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Research on Multi-Objective Planning Methods in Resource Integration Strategies of Physical Education in Private Colleges and Universities in Wuhan Region

Jinhua Zhu[1], Fei Dai[1,✉]

[1] *Wuchang Institute of Technology, Wuhan, Hubei, 430065, China*

ABSTRACT

With the progress of the times, the scientific and reasonable planning of physical education infrastructure and resources is an important way to realize the fair development of education. Firstly, a physical education resource input-output evaluation index system and a multi-objective optimization model of resource allocation to improve the utilization rate of physical education resources are constructed for the integration of physical education resources in Wuhan private colleges. In order to achieve the effect of enhanced spatial traversal ability, the collision range of raindrops is expanded by adding the hybrid collision strategy and introducing the adaptive collision factor, and the artificial raindrop algorithm with the introduction of hybrid collision and stretching is proposed on the basis of the original artificial raindrop algorithm. The improved artificial raindrop algorithm is compared with different optimization algorithms for simulation comparison experiments and model solving. The results show that the improved artificial raindrop algorithm converges faster and with higher accuracy, while the multi-objective optimization model proposed in this paper achieves the balanced development goal of physical education resources integration and allocation in Wuhan private colleges and universities.

Keywords: educational resources integration, multi-objective optimization, artificial raindrop algorithm, physical education resources

1. Introduction

Private colleges and universities in Wuhan region are an important part of higher education in Hubei Province, and the integration of resources in physical education and sports in private colleges and universities plays a key role in accelerating the development of private education and enhancing the core competitiveness of private colleges and universities [1-3]. By integrating internal and external resources in a scientific and reasonable way, it can realize the optimal allocation of resources, thus

✉ Corresponding author.
E-mail address: 18062686616@163.com (F. Dai).
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generating significant educational benefits and maximizing the competitive advantages of private colleges and universities [4-6].

In recent years, the position of physical education in colleges and universities in schools has received more and more attention. However, due to the uneven resources and the limitations of traditional teaching methods, physical education teaching faces many challenges. In order to improve the quality and effect of physical education teaching, the integration of physical education teaching resources is needed [7-10]. The integration of physical education resources in colleges and universities has important significance importance. First, by integrating different types of physical education resources, it can provide more opportunities for teachers and students to interact and cooperate, and promote students' active participation and independent learning [11-14]. Secondly, by integrating physical education resources, we can broaden the teaching content, meet the diversified needs of students, and stimulate students' interest and learning motivation [15-17]. In addition, through the integration of high-quality physical education resources, it can help to improve the quality and effect of teaching and promote the development of students' comprehensive quality. The current methods of physical education resources integration mainly include, integrating online resources, integrating on-campus resources, and integrating community resources [18-21]. However, in terms of the current integration of educational resources in colleges and universities, there are mainly problems such as unbalanced resources, insufficient teacher training, and low interest of students, which require colleges and universities to formulate specific integration programs and provide corresponding training and support, in order to help students' physical and mental health and comprehensive development [22-25].

In order to rationalize and maximize the benefits of physical education resources integration in private colleges and universities in Wuhan, the input-output evaluation index system of physical education resources was constructed, and the multi-objective function model of physical education resources utilization efficiency and allocation efficiency was proposed. Subsequently, in order to improve the algorithm's ability to traverse the solution space, a hybrid collision strategy is added on the basis of the original artificial raindrop algorithm to expand the collision range of raindrops. Meanwhile, the stretching operation is performed on the raindrop pool to make it effectively guide the raindrop flow direction, so as to ensure the algorithm search efficiency. Finally, the improved artificial raindrop algorithm is used to carry out experimental simulation and model solving to realize the multi-objective integration planning of physical education resources in private colleges and universities in Wuhan.

2. Integration and Optimization of Physical Education Resources in Private Colleges and Universities in Wuhan Area

2.1. Construction of Evaluation Indicator System for Resource Integration in Kinesiology

“Efficiency” is one of the indicators of resource integration. The resource integration of physical education in private universities involves the issue of how to rationally allocate the limited resources of universities to obtain the maximum educational output with the minimum input. Considering that the education system is a complex system with multiple inputs and outputs, the relationship between inputs and outputs is difficult to be quantified and measured, therefore, to improve the efficiency of resource integration of physical education in private colleges and universities and to integrate physical education resources, it is necessary to firstly construct the index system of physical education and sports in private colleges and universities and the mathematical model of multi-objective optimization.

In order to construct the input-output index system of educational resources, we choose the indicators of input and output of physical education resources in private colleges and universities, and focus on two issues, namely, “the support form of physical education resources in private colleges and universities” and “whether the above evaluation index system can completely support the physical education resources in private colleges and universities". The two issues are centered on "the support form of physical education resources in private universities" and "whether the above evaluation index system can completely support physical education in private universities", and the input-output index system of physical education resources in private universities is shown in Table 1. It can be seen that the resource input-output index system of private colleges and universities in physical education has two first-level indicators of physical education resource input and output, six second-level indicators of human resources and material resources, and 12 third-level indicators of the number of full-time and part-time teachers and the number of administrative teachers, etc. The establishment of the index system provides a theoretical framework for the construction of the multi-objective optimization model.

Table 1. Educational resources input one output index system

Primary indicator	Secondary indicator	Tertiary index	Symbol
Physical resources input indicators	Human resources	The number of teachers who are part-time	I1
		Number of administrative teachers	I2
		Special instruction number	I3
	Material resources	The value of physical instruments/Million yuan	I4
		Practice platform housing area/Square meter	I5
		Education base area/Square meter	I6
	Financial resources	Physical expenditure/Million yuan	I7
Physical resources output indicators	Talent culture	The number of education students	O1
		Student constitution	O2
		Sports competition awards / project	O3
	Scientific research	The number of academic papers, the number of works and the total number of subjects/term	O4
	Social services	The value of the transformation of sports research/Million yuan	O5

2.2. *Multi-Objective Planning Model for Resource Integration in Kinesiology*

2.2.1. Multi-objective optimization analysis. In order to optimize the integration of the resources of physical education and sports in private colleges and universities, the following two objectives are proposed.

1) Enhance the efficiency of utilizing physical education resources in private colleges and universities. That is, to organize limited resources to maximize physical education output.

2) Improve the allocation efficiency of physical education resources in private colleges and universities. That is, to maximize the proportion of physical education resources in each input resource, while also considering the complexity and specificity of each resource, the degree of impact on educational outcomes, so that each resource is effectively allocated to the most adaptable aspects.

2.2.2. Multi-objective optimization model construction：

1) Utilization efficiency of physical education resources integration. The integration of physical education resources in colleges and universities is affected by many factors, and its allocation is a non-simple linear allocation, and the ultimate goal is to maximize the educational results, i.e., the efficiency of physical education resources integration is the ratio of educational output to educational input, which is expressed as follows:

$$U = \frac{\sum_{i=1}^{m} \mu_j O_j}{\sum_{i=1}^{n} \varphi_i I_i} \tag{1}$$

Where: i, j respectively, the resource elements and educational results elements; O_j, I_i respectively, the amount of resource output, input; φ_i, μ_j respectively, the weight of each educational resource input indicators, output indicators. The greater the value of U, the greater the proportion of inputs and outputs, the greater the efficiency of resource utilization, the more rational the combination of production factors, and vice versa.

2) Physical education resources integration allocation efficiency. According to the input-output index system for resource integration of physical education in colleges and universities. The objective function expression of the resource integration configuration of physical education in the kth university and the ith university is as follows:

$$\begin{gathered} A_{ki} = \frac{X_k + \Delta X_k}{S_k} (k = 1, 2, \cdots, K) \\ s.\ t.\ A_{ki} < 1 (i = 1, 4) \\ 0 \leq A_{ki} \leq 1 (i = 2, 3) \\ A_{ki} > 1 (i = 5, 6, 7) \end{gathered} \tag{2}$$

Where: S_k is the number of students in the knd college; X_k and ΔX_k represent the average student value and change of each resource element of sports in the kth college, respectively.

2.2.3. Construction of the objective function model. Considering the objective function of Eq. (1) and Eq. (2) together, the multi-objective optimization function for resource integration in kinesiology is obtained as:

$$\max U_k = \frac{\sum_{j=1}^{m} \mu_j O_j}{\sum_{i=1}^{n} \varphi_i I_i} \tag{3}$$

$$\max F_k = \sum_{i=1}^{n} \varphi_i A_{ki}, k = 1, 2, \cdots, k \tag{4}$$

Where: $\max U_k$ is the utilization efficiency of educational resources in each university should seek the maximum possible; $\max F_k$ is the allocation efficiency of educational resources in each university should seek the maximum possible.

2.2.4. Weighting of input-output indicators. Resource input indicators for physical education I_1-I_7 and output indicators $O_1 - O_5$ have different degrees of influence on physical education teaching, therefore, it is necessary to calculate the weights of each factor using the entropy weight method, based on the calculation results, using the Delphi method to carry out expert opinion solicitation on the reasonableness and effectiveness of the evaluation index weights, and finally obtain the innovative and entrepreneurial education resources after two rounds of solicitation, feedback and revision of the closed-loop process The weights of input-output indicators are shown in Tables 2-3 respectively.

As can be seen from the table, among the various input resources, the special funds for college physical education resources have the largest weight (0.2575), which means that they have the greatest influence on the output of physical education, followed by the number of full-time and part-time teachers in physical education, the total value of assets of physical education teaching instruments and equipment, and the area of practice platform rooms. Among the indicators of educational outputs, the transformation of physical education research results, awards of physical education competitions, and students' physical fitness have become the main observation indicators.

Table 2. Physical resources input index weight φ_i

Input weight / φ_i	Numerical value
The number of teachers who are part-time / φ_1	0.2167
Number of administrative teachers / φ_2	0.7724
Special instruction number / φ_3	0.0974
The value of physical instruments/ φ_4	0.2214
Practice platform housing area/ φ_5	0.0855
Education base area/ φ_6	0.1193
Physical expenditure/ φ_7	0.2575

Table 3. Physical resources output index weight μ_j

Physical resources output index weight / μ_j	Numerical value
The number of education students / μ_1	0.1934
Student constitution / μ_2	0.2191
Sports competition awards / μ_3	0.2245
The number of academic papers, the number of works and the total number of subjects / μ_4	0.2065
The value of the transformation of sports research / μ_5	0.2557

2.3. Improved artificial raindrop algorithm for resource planning in kinesiology

2.3.1. Artificial raindrop algorithm and process. Artificial raindrop algorithm (ARA) is a population-based heuristic algorithm, belonging to the swarm intelligence algorithm, which firstly originated from the raindrop computation model, and then formed the artificial raindrop algorithm through continuous improvement. Artificial raindrop algorithm is inspired by the phenomenon of rainfall in nature, and the rainfall process in nature is abstracted and simulated so as to be applied to the design of optimization algorithms [26]. By analyzing the phenomena of raindrop formation, raindrop descent, raindrop collision, raindrop flow, raindrop pool renewal and water vapor renewal, the corresponding operators are designed respectively. The raindrop location elevation information is utilized to evaluate the excellence of individual raindrops, and the updating operation is completed by loop iteration of the corresponding operators [27]. The simulation scenario diagram of the artificial raindrop algorithm is shown in Fig. 1.

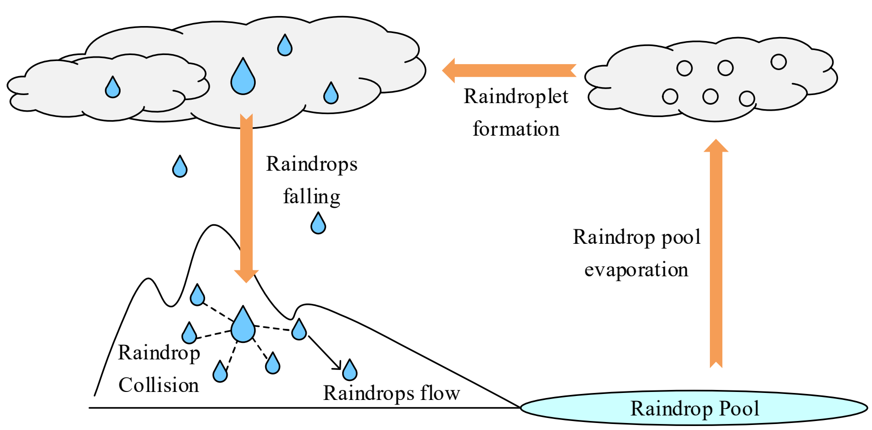


Fig. 1. The simulation scene diagram of artificial raindrop algorithm

The artificial raindrop algorithm simulates the natural phenomenon by dividing the optimization process of the algorithm into six stages, each of which corresponds to a different operator, namely, raindrop formation operator, raindrop descent operator, raindrop collision operator, raindrop flow operator, raindrop pool updating operator, and water vapor updating operator. The above six operators are described in detail below.

1) Raindrop formation operator. In nature, raindrops are formed by rising water vapor condensing continuously. The raindrop formation operator simulates the formation process of raindrops and defines the water vapor forming raindrops as water vapor vectors, and N water vapor vectors make up the initial population size. Among them, the ind water vapor vector in the population is defined as shown in equation (5) on the following page.

$$Vap_i = \left[vap_{1,i}, vap_{2,i}, \cdots, vap_{D,i}\right], i = 1, 2, \cdots, N \tag{5}$$

where D is the dimension of the water vapor vector and N is the population size.

Numerous water vapor vectors continuously coalesce and eventually form raindrops. Different water vapors contain different location information, so the aggregate center of the water vapor population is taken as the raindrop formation location. The raindrop formation operator is defined as shown in Eq. (6).

$$Rain = \left(\frac{1}{N}\sum_{i=1}^{N} Vap_{1,i}, \frac{1}{N}\sum_{i=1}^{N} Vap_{2,i}, \cdots, \frac{1}{N}\sum_{i=1}^{N} Vap_{D,i}\right) \tag{6}$$

2) Raindrop falling operator. After a raindrop is formed and descends downward due to gravity, defining N_Rain as the falling raindrop, the coordinate $Rain_d$ of a dimension may change during the raindrop's descent. The raindrop descent operator is defined as shown in equation (7).

$$N\_Rain_i = \begin{cases} random\left(F_d, C_d\right) & i = d \\ Rain_i & Other \end{cases} \tag{7}$$

where $random(F_d, C_d)$ is a random number between F_d and C_d.

3) Raindrop collision operator. When a raindrop falls to the ground, it collides with the ground and is impacted into several small raindrops. In order to maximize the simulation of the raindrop collision scene, it is assumed that the raindrop collision generated by the small raindrops in the form of an approximate normal distribution falls around. The raindrop collision operator is defined as shown in Equation (8).

$$S\_Rain_i = N\_Rain + \left(N\_Rain - Vap_k\right) \cdot sign\left(a - 0.5\right) \cdot \log b \tag{8}$$

where a and b are denoted as any random numbers between $[0,1]$, $sign(\cdot)$ is a sign function, and Vap_k is any water vapor vector in the water vapor population.

4) Raindrop flow operator. Small raindrops generated by the collision fall randomly at different locations and have a tendency to flow toward lower altitudes due to geographic location factors. The raindrop flow direction is determined by a linear combination of two sub-directions $o1$ and $o2$, as shown in Eq. (9).

$$\begin{aligned} o1_i &= \left(LOC_{k_1} - S\_Rain_i\right) \cdot sign\left(f\left(LOC_{k_1}\right) - f\left(S\_Rain_i\right)\right) \\ o2_i &= \left(LOC_{k_2} - S\_Rain_i\right) \cdot sign\left(f\left(LOC_{k_2}\right) - f\left(S\_Rain_i\right)\right) \\ o_i &= \zeta \cdot random1_i^2 \cdot o1_i + \zeta \cdot random_i \cdot o2_i \end{aligned} \tag{9}$$

where ζ is the raindrop flow factor and LOC_{k1} and LOC_{k2} denote any two positions in the raindrop pool, respectively. The definition of raindrops after flow is shown in Eq. (10).

$$N\_S\_Rain_i = S\_Rain_i + o_i, i = 1, 2, \cdots, N \tag{10}$$

In general practical scenarios, raindrops always flow towards lower elevations. Therefore, the flow of raindrops whose elevation is higher than the elevation of the raindrops before the flow is defined as invalid flow. In nature, raindrops always stop flowing due to external factors, in order to simulate this phenomenon, so add MF parameter to control the maximum number of raindrops flow.

5) Raindrop pool update operator. The artificial raindrop algorithm introduces the concept of raindrop pool to save the small raindrops with the lowest position information in each iteration $Best^G$, and sets the upper limit of the raindrop pool to save raindrops as N.

When the number of raindrops saved in the raindrop pool exceeds the upper limit of the raindrop pool, the small raindrops in the existing raindrop pool are randomly deleted to avoid the algorithm falling into a local optimal solution. The raindrop pool update operator is defined as shown in Equation (11).

$$P\_Rain^{G+1} = P\_Rain^G \cup Best^G \tag{11}$$

6) Water vapor update operator. The artificial raindrop algorithm uses the water vapor updating operator for the retention of good individuals. Taking the concatenation set of Vap^G and New^G, the sorting algorithm is applied to select the first N individuals with low elevation as the initial population for the next round of iteration, as shown in Eq. (12).

$$Vap^{G+1} = Vap^G \cup New^G \tag{12}$$

The artificial raindrop algorithm provides parameter MAX as the maximum number of iterations of the algorithm and records the current number of iterations of the algorithm through variable $ITER$. When $ITER$ is less than or equal to the maximum number of iterations MAX, the algorithm continues to iterate, otherwise it stops iterating.

2.3.2. Introduction of artificial raindrop algorithm with hybrid collision and stretching. The original artificial raindrop algorithm (ARA) has great potential in solving some continuous complex optimization problems, but ARA also has shortcomings, firstly, the collision of individual raindrops lacks in ensuring the population diversity, and secondly, ARA has the problem of early convergence.

Based on the above two considerations, this paper explores a kind of artificial raindrop algorithm (MEARA) that introduces hybrid collision and stretching strategy on the basis of ARA. On the basis of maintaining the original concept and structure of ARA, it adopts the hybrid collision strategy for the problem of population diversity and introduces the adaptive collision factor in the collision process of raindrops, which expands the collision range of raindrops, and achieves the effect of enhancing the ability of traversing the solution space; for its search efficiency, it adopts the hybrid collision strategy to ensure that it can be used to solve the problem. For the search efficiency problem, the method used is to add the stretching operation in the update operator of the raindrop pool, to ensure that the potential energy of the raindrops in the raindrop pool is at a lower level through the stretching operation, and then use the raindrops with the lowest potential energy in the raindrop pool to guide the direction of raindrop flow, so as to improve the search efficiency of the raindrop flow process, and to solve the problem of precocious convergence of the ARA. The flow schematic of the improved artificial raindrop algorithm is shown in Figure 2.

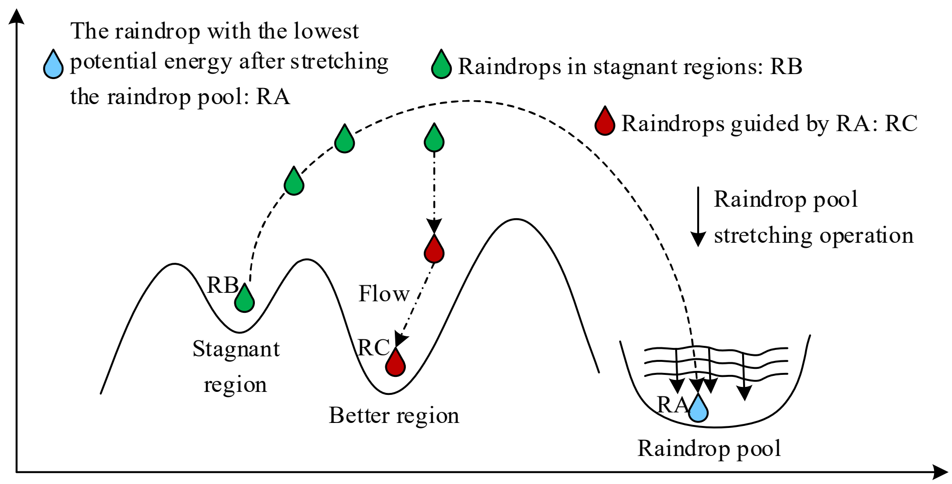


Fig. 2. The schematic diagram of MEARA raindrop flow

1) Raindrop pool stretching operation. A counter is added to the operation of updating the raindrop pool, and if the potential energy value of the raindrops updated to the raindrop pool does not change for more than 10 times, the algorithm is considered to be stagnant and trapped in a fixed region. At this point, a stretching operation is performed on all raindrops in the raindrop pool to re-update the pool, and then the raindrop with the lowest potential energy in the raindrop pool is taken as the intervened raindrop to participate in the next generation of collisions and flows. The stretching operator of the raindrop pool can be expressed by Eq. (13).

$$\begin{cases} c = \dfrac{RP\_value - RP\_\min\_value}{RP\_avg\_value - RP\_\min\_value} \\ RP\_L = RP + \left(c \cdot Rand \cdot \left(RP\_\min\_value - RP\_\max\_value\right)\right) \end{cases} \tag{13}$$

Where c is the stretching factor, RP_value is the potential energy of the raindrops in the current pool of raindrops to be stretched, $RP\_\min\_value$ is the minimum value of the potential energy of all the raindrops in the current pool of raindrops, $RP\_\max\_value$ is the maximum value of the potential energy of all the raindrops in the current pool of raindrops, RP_avg_value is the average value of the potential energy of all the raindrops in the current pool of raindrops, Rand is the random number in $[0,1]$, RP is the raindrops in the current pool of raindrops to be stretched, and RP_L is the raindrops after stretching.

2) Hybrid collision operation of raindrops. The collision operation of the original ARA is to use a single raindrop to collide N small raindrops, which is not good in terms of population diversity. In this paper, we take the large raindrops formed by the water vapor and the raindrops intervened after the update of the raindrop pool to carry out the mixed collision, so that the collision range of the raindrops becomes larger; at the same time, we introduce the self-adaptive collision factor, which ensures that the collision range will be large enough in the early iteration process and gradually become smaller in the later process. The collision range becomes smaller gradually in the later process. This not only strengthens the ability of the raindrop to traverse the solution space, but also ensures the correctness of the overall flow direction of the raindrop in the late iteration. The collision operator of raindrops can be expressed by Eq. (14).

$$\begin{cases} R_{\min}(k) = \min\left(Rain\_drop(k), RP\_Intervene(k)\right) \\ R_{\max}(k) = \max\left(Rain\_drop(k), RP\_Intervene(k)\right) \\ \Delta R(k) = R_{\max}(k) - R_{\min}(k) \\ \alpha = \alpha_e + \dfrac{\alpha_s \cdot (iter - i)}{iter} \\ Small_R aindrop(k) = random \\ \left[R_{\min}(k) - \alpha \cdot \Delta R(k), R_{\max}(k) + \alpha \cdot \Delta R(k)\right] \end{cases} \tag{14}$$

Where, k is the dimension, α_e, α_s are the collision factors, α_e is a value greater than 0 for expanding the search, α_s is a value less than 0 for narrowing the search, iter is the total number of iterations, i is the current number of generations, $Small\_Raindrop$ is the small raindrops from the collision, $RP\_Intervene$ is the intervened raindrops in the raindrop pool, and $Rain\_drop$ is the large raindrops formed by water vapor in the current iteration.

3) Flow operator for raindrops. In the flow process of raindrops, compared with ARA, another flow factor is added to speed up the convergence of the algorithm, while the intervening raindrops after the update of the raindrop pool are used to guide the direction of the raindrops' flow to improve the efficiency of searching in the flow process of raindrops. The flow operator of raindrops can be expressed by Eq. (15).

$$\begin{cases} d_i = \tau_g \cdot rand1_i \cdot \\ \left(RP\_Intervenee_k^G - Small\_Raindrop_i^G\right) \\ +\tau_p \cdot rand2_i \cdot \left(RP_k^G - Small\_Raindrop_i^G\right) \\ New\_Small\_Raindrop_i^G \\ = Small\_Raindrop_i^G + d_i, i = 1, 2, \ldots, N \end{cases} \tag{15}$$

Where RP_Intervene is the raindrops in the raindrop pool after the intervention is performed, Small_Raindrop is the raindrops to be flowed in the current generation, RP is the raindrops randomly selected from the raindrop pool in the current generation, τ_g is the globally-guided flow factor, τ_p is the locally-guided flow factor, $rand1$ and $rand2$ are the random numbers in the interval $[-1,1]$, and d_i is the flow direction.

3. Experiment and analysis of resource integration planning for college kinesiology classes

3.1. *Experiments on the improvement of the artificial raindrop algorithm*

In order to evaluate the performance of MEARA, two aspects are considered, namely, convergence speed and solution accuracy, which is the optimal value that the algorithm searches for after the completion of iterations; and convergence speed, which is the speed of convergence of the curve under the condition of the same number of iterations. This experiment selected six commonly used test functions: $F_1 - F_6$, the specific information is shown in Table 4. Function $F_1 - F_3$ is a multi-peak function with multiple local extremes, and function $F_4 - F_6$ is a single-peak function. The optimal value of Rosenbrock is relatively difficult to search, which is a multivariate correlation function, and the Quartic function carries noise. Therefore, these functions are better able to test the optimization performance of the algorithm.

Table 4. The information table of test functions

Function name	Expression	Range	Extreme

			value
Ackley	$F_1(x)=-20e^{-0.2*\sqrt{\frac{\sqrt{D}\sum_{i=1}^{D}x_i^2}{2}}}-e^{\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)}+20+e$	[-30,30]	0
Rastrigin	$F_2(x)=\sum_{i=1}^{D}\left[x_i^2-10\cos\left(2\pi x_i\right)+10\right]$	[-5.11,5.11]	0
Griewank	$F_3(x)=\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	[-500,500]	0
Rosenbrock	$F_4(x)=\sum_{i=1}^{D-1}\left[100\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)^2\right]$	[-20,20]	0
Quartic	$F_5(x)=\sum_{i=1}^{D}i*x_i^4+random[0,1)$	[-1.23,1.23]	0
Schwefel's 2.21	$F_6(x)=\max\left\{\lvert x_i\rvert,1\le i\le D\right\}$	[-90,90]	0

In the simulation experiments of this paper, optimization operations are performed under the same conditions using ARA, the dynamic weight PSO algorithm (WPSO), and the differential evolution algorithm (DE), and the optimization processes and results of MEARA and the three algorithms are compared to verify the performance of the algorithms.

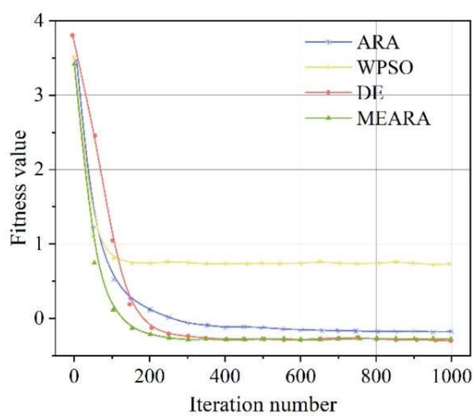
The experiments set the population size of each algorithm as N=30, the dimension of the test function variable D=30, the maximum number of iterations as $Iter_{max}$ =1000, C_1 =3, C_2 =3, ω_{max} =0.8, ω_{min} =0.5, F=0.5, CR=0.6, and each test function is run independently for 30 times, and its average value is taken. The experimental statistical results include the mean (Mean) and standard deviation (Std) of the 30 optimization results, which are shown in Table 5, where the bolded values indicate the average optimal results obtained by comparing the algorithms running 30 times on the corresponding functions.

From the simulation results, it can be seen that the DE algorithm performs better than other algorithms in the test function F_1, and has a strong exploration ability in this function.The ARA algorithm performs slightly better than the WPSO algorithm in functions F_1 and F_3, and slightly better than the DE algorithm in function F_5, but it is only slightly higher than the DE algorithm in some of the functions, and it cannot perform better in most of the functions. The MEARA proposed in this paper is based on the introduction of hybrid collision and stretching strategy of ARA, which increases the exploration and mining ability of the algorithm to the optimal solution, and the results show that, except for the optimal result of function F_1 which is slightly lower than the DE algorithm, the solution accuracy of MEARA is better than that of ARA, WPSO, and DE for the other test functions, which proves that the introduction of the hybrid collision and stretching strategy of MEARA is effective.

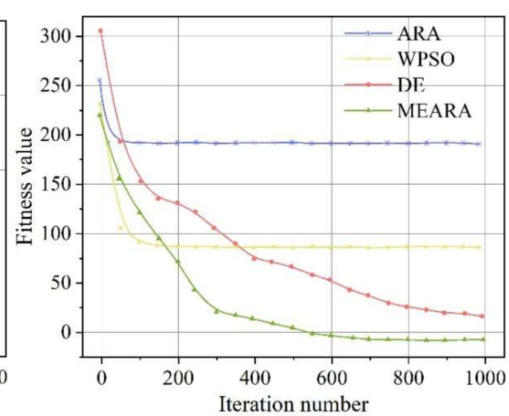
Table 5. The comparison table of experimental results

Test function		MEARA	ARA	WPSO	DE
F1	Mean	4.41E-07	5.93E-02	9.65E-01	2.54E-07
	Std	3.64E-07	5.11E-02	1.51E-01	8.17E-08
F2	Mean	1.77E-04	1.97E+02	9.28E+01	2.65E+01
	Std	7.58E-03	5.71E+01	3.18E+01	1.31E+01
F3	Mean	1.22E-15	8.59E-05	2.67E-01	2.81E-13
	Std	3.69E-15	7.18E-05	3.95E-01	4.31E-13
F4	Mean	1.83E+02	1.69E+02	7.90E+03	2.45E+01
	Std	1.67E-01	2.87E+02	4.57E+03	5.25E-01
F5	Mean	8.45+00	1.61E+01	9.51E+01	1.69E+01
	Std	1.79E+00	1.91E+00	3.32E+00	1.97E+00
F6	Mean	1.79E-05	4.79E-01	2.02E-01	3.16E-02
	Std	5.92E-05	2.62E+00	8.45E-01	9.51E-02

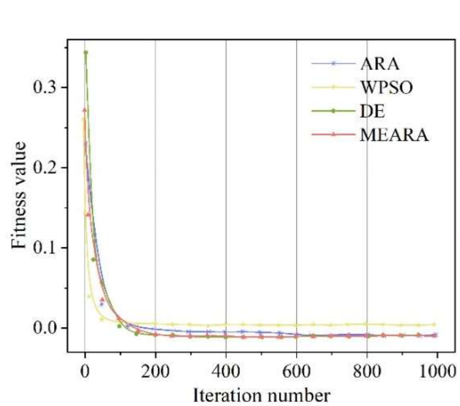
Fig. 3 shows the convergence curves of the four algorithms in terms of the average fitness values for 30 times on different test functions. From the algorithm convergence graphs, it can be seen that MEARA converges faster and has higher solution accuracy in most of the functions compared to the other three algorithms. The fast convergence of MEARA is due to the fact that the raindrops in the population dynamically change the flow step size in each iteration according to the different potential energy differences, which suggests that the introduction of the backward learning strategy and the adaptive flow factor mechanism effectively enhances the convergence speed of the algorithm.



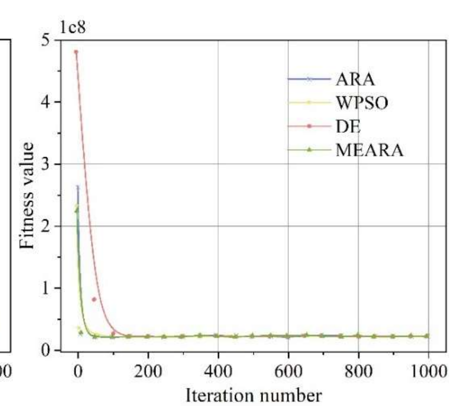
(a) Ackley 30 average



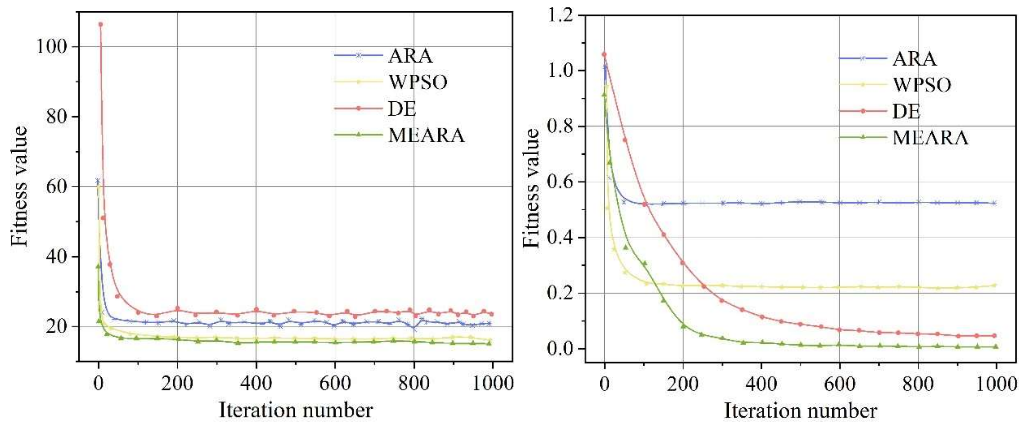
(b) Rastrigin 30 average



(c) Griewank 30 average



(d) Rosenbrock 30 average



(e) Quartic 30 average (f) Schwefel's Problem 2.21 30 average

Fig. 3. Convergence curves of four algorithms on test function

3.2. *Example analysis of the algorithm*

The optimization results of the integration model for physical education resources in university districts are shown in Table 6. Each line in the table represents a university district resource allocation optimization results, showing the optimization results of resource allocation under the physical education resource allocation model in each university district in Wuhan, followed by the university district SC101 as an example, respectively, for the allocation of physical education resources to elaborate:

1) The current educational base area (A) of the university district SC101 is 8794 square meters, and after the simulation experiment, the educational base area (newA) that needs to be newly allocated to the university district SC101 is 10,157 square meters, so the optimized allocation of the educational base area of the university district SC101 is 18,915 square meters.

2) The current number of full-time and part-time tenured teachers (G) in University District SC101 is 345, and the number of full-time and part-time tenured teachers (newG) that will need to be newly assigned to University District SC101 after the simulation experiment is 1,375, so the optimized number of full-time and part-time tenured teachers assigned to University District SC101 is 1,720.

3) The current practice platform room area (B) for University District SC101 is 19,234 square meters, and the new practice platform room area (newB) that needs to be allocated to University District SC101 after the simulation experiment is 20,284 square meters; therefore, the optimized allocation of practice platform room area for University District SC101 is 39,518 square meters.

4) The current physical education instrumentation (C) for University District SC101 is 357 units, and the new physical education instrumentation (newC) that needs to be allocated to University District SC101 after the simulation experiment is 759 units, therefore, the total number of physical education instrumentation in University District SC101 after the allocation of the optimization is 1,116 units.

5) The current athletic funding investment (E) for University District SC101 is 3.45 million yuan, and after the simulation experiment, the athletic funding investment (newE) that needs to be newly allocated to University District SC101 is 7.51 million yuan, therefore, the optimized allocation of athletic funding investment for University District SC101 is 10.96 million yuan.

Table 6. The Optimization results of educational resource allocation in university district

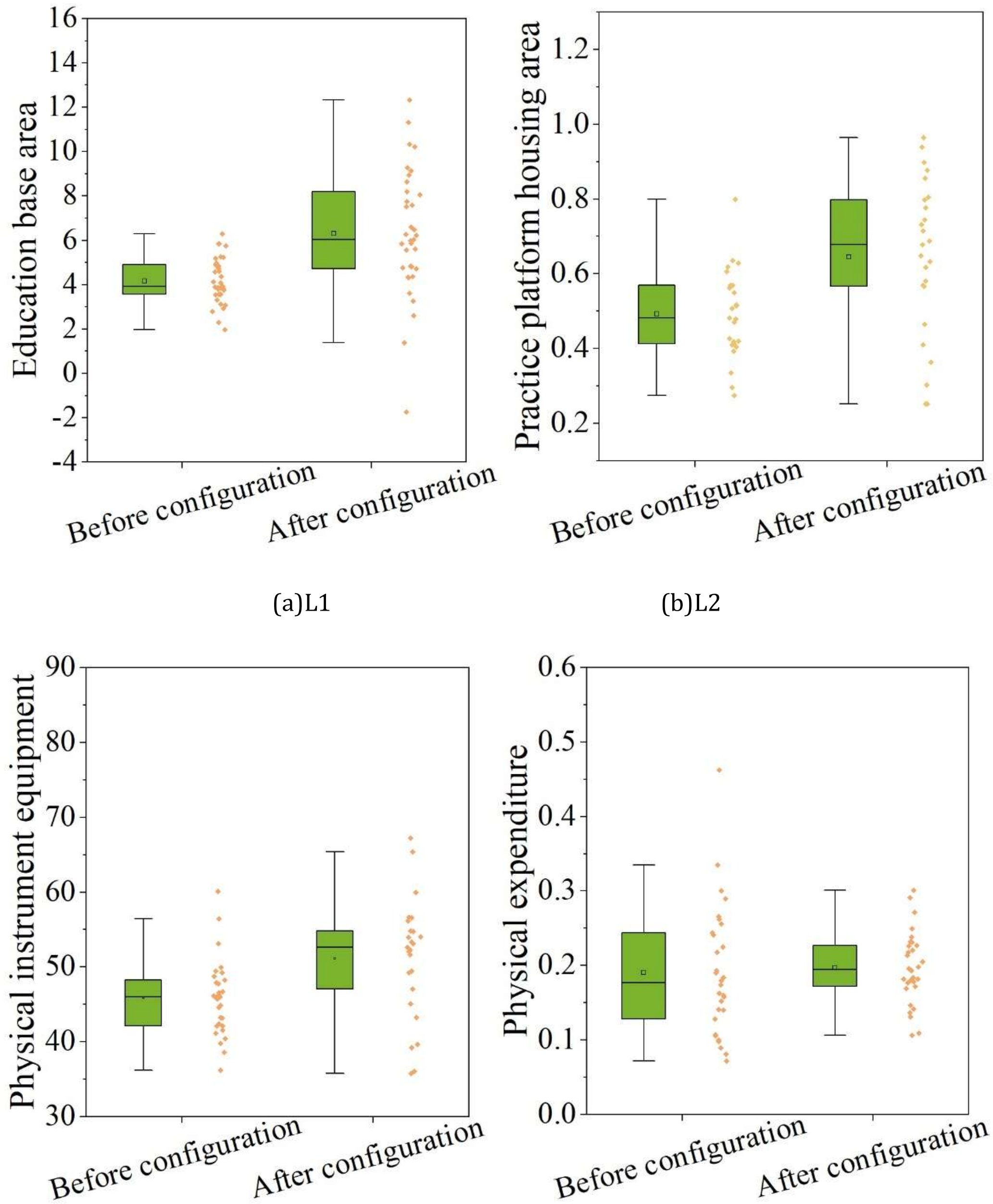
	A	G	B	C	E
SC101	18915	1720	39518	1116	1096
SC102	21687	1744	22935	999	1193
SC103	29833	2026	39876	1578	1722
SC104	29593	3280	97722	2133	1426
SC105	29755	2637	24717	1152	708
SC106	23563	1729	42351	1228	2145
SC107	16746	1115	96746	768	1363
SC108	26276	1805	16523	1156	1261
SC109	13722	796	94038	1194	1431
SC110	20104	2402	70697	1115	1532
SC111	22340	1337	66370	1364	1261
SC112	27767	1452	79139	1391	2725
SC113	10989	963	66407	1239	890
SC114	76750	6220	92829	4176	8529
SC115	89583	7178	39706	4258	7503
SC116	90642	7487	54908	3028	4141
SC117	56748	4464	88200	2001	6392
SC118	42002	2281	75375	1750	927

Since the integrated allocation of physical education resources in university districts is based on the schools under the jurisdiction of the university districts within the university districts, the coordinated allocation of physical education resources among the university districts is carried out in each university district as a whole. University District SC101 is used as an example to demonstrate the need for optimal allocation of the schools under its jurisdiction, as shown in Table 7.

Table 7. School resource allocation for school allocation

	Human resources	Material resources	Financial resources	Talent culture	Social services
SCH1	6629	665	95093	245	263
SCH2	1337	202	28279	74	147
SCH3	2894	543	38039	169	124
SCH4	1805	60	22761	83	43

Box plots can be more intuitive to determine the bias information of the data. In Figure 4, which shows the before and after comparison of the allocation values of physical education resources in the university district, Figure (a) can be observed that the average level of the area of the educational base in the university district before the allocation is about 4, and the average level of the area of the educational base in the university district after the allocation is about 6; Figure (b) can be observed that the average level of the area of the practice platform room in the university district before the allocation is about 0.42, and the average is about 0.63; Figure (c) observes that the average level of sports instrumentation and equipment in the pre-allocation university zone is about 45 and the average level of sports instrumentation and equipment in the post-allocation university zone is about 53; and it can be observed from Figure (d) that the average level of investment in sports funding in the pre-allocation university zone is about 0.19 and the average level of investment in sports funding in the post-allocation university zone is 0.2.



(a)L1 (b)L2

(c)L4 (d)L4

Fig. 4. The comparison of the resource allocation of each indicator

In order to more intuitively observe the comparison between the physical education categories before and after the configuration of the university districts, the balance of the university districts before and after the allocation of educational resources is now represented by a line graph, as shown in Figure 5. From the figure, it can be concluded that before the configuration experiment, the coefficient of variation of resource allocation of SC101 physical education categories in university districts is 0.31, and after the configuration experiment, the coefficient of variation of resource allocation of SC101 physical education categories in university districts is 0.21; the coefficient of variation of resource allocation of SC101 physical education categories in university districts is 0.77, and the coefficient of variation of resource allocation of SC101 physical education categories in university districts is 0.56, and the intra-university district variability becomes lower, indicating a tendency toward balanced development among the university districts.

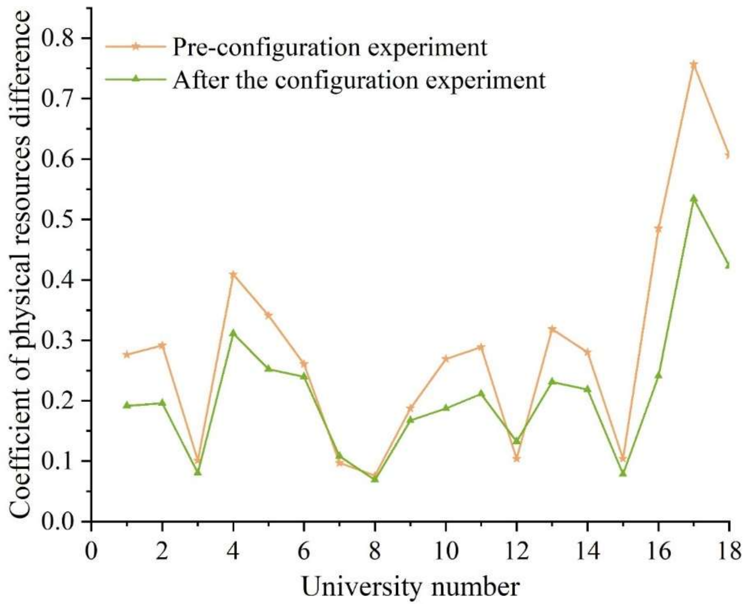


Fig. 5. The comparison of the balance before and after configuration

4. Conclusion

The study constructs the input-output evaluation index system of physical education resources, and proposes a multi-objective function model for the utilization efficiency and allocation efficiency of resources in physical education. On the basis of the original artificial raindrop algorithm, the hybrid collision strategy and stretching operation are added to improve the artificial raindrop algorithm and further improve the optimization performance of the algorithm. The experimental results show that the MEARA studied in this paper performs better than other algorithms, with faster convergence speed and higher accuracy. Subsequently, taking each university district in Wuhan as an example, the MEARA algorithm is applied to carry out simulation experiments, and the optimized resource allocation strategy of each university district is obtained, which verifies that the model designed in this paper can achieve the balanced development of sports resources resource allocation.

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