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Article

Research on the Optimization Scheme of Intelligent Algorithms in the Improvement of Cyber Attack and Defense Ability of Students in Applied Colleges and Universities

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Abstract: Enhancing students' cyber defense capabilities is a crucial measure to help them maintain their ability to identify threats and protect their legitimate rights and interests. In light of this, this study integrates and analyzes the influencing factors of cyber defense capability cultivation among students in applied universities, employs the entropy weight method to rank and combine these factors based on their importance, and optimizes the optimal combination tailored to students' individual circumstances. A two-level fuzzy comprehensive evaluation system is established to assess students' cyber defense capabilities. An improved particle swarm optimization algorithm is employed to solve the optimization model, followed by numerical simulation experiments. Experimental results indicate that compared to other improved multi-objective algorithms, the proposed algorithm demonstrates excellent convergence and diversity, and effectively achieves the enhancement of cyber defense capabilities based on this algorithm. Based on the actual assessment and feedback of this method from a certain applied university, measures to enhance network defense capabilities are proposed, namely, ensuring the effectiveness of network security ideological and political management through institutional safeguards, publicity and education, technical support, security management assessments, and the cultivation of high-quality management teams.

Keywords: fuzzy comprehensive evaluation method; entropy weight method; multi-objective particle swarm optimization algorithm; network defense capabilities

1. Introduction

With the rapid development of massive information on the internet, information technology has also grown at an unprecedented pace, offering new service models for the education of university students [1]. However, students often struggle to navigate the vast sea of information and data to selectively choose the information they need based on their individual requirements. In the teaching process of higher education institutions, numerous issues arise, such as students failing to grasp concepts, leading to diminished interest in learning, or teachers adopting a “come-and-go” teaching style that results in insufficient communication between teachers and students, and teachers being unable to promptly track students' learning progress. These issues significantly impair teaching effectiveness [2-3]. The traditional teacher-centered educational model is no longer sufficient to stimulate students' enthusiasm for learning or their proactive engagement in the learning process. During their on-campus learning process, students leave a large amount of learning traces in activities such as MOOCs, library book borrowing, and browsing campus websites [4-5]. Utilizing students' learning traces, analyzing their interest and preference data through intelligent algorithms, and developing a personalized course system to dynamically adjust training plans and improve higher education institutions' capability development mechanisms have become urgent issues to address [6-8].

Personalized recommendation services have effectively addressed users' “information overload” challenges to a certain extent, significantly improving learning efficiency and playing a positive role in students' skill development. The research results in [9] indicate that the proposed recommendation scheme can provide students with learning resources that match their abilities, while also controlling the difficulty level of learning resources within students' capabilities and offering appropriate resources to stimulate their potential. The personalized learning resource recommendation system constructed in [10] achieved an average relevance score of 4.41 for the recommended resources, meeting students' actual needs. Under the personalized teaching model, each student's academic performance improved by 10% to 20%. Literature [11] designed a personalized recommendation algorithm for online learning resources targeting college students' innovation and entrepreneurship. The collected learning behavior data was used to extract students' learning preferences. This method achieved a high recommendation accuracy rate and provided reliable recommendation results for students, thereby enhancing their employment capabilities. Literature [12] pointed out that applying the ELO algorithm to a tourism platform can accurately match tourism needs, making the platform more competitive while also fostering students' innovative capabilities and entrepreneurial practices. Literature [13] proposed an industry-education integration English reading teaching approach to enhance students' interest in English, utilizing new media for reading training while combining machine learning for reading resource recommendations. This method not only enhances students' interest in English learning but also cultivates their innovative thinking abilities.

Additionally, as data volumes continue to expand, the algorithms relied upon by personalized recommendation systems face ongoing demands for updates and upgrades. By improving existing algorithms, it is possible to better capture user preferences, enhance recommendation accuracy, and achieve real-time delivery of personalized content [14-15]. Literature [16] constructed a personalized education system based on internet technology and utilized intelligent algorithms to increase the system's personalized recommendation accuracy rate from 70.35% to 75.68%. Test results indicated that the intelligent algorithm-based personalized education system improved students' academic performance and enhanced the overall performance of the class. Literature [17] analyzed the optimization efficiency of four multi-objective evolutionary algorithms: NSGAII, IBEA, PESA2, and SPEA2. Experimental results confirmed the effectiveness of the NSGAII algorithm in extracting suitable personalized rules for course adaptation, achieving a learning resource recommendation accuracy rate of 93% for the personalized model.

As evident from the above literature, artificial intelligence has enriched educational content, customized it according to individual needs, and provided warnings about anticipated learning difficulties. Personalized education has redefined the role of teachers and optimized the teaching environment to enhance the learning experience [18].

The article first uses the entropy weight method to analyze the relative proportions of various influencing factors on the improvement of network attack and defense capabilities among students at applied universities. Based on the analysis results, a multi-objective optimization model for enhancing students' network attack and defense capabilities at applied universities is constructed, and a two-level fuzzy comprehensive evaluation system is established. Subsequently, a dual-population collaborative multi-objective particle swarm optimization algorithm is proposed to solve this optimization model. This algorithm expands the search space and enhances the algorithm's global search capability through a dual-population collaborative evolution strategy, while incorporating Lévy flight to ensure population diversity and improve algorithm convergence efficiency. Finally, comparative experiments were conducted with several improved algorithms on multi-objective and high-dimensional multi-objective test problems. Based on actual evaluations and feedback from students and relevant experts at a certain applied university, measures to ensure the construction of a cybersecurity ideological and political management mechanism were proposed.

2. Model for improving the cyber defense capabilities of college students

2.1. Sample Acquisition and Weight Analysis

2.1.1. Sample sources

A survey questionnaire was administered to students at applied universities to collect data. The factors influencing the improvement of students' cyber defense capabilities were categorized into five major categories: personal factors, family factors, school factors, mentor factors, and social factors. These categories correspond to the following questions in the questionnaire: Questions (1–9), Questions (10–18), Questions (19–27), Questions (28–36), and Questions (37–45). The aforementioned five influencing factors were defined as first-level indicators, with the corresponding questions under each first-level indicator serving as second-level indicators. The scores assigned by each respondent to the questions corresponding to the five factors were statistically analyzed and summed to obtain the total score for each factor.

2.1.2. Analysis of the weights of primary indicators

Based on specific samples, the entropy weight method was used to determine the weights of each indicator. By combining the survey samples, the weights of each factor on the microenvironment for building college students' network attack and defense capabilities were compared.

The specific weight comparisons for each factor are shown in Figure 1. The weight calculation results of the entropy weighting method indicate that the weights for personal factors, family factors, school factors, mentor factors, and social factors are 21.054%, 15.379%, 37.821%, 15.738%, and 10.008%, respectively. From these results, we can conclude that school factors are the most important factor in enhancing the network defense capabilities of applied university students. The level of the school, its resources, and the campus atmosphere have a subtle yet significant influence on the enhancement of students' network defense capabilities at applied universities. Personal factors and family factors also account for a relatively high proportion.

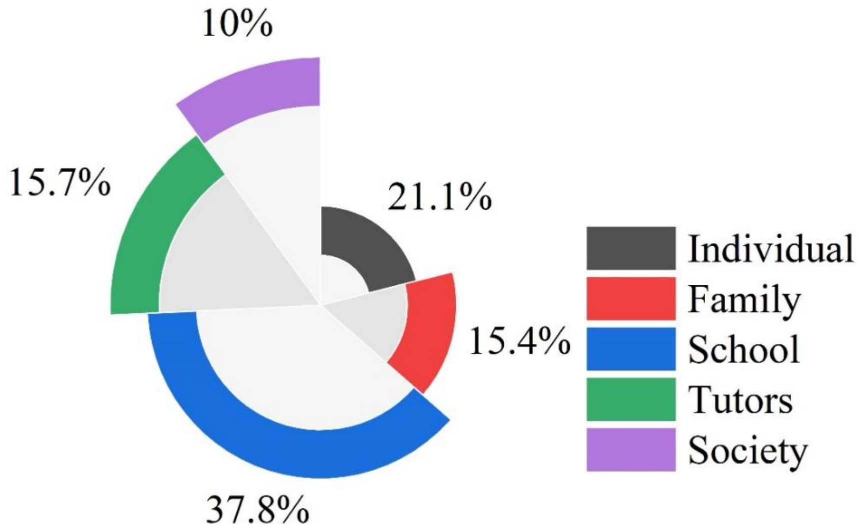


Figure 1. The specific weights of each factor are compared.

2.2. Model Construction

The entropy weight method can determine the weights of each indicator, but since the process of establishing an environment for improving students' network attack and defense capabilities is relatively complex and specific, the model must comprehensively consider the influence of external factors and students' own qualities, and meet multiple optimization objectives. First, consider the influence of external factors. Apply the entropy weighting method to calculate the weights of the secondary indicators in the sample, and combine them with the weights of the primary indicators to establish a multi-objective optimization model for various influencing factors. Take the improvement of students' network attack and defense capabilities as the dependent variable, and the influencing factors as the independent variables to construct a multi-objective optimization model for the improvement of students' network attack and defense capabilities:

$$
\begin{cases}
Y_j = w_{9(j-1)} + w_{9j-8} + \dots w_{9j} \\
Z_j = x_{9(j-1)} + x_{9j-8} + \dots x_{9j} \\
T_j = Y_j Z_j - W_j \times 36 \\
F(x_1, x_2, \dots\dots x_{45}) = \sum_{i=1}^{45} (x_i \times w_i) \\
s_2 \geq F(x_1, x_2, \dots\dots, x_{45}) \geq s_1 \\
1 \leq s_i \leq 5 \\
\sum_{i=1}^{i=45} w_i = 1
\end{cases} \tag{1}
$$

In Equation (1), Y represents the sum of the weights of the secondary indicators corresponding to each primary indicator. W represents the weights of the primary indicators that have been calculated. F represents the total score. w_i represents the weight of the i th indicator. x_i represents the score of the i th indicator. i represents the sequence number of the secondary indicator. j represents the sequence number of the primary indicator. Z represents the sum of the scores of the secondary indicators corresponding to each primary indicator. T represents the difference between the optimized weighted total score of each primary indicator and the previously calculated weighted total score of the primary indicators.

The total score is directly proportional to the quality of improvement in students' network attack and defense capabilities. In the survey questionnaire, the evaluation scores for each secondary indicator are divided into 1–5 points, representing “very unsatisfactory,” “somewhat unsatisfactory,” “unsure,” “somewhat satisfactory,” and “very satisfactory,” respectively. The quality of innovative talent cultivation is also divided into five levels from 1 to 5. Additionally, during the model solution process, it is assumed that $S_1 = 3$ and $S_2 = 4$, meaning that the quality of innovative talent cultivation is rated between 3 and 4, with solutions closer to 4 being better. This is optimization objective one.

If the scores for all secondary indicators are 4, then under the condition that each primary indicator covers 9 secondary indicators, the total score for each primary indicator is 36, and it is not affected by the weights. Therefore, in the above difference equation τ, the original total score for each primary indicator is set to 36, and on this basis, the optimization objective is to minimize the difference T between the weighted total score of the optimized primary indicators and the weighted total score of the primary indicators obtained above. This is optimization objective two.

Second, establish a secondary fuzzy comprehensive evaluation system to assess the improvement of students' network attack and defense capabilities. The specific steps are as follows:

Step 1: Establish a factor set for comprehensive evaluation

The factor set is the collection of all factors influencing the evaluation object, typically denoted as U, where $U = \{u_1, u_2, \cdots, u_n\}$. The factors influencing students' network attack and defense capabilities are divided into two levels from outer to inner, as shown in Table 1.

Table 1. Set of factors for innovative development.

Primary indicator	Secondary indicator
Technical ability	Knowledge of basic network
	Estimation tools and technical proficiency
	Vulnerability detection and analysis ability
Practical experience	Combat frequency
	Diversity of scene exposure
	Emergency response and resistance
Thinking pattern	Attacker thinking
	Innovation and breakthrough ability
	Risk assessment and decision making

Ethical law	Legal meaning and compliance
	Attack behavior and self-discipline

Step 2: Establish a comprehensive evaluation set

The evaluation set is a collection of evaluation results, denoted by V, where $V=\{v_1, v_2, \cdots, v_m\}$. Based on the actual situation, the evaluation set for the improvement of students' network attack and defense capabilities based on the survey questionnaire samples is: $V=\{\text{Excellent}v_1, \text{Good}v_2, \text{Medium}v_3, \text{Poor}v_4, \text{Very bad}v_5\}$

Step 3: Determine the weights of each factor

Using the results of the entropy weight method, compare to obtain the weight matrices for the four primary factors. Similarly, obtain the weight matrices for the secondary factors relative to their respective primary factors.

Step 4: Determine the single-factor fuzzy evaluation matrix

Fuzzy statistical methods are used to determine membership functions based on the results of the questionnaire survey. Membership degrees are defined using membership frequencies. After organizing and statistically analyzing the results, the single-factor fuzzy evaluation matrix is obtained:

Based on the fuzzy evaluation matrix, the fuzzy transformation yields $B=A\cdot R=[b_1, b_2, b_3, b_4, b_5]$. After normalizing B, we obtain $B^{'}=\left[\frac{b_1}{b}, \frac{b_2}{b}, \frac{b_3}{b}, \frac{b_4}{b}, \frac{b_5}{b}\right]$, where $b=\sum_{i=1}^{5} b_i$. Based on this, the comprehensive evaluation value can be calculated.

2.3. Dual-Population Cooperative Multi-Objective Particle Swarm Optimization Algorithm

2.3.1. Basic Particle Swarm Optimization Algorithm

The Particle Swarm Optimization (PSO) algorithm is widely used in many optimization problems due to its ease of implementation and simple parameters. Let the search space be D and the number of particles be N. The position of the i th particle is represented as $X_i=(x_{i1}, x_{i2}, \cdots, x_{i0})$ and the historical optimal position of the i th particle during flight is represented as $P_i=(p_{i1}, p_{i2}, \cdots, p_{iD})$ Let P_g be the optimal value of all $P_i(i=1,2,\cdots,n)$ [19], and the velocity of the i th particle is $V_i=(v_{i1}, v_{i2}, \cdots, v_{iD})$ The position-velocity update formula for each particle is:

$$V_{id}^{k}=WV_{id}^{k}+c_1 rand()(p_{id}^{k}-x_{id}^{k})+c_2 rand()(p_{gd}^{k}-x_{id}^{k}) \tag{2}$$

$$x_{id}^{k+1}=x_{id}^{k}+v_{id}^{k+1}, \quad 1<i<N, \quad 1<d<D \tag{3}$$

Where: c_1 and c_2 are acceleration factors. k is the current iteration count. rand() is a random number between [0, 1]. W is the inertia factor.

2.3.2. Dual-population cooperative multi-objective particle swarm optimization algorithm

To maintain particle diversity and enable the particle swarm to evolve in a better direction, this paper introduces a Lévy flight update strategy when updating the positions of particles.

(1) Main particle swarm evolution method

Particle swarm optimization algorithms are prone to getting stuck in local optima in the later stages and experiencing a reduction in population diversity. To expand the diversity of the particle swarm and improve the convergence accuracy of the algorithm, this paper combines Lévy flight with the particle swarm algorithm. Lévy flight is a non-Gaussian stochastic process that updates particle states by changing particle positions. In the improved particle swarm position update formula, the position for the next generation is determined by both the current position and the transition probability. Although Lévy flight can enhance the diversity of the particle swarm and expand the search range, it cannot guarantee that the new solutions found are necessarily better than the original solutions. Therefore, this paper adopts a greedy update evaluation strategy to calculate the fitness of particles after updating their positions based on Lévy flight. If the updated solution is better than the original solution, it is retained.

The position update formula is:

$$x=\begin{cases}x_{id}^{k}+a\oplus Levy(\beta) & fit(x_{id}^{k+1})>fit(x_{id}^{k+1})\\ x_{id}^{k}+v_{id}^{k} & fit(x_{id}^{k+1})<fit(x_{id}^{k+1})\end{cases}\tag{4}$$

Where: $a=a_0(x_{id}-p_{sl})$ represents the step size information, which is used to control the range of random search, and a_0 is a constant ($a_0=0.01$). x_{id} represents the current particle position [20]. v_{id} represents the current particle velocity. $\oplus$ denotes the dot product. Lévy $(\beta)\sim|x|^{(-1-\beta)}$ $(0<\beta<2)$.

This paper uses the fitness variance of particles in the iteration to determine whether they have fallen into a local optimum. Assuming that the main particle swarm has iterated t times, calculate the fitness variance of each particle in the main particle swarm:

$$\overline{x}=\frac{x_{i1}+x_{i2}+\cdots+x_{it}}{t},\quad t\in\{1,2,\cdots,F\}\tag{5}$$

$$D_i=\frac{(x_{i1}-\overline{x_i})^2+(x_{i2}-\overline{x_i})^2+\cdots+(x_i-\overline{x_i})^2}{t}\tag{6}$$

Where: x_i denotes the mean fitness value of the i th particle after t iterations. D_i denotes the variance of the i th particle. F denotes the number of non-dominated solutions in the main particle swarm. A smaller variance indicates smaller changes in fitness values during iteration, making it more likely to get stuck in a local optimum. The cloud model algorithm can enhance the global search capability of the particle swarm algorithm, so the normal cloud model algorithm is adopted to update individuals in the main particle swarm during the later stages of iteration. The cloud model algorithm is represented by three metrics: Ex, En, He , where: Ex denotes the center of the newly generated individuals. En denotes the range of evolutionary variation for individuals, with the current fitness variance σ^2 serving as the dynamic search range for En . He denotes evolutionary hyperentropy, indicating the stability range of evolutionary variation for individuals; the larger He is, the greater the uncertainty. Let $\frac{En}{5}=He$, and generate a set of cloud droplets equal in number to the space. If the new solution is better than the original individual, it is used to replace it.

(2) Sub-particle group evolution method

The evolutionary method for individuals in the sub-particle swarm first adopts the standard particle swarm evolutionary method. When the updated individual is inferior to the original individual, a chaotic mapping is used to increase the diversity of the sub-particle swarm, enabling the sub-particle swarm to obtain more potential optimal solutions during the optimization process. This paper applies a k -order Chebyshev chaotic mapping to map individuals. It is proven that when the number of individuals is even, the randomness of the generated sequence is better. In the experiment, $k=4$ is selected to update individuals in the sub-particle group, and the individual update method is as follows:

$$x^{'}=WV_{id}^{k}+c_1\,\mathrm{rand}()(p_{sd}^{k}-x_{id}^{k})+c_2\,\mathrm{rand}()(p_{sd}^{k}-x_{id}^{k})\tag{7}$$

$$x^{'}=\cos(k\arccos x),\quad k\geq 2\tag{8}$$

After updating the individuals in the particle swarm, the Pareto non-dominated relationship is used to select the non-dominated solution sets from the main particle swarm and the sub-particle swarm. When there are equal non-dominated solutions in both particle swarms, this represents the optimized result value. If there are no equal solutions, the evaluation criteria are used to assess the quality of the solutions.

(3) Algorithm Flowchart

The flowchart of the dual-population collaborative multi-objective particle swarm optimization algorithm is illustrated using two objective functions (maximization (F_1, F_2)) as an example. The flowchart of the dual-population collaborative multi-objective particle swarm optimization algorithm is shown in Figure 2.

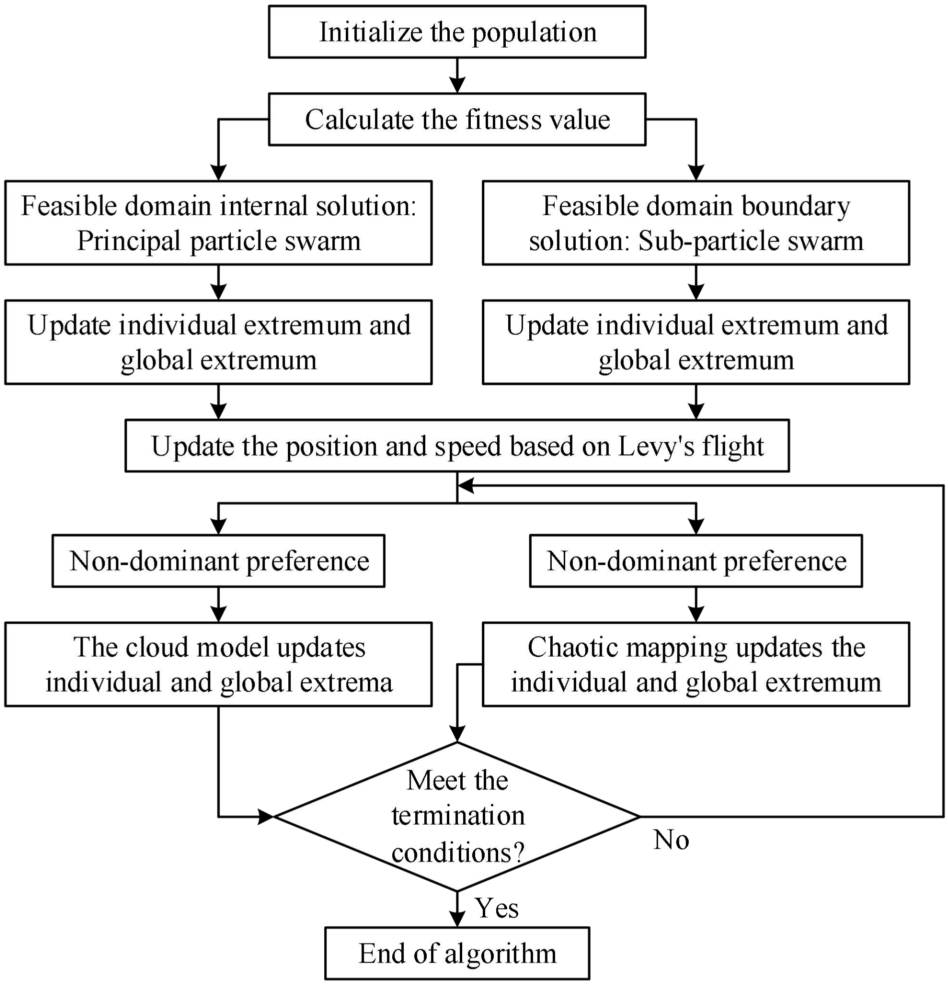


Figure 2. The optimization algorithm process of the multi-target particle swarm.

The steps of the two-population cooperative multi-objective particle swarm optimization algorithm are as follows:

1) Initialize the various parameters of the particle swarm algorithm and generate the main particle swarm and the sub-particle swarm.

2) Calculate the fitness value of each particle and select the local extrema and global extrema of the two populations based on the fitness values.

3) Update the velocity and position of the particle swarm using Equations (3) and (5).

4) Evaluate the variance results of the main particle swarm. If there is a possibility of getting stuck in a local optimum, update the individuals using the cloud model algorithm. For the sub-particle swarm, update the individuals using the k -order Chebyshev chaotic mapping.

5) Calculate the fitness values of the individuals. When the Pareto solution set exceeds the upper limit, the main particle swarm and the sub-particle swarm use the Pareto non-domination relationship to select excellent individuals. If the two particle swarms have equal non-dominated solutions, that solution is the optimized result value. If there are no equal non-dominated solutions, the evaluation criteria are used to evaluate the quality of the solutions and obtain the optimized result value.

6) Determine whether the iteration termination condition is met. If not, repeat steps 3) to 5). If met, terminate the algorithm.

3. Experiments and analysis of results

3.1. Experimental testing of improved particle swarm algorithm performance

3.1.1. Experimental setup

To evaluate the performance of the algorithm proposed in this paper, simulation experiments were conducted on six benchmark problems: DTLZ1 to DTLZ5 and WFG9, each with three objectives. The multi-objective optimization algorithms compared include: Non-Dominated Sorting Genetic Algorithm

(NSGA-II), Multi-Objective Evolutionary Algorithm based on Decomposition with Covariance Adaptive Evolutionary Mechanism (MOE-ADCMA), Cluster-Based Adaptive Multi-Objective Evolutionary Algorithm (CAMOEA), Multi-Search Strategy Multi-Objective Particle Swarm Optimization (MMOPSO), and Competition Mechanism-Based Multi-Objective Particle Swarm Optimization Algorithm (CMOPSO). The population size for all six algorithms was set to 100.

To further evaluate the performance of the proposed algorithm in handling MOPs, it was compared with four high-dimensional multi-objective algorithms on test problems with 5, 10, and 15 objective functions. The compared algorithms include: the Non-Dominated Sorting Genetic Algorithm (NSGA-III) based on reference points, the Evolutionary Algorithm (RSEA) based on radial space partitioning, the novel Multi-Objective Particle Swarm Algorithm (novelMOPSO, NMPSO), and the Reference Vector-Guided Evolutionary Algorithm (RVEA). For objective dimensions of 5, 10, and 15, the population sizes for the five algorithms were set to 126, 230, and 240, respectively. To make the algorithms applicable to scalable multi-objective test problems, the density metric used in this study was replaced with a diversity estimation metric based on transfer in this experiment.

In the test experiments, the decision variable dimension of DTLZ1 was set according to the objective dimension. The decision variable dimensions of the remaining test functions were set as follows. In all algorithms, the external archive set size was equal to the population size, with a maximum iteration count of 1,000. Each algorithm was independently run 30 times on each test problem. To ensure fair comparison, the other parameter settings of the comparison algorithms were referenced from the original literature. The algorithm was run on a Windows 10 operating system, Intel Core i7-9700K CPU, 64 GB memory, and MATLAB 2016a. The source code for the comparison algorithms was provided by PlatEMO.

3.1.2. Analysis of experimental results

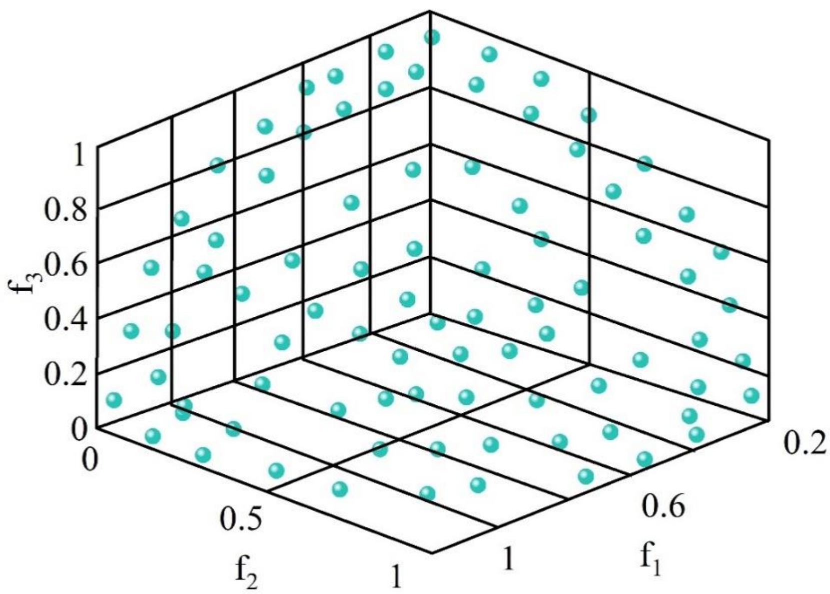
IGDHV employs the inverse generation distance and hypervolume metrics to quantitatively evaluate the performance of multi-objective optimization algorithms. The Wilcoxon signed-rank test is used to perform significance analysis on the experimental results. The mean and standard deviation of multiple independent replicate test results are adopted as the evaluation criteria for the algorithms. All evaluation metric values are expressed as "mean (standard deviation)." Bold text indicates that the algorithm in the corresponding row has the best evaluation metric value for the test problem in the corresponding column. "+", "-", and "=" indicate that, under a Wilcoxon two-tailed test with a significance level of 0.05, the metric values obtained by the algorithm in this paper are significantly better than, significantly worse than, or approximately equal to those of the algorithm in the corresponding column, respectively.

The IGD results obtained for different test problems are shown in Table 2. The Pareto frontier diagrams for each algorithm on selected test problems are shown in Figure 3 (Figures a–c represent the Pareto frontier diagrams for the proposed method on the DTLZ3, DTLZ5, and WFG9 test problems, respectively). As shown in Table 2, the proposed method achieves 9 optimal IGD values and 1 suboptimal value across the 6 test problems. MOEADCMA achieves 1 optimal IGD value. On the DTLZ2 test problem, the proposed method is slightly inferior to MOEADCMA but superior to the other four algorithms. As shown in the figure, on the DTLZ3 (multi-modal PF) problem, the proposed method achieves a relatively uniform PF distribution, maintaining good diversity and convergence. On the DTLZ5 (multi-peak PF) problem, the proposed method demonstrates the best overall performance. In the WFG9 (non-decomposable PF) problem, the proposed method achieves the best overall performance. This demonstrates that the proposed method can achieve good overall performance when handling different complex multi-objective problems. The reason is that the proposed method adopts different search strategies for particles with different roles, enabling the population to search both around the optimal particles and across the entire objective space. The role partitioning metric used in this study effectively avoids the influence of extreme points on the algorithm, ensuring its convergence and diversity. Therefore, from the results, the proposed method can handle different MOPs problems. In the six test problems, the proposed method exhibits a better average IGD than other algorithms, demonstrating superior convergence and distribution.

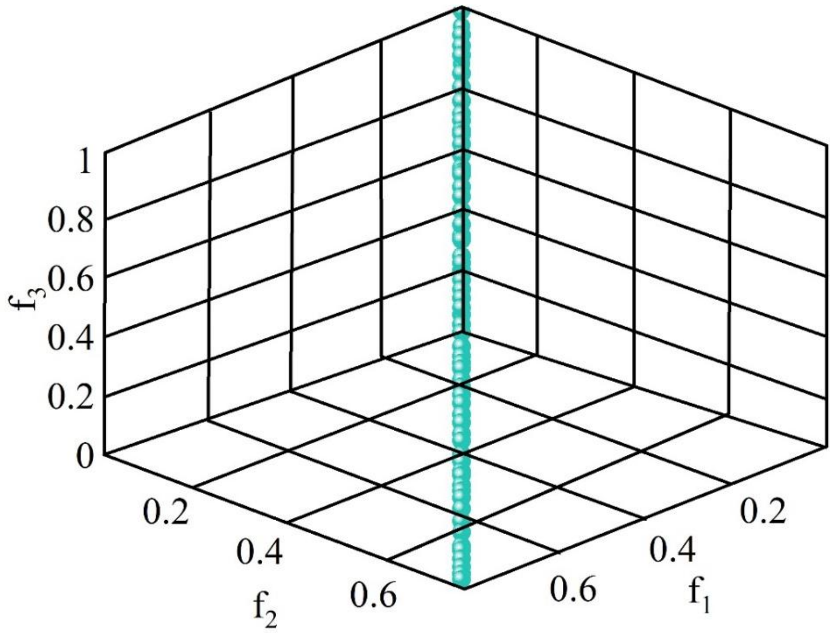
Table 2. IGD results from different test problems.

Test problem	MOEADCMA	CAMOEA	NSGAII	MMOPSO	CMOPSO	Ours
DTLZ1	1.986×10^{-2}	2.267×10^{-2}	2.7349×10^{-2}	1.1981×10^{-1}	7.849×10^{-1}	2.011×10^{-2}
DTLZ2	5.4117×10^{-2}	5.7829×10^{-2}	6.8154×10^{-2}	7.0645×10^{-2}	5.8689×10^{-2}	5.6503×10^{-2}
DTLZ3	$1.9955\times10^{+0}$	5.8362×10^{-2}	6.858×10^{-2}	2.2842×10^{-1}	$3.748\times10^{+1}$	5.3016×10^{-2}
DTLZ4	9.5922×10^{-2}	5.5673×10^{-2}	9.6155×10^{-2}	7.2253×10^{-2}	5.9863×10^{-2}	5.6645×10^{-1}

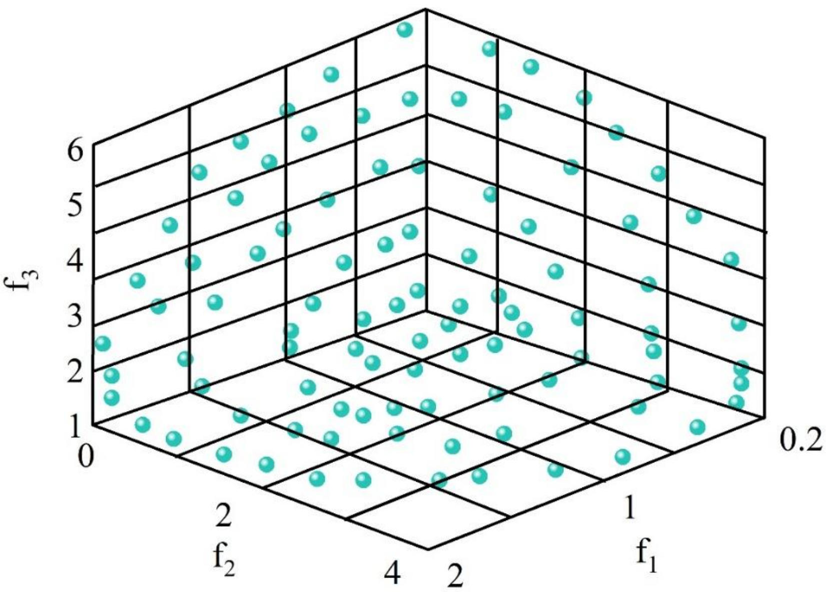
DTLZ5	2.3422×10^{-2}	5.0968×10^{-3}	5.7248×10^{-3}	6.4873×10^{-3}	6.1311×10^{-3}	4.2197×10^{-1}
WFG9	3.1833×10^{-1}	2.4501×10^{-1}	2.8118×10^{-1}	2.8582×10^{-2}	2.1452×10^{-3}	2.0784×10^{-1}
+/−/=	1/9/0	0/9/1	0/10/0	0/10/0	0/9/1	



(a) DTLZ3-Ours



(b) DTLZ5-Ours



(c) WFG9-Ours

Figure 3. Pareto front of some test problems.

The HV results obtained from different test problems are shown in Table 3. As can be seen from the table, the method proposed in this paper obtained three optimal values in six test problems. CAMOEA obtained one optimal value, CMOPSO obtained one optimal value, and MOEAD-CMA obtained one optimal value. On the WFG9 test problem, the metric values of the proposed method are similar to those of CAMOEA. On the DTLZ2 multi-peak function test problem, although the proposed method does not perform as well as CMOPSO, its mean value is also relatively large, outperforming the other four algorithms. This validates the effectiveness of the method proposed in this study. Ordinary particles and follower particles enhance their search capabilities through significant mutation. Elite particles undergo smaller variations to minimize disturbances to their search behavior, facilitating the attainment of global optimal solutions. The algorithm proposed in this study achieves optimal values on the complex test problems of the multi-peak function DTLZ5 and the biased function DTLZ4. On the other four test problems, the mean values of the proposed method outperform those of other algorithms, demonstrating superior overall performance.

Table 3. HV results from different test problems.

Test problem	MOEADCMA	CAMOEA	NSGAII	MMOPSO	CMOPSO	Ours
DTLZ1	8.4111×10^{-1}	8.4051×10^{-1}	8.0789×10^{-1}	6.8816×10^{-1}	3.5888×10^{-1}	8.538×10^{-1}
DTLZ2	5.6342×10^{-1}	5.588×10^{-1}	5.3794×10^{-1}	5.2305×10^{-1}	5.5838×10^{-1}	5.5349×10^{-1}
DTLZ3	3.5758×10^{-1}	5.2396×10^{-1}	5.1232×10^{-1}	4.5562×10^{-1}	$0\times10^{+0}$	5.4707×10^{-1}
DTLZ4	5.6033×10^{-1}	5.444×10^{-1}	5.2503×10^{-1}	5.4196×10^{-1}	5.4661×10^{-1}	5.4676×10^{-1}
DTLZ5	1.9755×10^{-1}	2.0078×10^{-1}	1.9584×10^{-1}	2.1683×10^{-1}	2.0689×10^{-1}	1.9827×10^{-1}
WFG9	4.5806×10^{-1}	5.1448×10^{-1}	4.9872×10^{-1}	5.1155×10^{-1}	5.1781×10^{-1}	5.0919×10^{-1}
+/−/=	1/10/0	3/6/2	0/10/0	0/10/0	2/8/1	

The IGD metric results on the test functions with 5, 10, and 15 objectives are shown in Table 4. As can be seen from the table, the proposed method achieved 4 optimal values on 9 test problems, while NSGA-III achieved 1 optimal value. This indicates that the proposed algorithm has certain advantages in handling high-dimensional multi-objective problems. As the number of objectives increases, the values obtained by each algorithm show an upward trend, and the optimization difficulty also gradually increases. Although the proposed algorithm is designed for multi-objective optimization problems with 2 or 3 objective dimensions, compared to other high-dimensional multi-objective algorithms, the proposed method demonstrates better overall performance on some problems as the number of objectives increases, showcasing its potential for handling high-dimensional multi-objective problems. This suggests that using different search strategies for particles with different performance characteristics can aid in addressing high-dimensional multi-objective problems.

Table 4. IGD results in the test function.

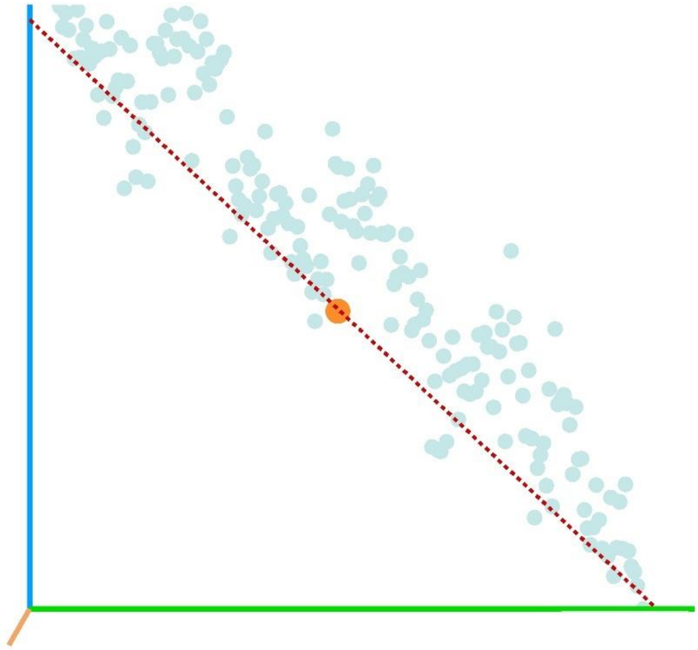
Test problem	Target number	NSGA-III	RSEA	RVEA	NMPSO	Ours
DTLZ1	5	6.1376×10^{-2}	7.5658×10^{-2}	6.1711×10^{-2}	6.4966×10^{-2}	5.8412×10^{-2}
	10	1.3975×10^{-1}	1.6507×10^{-1}	1.3591×10^{-1}	1.6912×10^{-1}	1.0827×10^{-1}
	15	1.821×10^{-1}	1.857×10^{-1}	1.3233×10^{-1}	$1.0594\times10^{+0}$	1.4414×10^{-1}
DTLZ2	5	2.0057×10^{-1}	2.4513×10^{-1}	1.8343×10^{-1}	2.0828×10^{-1}	2.0421×10^{-1}
	10	4.8088×10^{-1}	5.4706×10^{-1}	4.5492×10^{-1}	4.2089×10^{-1}	4.062×10^{-1}
	15	6.7926×10^{-1}	6.8362×10^{-1}	5.36×10^{-1}	6.6867×10^{-1}	5.4171×10^{-1}
WFG9	5	$1.1897\times10^{+0}$	$1.1979\times10^{+0}$	$1.1209\times10^{+0}$	$1.1653\times10^{+0}$	$1.3662\times10^{+0}$
	10	$4.6007\times10^{+0}$	$4.8845\times10^{+0}$	$4.5702\times10^{+0}$	$4.1179\times10^{+0}$	$4.0861\times10^{+0}$
	15	$8.0749\times10^{+0}$	$8.9934\times10^{+0}$	$7.5444\times10^{+0}$	$7.666\times10^{+0}$	$7.4048\times10^{+0}$
+/−/=		4/10/0	1/12/1	6/8/1	2/11/2	

3.2. Analysis of the Improvement of Network Attack and Defense Capabilities of Students at Applied Universities

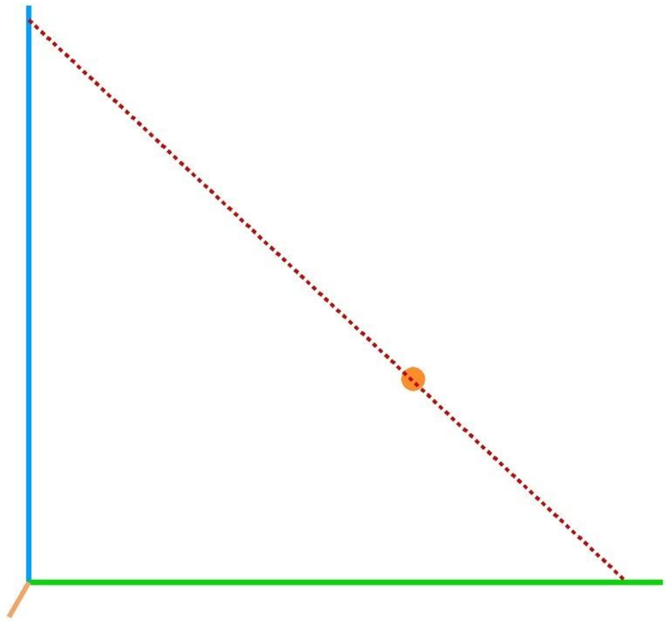
This section of the experiment conducts empirical research using a certain applied university as an example, distributing a total of 100 questionnaires to students, all of which were valid. During the assessment and weighting statistics phase, there were significant differences between students and enterprises in the weighting assessment of skill knowledge. The weights of each variable and the multi-objective optimization weights are shown in Table 5. The Pareto charts for the weights of each variable and the multi-objective optimization weights are shown in Figure 4 (Figures a–d represent the Pareto charts for the four dimensions of technical ability, practical experience, thinking patterns, and ethics and law, respectively). After multi-objective optimization calculations, the model software presented results indicating the need to focus on multiple dimensions, thereby achieving more effective improvements in students' network attack and defense capabilities. In terms of technical ability, students and experts had largely consistent analyses of the weighting of knowledge point requirements. In terms of mastery of basic network knowledge, proficiency in estimation tools and techniques, and vulnerability discovery and analysis capabilities, students assigned the highest weight (41.5%) to mastery of basic network knowledge. Through comprehensive fuzzy evaluation and multi-objective optimization, an intelligent algorithm optimization target was formed, which not only emphasizes control over key elements but also integrates the coordinated organization of diverse elements under these key elements.

Table 5. Variable weights and multi-objective optimization weights.

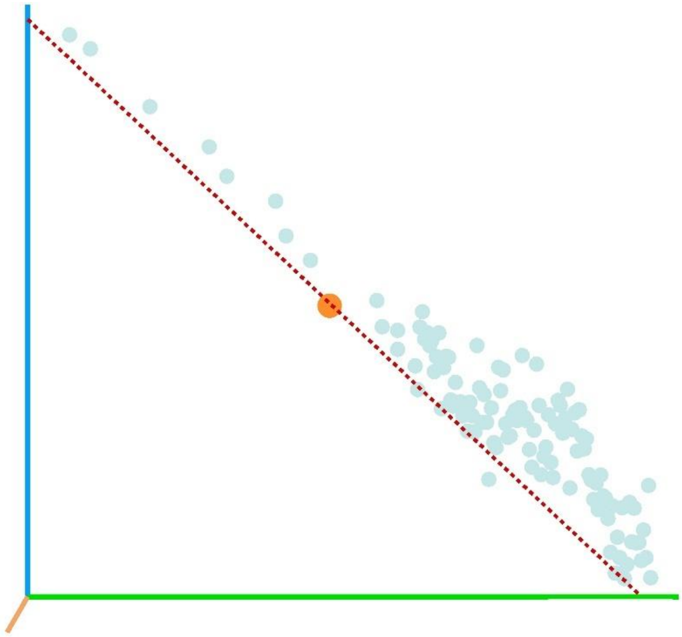
Primary indicator	Secondary indicator	Expert weight (%)	Student weight (%)	Optimized result (%)
Technical ability	Knowledge of basic network	35.5	41.5	39
	Estimation tools and technical proficiency	28.2	36.6	18.5
	Vulnerability detection and analysis ability	36.3	21.9	42.5
Practical experience	Combat frequency	38.9	25.6	15.5
	Diversity of scene exposure	27.1	23.5	22.8
	Emergency response and resistance	34	50.9	61.7
Thinking pattern	Attacker thinking	28.7	25	45.6
	Innovation and breakthrough ability	44.6	61.2	25.6
	Risk assessment and decision making	26.7	13.8	28.8
Ethical law	Legal meaning and compliance	54.2	43.6	48.7
	Attack behavior and self-discipline	45.8	56.4	51.3



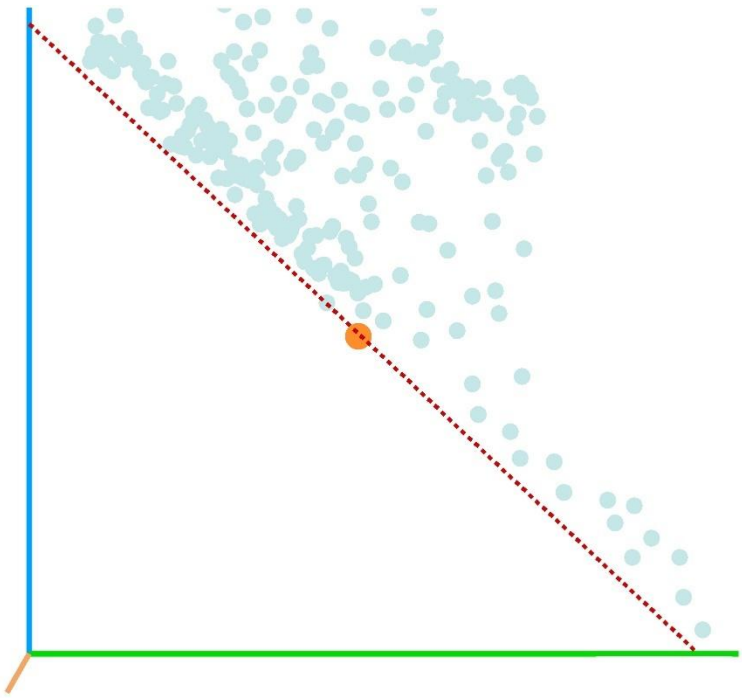
(a) Technical ability



(b) Practical experience



(c) Thinking pattern



(d) Ethical law

Figure 4. Pareto chart.

4. Guarantee Measures for the Construction of a Cybersecurity Ideological and Political Management Mechanism

4.1. Strengthen Environmental Shaping and Emphasize Value Promotion

Public education and environmental shaping form the foundation of management mechanism construction, particularly in cybersecurity ideological and political management. It is essential to further enhance the influence of information to convey correct value concepts to students and subtly shape their behavior. For instance, higher education institutions can organize cybersecurity-themed educational campaigns or host cybersecurity knowledge competitions to cultivate students' cybersecurity awareness and sense of responsibility. Additionally, they can create and display cybersecurity promotional posters on campus or release promotional videos to convey correct cybersecurity value concepts to students. Additionally, in terms of publicity, information circulation should be strengthened to ensure that advanced management concepts and value systems circulate smoothly within the campus. In this process, university teachers should establish good teacher-student relationships, pay attention to students' cybersecurity issues, and guide students to use the internet correctly and prevent cybersecurity risks through classroom discussions and individual tutoring. At the same time, universities should establish cybersecurity monitoring and feedback mechanisms to promptly identify and resolve students' cybersecurity issues. A cybersecurity reporting platform can be established to encourage students to actively report cybersecurity issues, ensuring the safety and stability of the campus network environment.

4.2. Strengthen Supervision and Evaluation, and Continuously Optimize and Improve

During the construction of a cybersecurity ideological and political management mechanism for students at applied universities, supervision and evaluation systems can be utilized to continuously optimize management effectiveness. First, universities should establish a supervision mechanism for cybersecurity ideological and political management, clearly defining supervision responsibilities and procedures. Specialized supervision departments or committees should be established within the campus, staffed by faculty and students, to oversee the implementation of cybersecurity ideological and political management work and promptly identify and address issues. Second, universities should also establish an evaluation system for cybersecurity ideological and political management, develop evaluation indicators and standards, and conduct regular assessments and inspections of cybersecurity ideological and political management work to promptly identify issues and propose improvement measures. Third, during the construction of the cybersecurity ideological and political management mechanism for students, efforts should be made to further enhance information flow, using open, fair, and transparent information to demonstrate management outcomes and methods.

4.3. Specialized course education, practicing values

Cybersecurity education and ideological and political education in higher education institutions are both conducted through courses, which serve as one of the vehicles for establishing management mechanisms. Therefore, efforts should be made to integrate cybersecurity education with ideological and political education, designing specialized courses that can be offered as elective or general education courses. Course content should cover cybersecurity knowledge, ideological and political theory, and practical case studies. Course design should be tailored to students' needs and characteristics, emphasizing the integration of theory and practice to enhance students' cybersecurity awareness and ideological and political literacy. To further enhance the educational value of the courses, a training system should be established within the management framework to organize teacher training programs aimed at improving educators' capabilities in integrating cybersecurity and ideological and political education. Training content should include cybersecurity knowledge, teaching methods, and case analysis. Additionally, universities should provide teachers with resource support, such as textbooks, supplementary materials, and teaching resources, to assist them in effectively delivering cybersecurity and ideological and political integration courses. Furthermore, based on the established management mechanisms, students should be organized to participate in practical activities, with specified activity cycles, scopes, and participants. Through hands-on operations and project involvement, students can enhance the practical effectiveness of cybersecurity and ideological and political education integration courses. For example, universities can organize cybersecurity drills and simulated attack-defense competitions to allow students to personally experience the challenges and response methods of cybersecurity.

4.4. Building a high-quality team and bringing together core strengths

In the construction of a cybersecurity and ideological and political education management mechanism for college students, it is essential to build a high-quality management team, consolidate core management capabilities, and ensure the effective implementation of the management mechanism. Building a high-quality management team requires long-term efforts and sustained investment, typically achieved through methods such as talent training and incentive programs. The construction and optimization of management mechanisms demand professional expertise; universities should strengthen the cultivation of cybersecurity and ideological and political education management specialties to nurture management talent equipped with both cybersecurity technical skills and ideological and political theory knowledge. In daily work, experts and advisors in the fields of cybersecurity and ideological and political education management should be invited to participate in relevant tasks, and activities such as expert lectures and seminars should be organized to guide management personnel in deeply understanding and researching the latest theories and practices in cybersecurity and ideological and political education management. Additionally, universities should establish incentive mechanisms to encourage management personnel to actively participate in cybersecurity and ideological and political education management work. Through measures such as providing awards for excellence and promotion opportunities, management personnel should be encouraged to take initiative, thereby enhancing management standards and work effectiveness. In student cybersecurity and ideological and political management, the construction of management mechanisms involves multiple stakeholders. Departments and personnel should coordinate and cooperate. Universities can strengthen communication and collaboration among team members through team-building activities, fostering a positive work environment and team cohesion.

5. Conclusion

This study constructs a multi-objective optimization model for enhancing college students' network attack and defense capabilities based on the results of entropy weight analysis, and establishes a two-level fuzzy comprehensive evaluation system. The dual-population cooperative multi-objective particle swarm optimization algorithm is employed to solve the optimization model, enabling a scientific assessment of the effectiveness of enhancing college students' network attack and defense capabilities in applied universities. The conclusions of the article are as follows:

Experimental results show that in six test problems, the proposed method obtained nine optimal values for IGD. In the DTLZ3 (multi-mode PF) problem, the PF distribution obtained by the proposed method was relatively uniform, maintaining good diversity and convergence. Compared with other improved multi-objective algorithms, the proposed method can obtain solution sets with good convergence and diversity in complex problems and demonstrates its potential for handling high-dimensional multi-objective problems.

Finally, through actual evaluations and feedback from students and relevant experts at a certain applied university, it was found that the highest weighting in the technical capability dimension was 41.5 for the mastery of basic network knowledge.

In summary, to enhance the network attack and defense capabilities of students at applied universities, it is necessary to further improve the management system, refine management mechanisms, and strengthen institutional safeguards. In daily ideological and political work, relevant courses should be established to achieve effective integration between course education and network security ideological and political management, thereby promoting the construction of a network security ideological and political management mechanism. In daily educational work, emphasis should be placed on the construction of publicity mechanisms, utilizing campus platforms to actively conduct educational activities, and implementing the basic principles of modern governance capabilities.

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