begin{pmatrix} 1 a_{12} a_{13} \\ \frac{1}{a_{12}} 1 a_{23} \\ \frac{1}{a_{13}} \frac{1}{a_{23}} 1 \end{pmatrix} \quad (5)$$

The chromosome is represented as $[a_{12}, a_{13}, a_{23}]$.

(2) Fitness Function: The fitness function is defined as the reciprocal of the Consistency Ratio CR, with the objective of minimizing CR to enhance the optimization effect of the matrix. The formula for the fitness function is given in Equation (6).

$$f(x) = \frac{1}{1 + CR} \tag{6}$$

(3) Selection: Employ the Roulette Wheel Selection method, where chromosomes with higher fitness values are selected based on their fitness scores to proceed to the next generation.

(4) Crossover: Select two chromosomes to undergo the crossover operation, during which parts of their genes are exchanged to generate new chromosomes. The mathematical representation of the crossover operation is as follows: [Note: The specific mathematical formula for crossover would depend on the type of crossover used (e.g., single-point, multi-point, uniform, etc.), but generally, it involves selecting crossover points and exchanging the gene segments beyond those points between the two parent chromosomes.]

$$\begin{cases} C_1 = \alpha \cdot P_1 + (1 - \alpha) \cdot P_2 \\ C_2 = \alpha \cdot P_2 + (1 - \alpha) \cdot P_1 \end{cases} \tag{7}$$

where P_1 and P_2 are the parent chromosomes, C_1 and C_2 are the offspring chromosomes, and α is the crossover coefficient.

(5) Mutation: Randomly select a gene within a chromosome and apply a random mutation to it. The formula for the mutation operation is as follows:

$$x`_i = x_i + \Delta x \tag{8}$$

where Δx represents a randomly varying value.

(6) Termination Condition: The algorithm terminates and outputs the optimal solution when either the number of iterations reaches a predefined limit or the fitness value no longer improves significantly. To enhance optimization efficiency, the improved algorithm introduces an adaptive mechanism, which incorporates additional adjustment steps within the Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). These adjustments are designed to dynamically adapt the algorithm's behavior based on the progress of the optimization process, thereby potentially achieving faster convergence and better-quality solutions.

1) Improvement of PSO: In Particle Swarm Optimization (PSO), a dynamic inertia weight ω_w is introduced to enable the inertia weight to be adjusted dynamically based on the number of iterations. The update formula for the inertia weight is as follows:

$$\omega_w = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min})}{T} \cdot t \tag{9}$$

where ω_{max} and ω_{min} represent the maximum and minimum inertia weights, respectively, T is the maximum number of iterations, and t is the current number of iterations. This improvement allows the algorithm to maintain a larger search space initially and gradually converge towards the later stages.

2) In the Genetic Algorithm, the crossover probability P_c and mutation probability P_m are dynamically adjusted based on changes in fitness values. The formulas for dynamically adjusting PC and PM are as follows: Note: Specific formulas for the dynamic adjustment of PC and PM would depend on the chosen adaptation strategy, but generally, they involve comparing the fitness of individuals or the population as a whole and adjusting the probabilities accordingly to encourage exploration or exploitation.

$$\begin{cases} P_c = P_{c_{\min}} + \dfrac{P_{c_{\max}} - P_{c_{\min}}}{1 + \exp(-k(f(x) - f_{avg}))} \\ P_m = P_{m_{\min}} + \dfrac{P_{m_{\max}} - P_{m_{\min}}}{1 + \exp(-k(f(x) - f_{avg}))} \end{cases} \tag{10}$$

where f_{avg} represents the average fitness of the current population, and k is an adjustment factor.

3) Convergence Criterion: During the convergence process of the algorithm, an improved stopping condition is introduced. Specifically, when the change in fitness values across consecutive generations falls below a predefined threshold, the algorithm is considered to have converged, and the iterations are terminated early to reduce computational time.

Among them, Equation (4) describes the speed update of particles in PSO, which is adjusted in combination with individual optimal and global optimal positions to achieve a balance between global search and local search. Equation (6) defines the fitness function, whose goal is to minimize the consistency ratio and optimize the weight distribution of the evaluation system. Equations (7) and (8) are used for crossover and mutation operations in genetic algorithm, respectively, to ensure the diversity of solutions and global search ability.

In summary, heuristic algorithms enhance the applicability of the Analytic Hierarchy Process (AHP) in complex evaluation systems by dynamically adjusting and optimizing the search path. The combination of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) improves the model's global search capability and adaptability, thereby facilitating more effective and efficient decision-making processes. IG-PSO algorithm combines the advantages of genetic algorithm (GA) and particle swarm optimization (PSO) to achieve more efficient weight optimization. Specifically, GA is good at global search, and can explore diversity in the solution space through operations such as selection, crossover and mutation, and avoid falling into local optimality. However, the convergence rate of GA is relatively slow and the optimization efficiency is low. By simulating swarm intelligence, PSO achieves global convergence at a faster speed, but it is easy to fall into local optimal solution in complex search space. IG-PSO combines the global search capability of GA with the fast convergence characteristic of PSO: Firstly, GA is used to explore the solution space extensively in the initial stage, and then PSO is used to accelerate the convergence to the optimal solution in the later stage. In addition, dynamic adjustment of the inertia weight in PSO makes it have a larger exploration range in the initial stage of search, and gradually converge in the later stage, so as to improve the overall performance and optimization effect of the algorithm.

3. Experimental analysis

3.1. Experimental setup

In the process of experimental setup (**Table 3**), the sources of experimental data encompassed multiple teaching courses in environmental engineering, covering practical data such as student feedback, usage records of teaching equipment, and the translation of teaching outcomes under various instructional scenarios. The data collection period spanned an entire academic year, ensuring comprehensiveness and authenticity through real-time tracking of teaching effectiveness and regular sampling of student evaluations.

The experimental platform setup encompassed both hardware and software environments. On the hardware side, the experiments utilized Intel processors released in 2019 and related equipment, guaranteeing the efficiency and stability of the computational processes. The software environment was based on MATLAB and Python, with MATLAB utilized for the construction of the judgment matrix, weight calculation, and consistency checks within the Analytic Hierarchy Process (AHP) model, while the Python platform was responsible for the optimization implementation of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), as well as the processing and analysis of experimental data.

Table 3. Experimental setup environment.

Hardware and Software Environment	Configuration
Processor	Intel Core i7-9700K
Memory	32 GB DDR4 2666 MHz
Hard Disk	1TB NVMe SSD
Operating System	Windows 10 Pro 64-bit
Software Platform	MATLAB 2019b, Python 3.7
Development Tools	Jupyter Notebook, Visual Studio

3.2. Analysis of experimental results

In the experiments conducted to evaluate the effectiveness of various algorithms in optimizing index weights, the Analytic Hierarchy Process (AHP) was compared with three heuristic optimization algorithms: the standard Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and the Improved Genetic-Particle Swarm Optimization (IG-PSO) hybrid algorithm. The comparisons were made based on the Consistency Ratio (CR) and convergence speed during the weight optimization process.

Table 4 presents the comparative results of the optimization effects of the index weights. It can be observed that different algorithms exhibit significant differences in the optimization process. Initially, all algorithms had a CR value of 0.15, indicating a relatively poor consistency before optimization. After optimization, PSO reduced the

CR value to 0.09, representing a 40% improvement in consistency. In contrast, GA achieved even better optimization results, reducing the CR value to 0.08 and improving consistency by 46%. However, GA required a higher number of generations (60) to converge, resulting in an increased convergence time of 5.8 seconds, highlighting its disadvantage in terms of convergence speed. The improved algorithm, IG-PSO, demonstrated excellent performance in both optimization effect and efficiency, ultimately reducing the CR value to 0.07, representing a 53% improvement in consistency, significantly outperforming both PSO and GA. Furthermore, IG-PSO achieved convergence in just 38 generations, with a convergence time of 3.5 seconds, reducing the time by 6.7 seconds and 2.3 seconds respectively compared to PSO and GA. These results indicate that IG-PSO, by combining the strengths of GA and PSO, is able to optimize index weights with faster speed and better results. Overall, IG-PSO outperforms the standard PSO and GA algorithms in terms of consistency improvement, convergence speed, and time efficiency, particularly when dealing with complex multi-dimensional evaluation systems.

Table 4. Comparison of index weight optimization effects.

Algorithm	Initial CR Value	Optimized CR Value	Number of Generations to Convergence	Convergence Time (seconds)	Consistency Improvement Rate (%)
AHP	0.15	0.12	-	-	20
PSO	0.15	0.09	45	4.2	40
GA	0.15	0.08	60	5.8	46
IG-PSO	0.15	0.07	38	3.5	53

To further validate the performance of the improved genetic algorithm-particle swarm optimization hybrid (IGA-PSO), a comparative analysis was conducted with four other commonly used algorithms. In addition to Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), Simulated Annealing (SA), Differential Evolution (DE), and Artificial Bee Colony (ABC) were also included. The primary metric for performance comparison was the Fitness Value under different iteration numbers. **Figure 1** illustrates the fluctuations and final convergence effects of each algorithm across varying iteration counts.

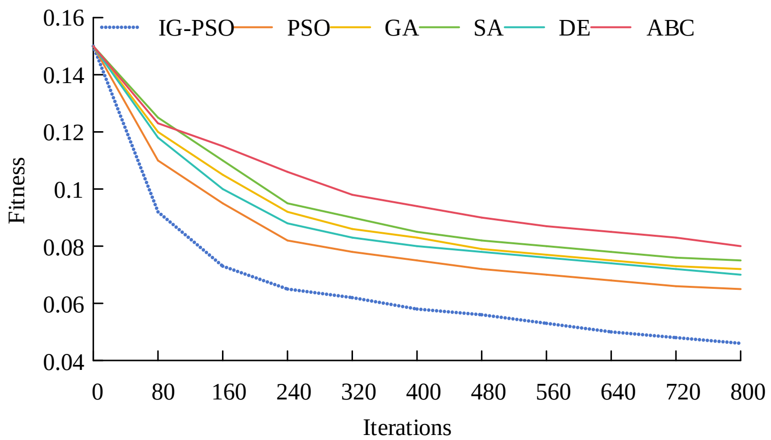

Figure 1. Comparison of performance among different algorithms.

In the initial iterations, the Fitness Value of IG-PSO rapidly declined to 0.092, significantly outperforming other algorithms, especially PSO and GA, which stood at 0.110 and 0.120, respectively. As the number of iterations increased, IG-PSO achieved 0.073 after 160 iterations, converging faster than PSO's 0.095 and GA's 0.105, demonstrating higher convergence efficiency. In the mid-to-late iterations, IG-PSO continued to lead, ultimately reaching a Fitness Value of 0.046 after 800 iterations, superior to PSO's 0.065 and GA's 0.072, as well as SA, DE, and ABC algorithms. Throughout all iteration stages, IG-PSO exhibited faster convergence speeds and better Fitness Values. By integrating the strengths of Genetic Algorithm and Particle Swarm Optimization, IG-PSO significantly enhanced search efficiency and global optimization capabilities, surpassing standard PSO, GA, and other comparative algorithms.

To validate the practical application effects of the evaluation system in teaching, a comparative experiment was conducted using teaching evaluation systems optimized by different algorithms. The experimental subjects were students from three different grades majoring in Environmental Engineering, and their practical teaching effectiveness was evaluated through an evaluation index system. Data sources encompassed four aspects: experimental performance, innovation ability, problem-solving ability, and cooperation ability. The practical application results are presented in **Table 5**. Although the IG-PSO optimized evaluation system has shown excellent results in experiments, it may face some challenges and limitations in the implementation of the system in actual teaching scenarios. First of all, there are great differences in teaching resources and practical conditions in different universities, especially the uneven availability of experimental equipment and school-enterprise cooperation opportunities, which may lead to great differences in the application effects of the evaluation system in different environments. Secondly, the implementation of the evaluation system needs a lot of data support, especially the performance evaluation of students in different practice links, and some universities may lack a long-term and systematic data collection mechanism. In addition, teachers' familiarity with the evaluation system and the subjective factors in the evaluation process may also affect the promotion effect of the system. Therefore, in the promotion and application, the specific conditions of each institution should be considered, and the evaluation model should be optimized through several iterations to ensure its adaptability and operability. Future studies can further explore how to adjust the weights of evaluation indicators to meet the needs of different teaching scenarios.

Table 5. Application effects in practical teaching.

Dimensions of Teaching Effectiveness	IG-PSO	PSO	GA	SA	DE
Experimental Performance	92.5	88.4	85.7	84.6	83.2
Innovation Ability	90.3	86	83.5	82.8	81.7
Problem-Solving Ability	91.8	87.5	84.9	84	83
Collaboration Ability	89.7	85.3	83.2	82.7	81.5
Comprehensive Score	91.1	86.8	84.3	83.5	82.4

4. Conclusion

In the context of emerging engineering education, the reform of the practical teaching system for environmental engineering majors aims to enhance teaching effectiveness and foster students' innovation capabilities, practical skills, and problem-solving abilities. Through the construction of a multi-dimensional evaluation model based on the Analytic Hierarchy Process (AHP), combined with Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for weight optimization, an Improved Genetic Algorithm-Particle Swarm Optimization Hybrid (IG-PSO) was proposed. Experimental results indicate that IG-PSO achieved the best optimization performance, reducing the consistency ratio to 0.046 after 800 iterations, significantly outperforming other algorithms. Simultaneously, the evaluation system optimized by IG-PSO demonstrated outstanding performance in practical teaching, with an experimental performance score of 92.5 and an innovation ability score of 90.3, both superior to those obtained by other comparative algorithms. Future research could extend the data samples through collaboration among multiple institutions to further validate the applicability and generalizability of the algorithm. The multidimensional evaluation model and optimization algorithm in this study are not only applicable to environmental engineering, but also can be extended to other engineering disciplines, such as mechanical engineering and civil engineering. By adjusting the weight of evaluation index and optimization algorithm, the practical teaching evaluation effect of each subject can be effectively improved, and the teaching reform and innovation ability cultivation can be promoted.

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