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ORIGINAL

RESEARCH ON PERSONALIZED PATH RECOMMENDATION OF COLLEGE PHYSICAL EDUCATION ONLINE TEACHING BASED ON IMPROVED PARTICLE SWARM OPTIMIZATION

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ABSTRACT

In recent years, colleges and universities have paid great attention to the education of physical health has the characteristics of strong on-site interaction and high requirements for venues and equipment. The construction of online teaching mechanism of college physical education is not only an opportunity but also a challenge for College Physical Education in China. The construction of online physical education teaching mechanism in Colleges and universities not only helps to improve the physical education teaching system in Colleges and universities in China, but also helps to enhance the importance of college teachers and students on physical education network teaching and promote the diversification of college physical education teaching methods. However, in practice, due to the imperfect construction of their own teaching platform, the lack of online teaching ability of physical education teachers, and the lack of online teaching resources, some colleges and universities in China have affected the quality of online physical education teaching to a certain extent. So, this article presents a personalized path recommendation method mabpso based on the improved particle swarm optimization algorithm for college physical education online teaching. First of all, it combs the literature about personalized teaching path recommendation and intelligent optimization algorithm at home and abroad; Secondly, a feature model (Leet) is constructed for educators and teaching resources; Third, it mainly solves the disadvantage of bspo, that is, it is easy to be trapped in the local optimization. The solution is to get rid of this problem by continuously improving the algorithm to get a more accurate algorithm with strong inhibition, so as to maximize the accuracy of teaching path recommendation and have a more accurate probability in the final calculation.

KEYWORDS: Particle swarm optimization; online teaching; personalized path; MABPSO

1. INTRODUCTION

In recent years, with the continuous development of network information technology in China, the combination of the Internet and people's teaching and work has become more and more close. The construction of online teaching mechanism of physical education in Colleges and universities is not only the requirement of the development of the times, but also of great significance for improving the quality of physical education in Colleges and universities, promoting the improvement of physical quality of college students and their all-round development. However, in practice, due to some college physical education teachers' unskilled operation of online teaching equipment and imperfect construction of College online teaching platform, the actual effect of the construction of college physical education online teaching mechanism in China is greatly reduced (ERGÜDEN, Deniz, ALTUN, ERGÜDEN, & Bayhan, 2019).

At the same time, some colleges and universities still have problems such as insufficient teaching resources and imperfect online teaching management system, so, the goal of online teaching cannot be implemented. (Braumann, Kraft, & Wagner, 2010) Therefore, colleges and universities need to further improve the construction of their own your own platform strengthen the training system, at the same time further optimize their own online physical education teaching management system, so as to improve the quality of the construction of online physical education teaching mechanism and promote the further improvement of the quality of physical education teaching and the comprehensive quality of students (Tao & Ma, 2021; Yang, 2021).

On the basis of studying some literatures, contents of this study summarizes the shortcomings in the field of personalized teaching path. As the research problem of this paper, it proposes a personalized path recommendation method mabpso based on Improved Particle Swarm Optimization Algorithm for online teaching of physical education in Colleges and universities. Through the relationship between teachers and teaching resources, the characteristic model of teachers and teaching resources is analyzed and constructed (Lang, 2015; Smith, 1970). At the same time, the basic binary particle swarm optimization algorithm is introduced, and its shortcomings are analyzed. Finally, the binary particle swarm optimization algorithm is optimized, It is improved on the basis of traditional particle swarm optimization algorithm mutation operator for exploring unknown space is proposed. Through the experimental analysis, it can be proved that the improved algorithm in this paper is more accurate than the other three algorithms, and it is also abler to get rid of local problems. The convergence accuracy and speed of the algorithm are improved (Karsai, Thompson, & Nelson, 2015).

2. Literature Review

The essence of providing individualized teaching path for teachers is to provide teaching resources in order for teachers. In the initial stage of computer-aided education, the learning guidance system provides a basic teaching service for teachers. At this stage, the personalized learning guidance system is insufficient. The application of collaborative filtering recommendation algorithm has effectively solved the problem of personalization, but there are inevitably problems of cold start and sparse data when solving the problem of personalized path recommendation. The rise of intelligent optimization algorithm provides a new solution to the individualized problem of teaching, which alleviates the phenomenon of many resources, resource confusion and cognitive load caused by teachers at present. As a series of technologies evolve more and more make use of machine teaching technology to personalized teaching path recommendation has further developed personalized teaching.

(Ge, 2016) applied the proposed collaborative filtering recommendation algorithm based on content clustering to the distance education network platform to provide teaching resources for educators (Ge, 2016); (Yen & Lu, 2003)introduced the collaborative filtering recommendation algorithm into the field of teaching resource recommendation. On the basis of in-depth analysis of the collaborative filtering algorithm, they proposed a model of the Teaching Resource Recommendation System.(Yen & Lu, 2003) In the personalized teaching path recommendation problem, relevant scholars have used a variety of intelligent optimization algorithms to solve and achieve successful application. (Pan, Zhou, & Shek, 2022) proposed a new model of full path teaching recommendation by using machine teaching technology (Xie, Liu, & Sun, 2016).

Based on the similarity of the characteristics of teachers, the model first gathers a group of teachers and conducts training to predict the teaching resource sequence and teaching performance in the teaching process, and then selects the personalized teaching full path from the predicted path results.(Celnik, Patterson, Kraft, & Wagner, 2009) (Liang Tingting et al.2019) used neural networks and collaborative filtering algorithms to realize personalized recommendation of teaching resources.(Ali & Tawhid, 2017)

(Zheng Qinghua 2020) and others proposed in their patents to use extreme speed neural network technology to realize personalized network teaching resources recommendation.(Q. Zheng, 2020) (Tan Mingxin et al.2019) used Bayesian network to measure the current knowledge level of teachers, and used Tan Bayesian network to predict the teaching style of teachers in the user model, so as to achieve personalized teaching resources recommendation for different teachers.(Hamburg & Collins, 2010; M. Jiang, Yu, He, Qian, & Bialas, 2023)

This chapter mainly summarizes the related literature of personalized teaching path recommendation (Atwood & Buck, 2020; Fu-yuan, 2008). In recent years, with the popularity of personalized online teaching, many researchers regard this field as the research object. Although many achievements have been obtained, there are still many challenges and problems to be solved by researchers. But generally speaking, China has made some achievements in the research of personalized path of online teaching of physical education in Colleges and universities (Meng, Jia, & Qin, 2010; Shi, 2012).

3. Research on personalized path recommendation of high efficient online physical education based on Improved Particle Swarm Optimization

There are many kinds of personalized teaching path recommendation technologies. Collaborative filtering recommendation technology is one of the most widely used technologies, but it has some shortcomings such as cold start and sparse data, while intelligent optimization algorithm technology can avoid the above problems; Therefore, using intelligent optimization algorithm to solve personalized teaching path recommendation problem has become a new research direction.

In this paper, the binary particle swarm optimization algorithm of intelligent optimization algorithm is used to solve the personalized teaching path recommendation problem. In this recommendation, particle swarm optimization has obvious disadvantages, such as insufficient speed and accuracy, resulting in low resource accuracy, poor path quality and slow speed in the path recommendation. In view of the above problems, this paper optimizes the binary particle swarm optimization algorithm to improve the convergence performance of the binary particle swarm optimization algorithm and further improve the speed and quality of teaching path recommendation.

3.1 Personalized teaching path recommendation model

When constructing the personalized teaching path optimization model, the personalized teaching path optimization that is to consider teachers and the characteristics of teaching resources, and can obtain a two-dimensional recommendation model of one teacher (P) and one teaching resource (R). As shown in Fig. 1.

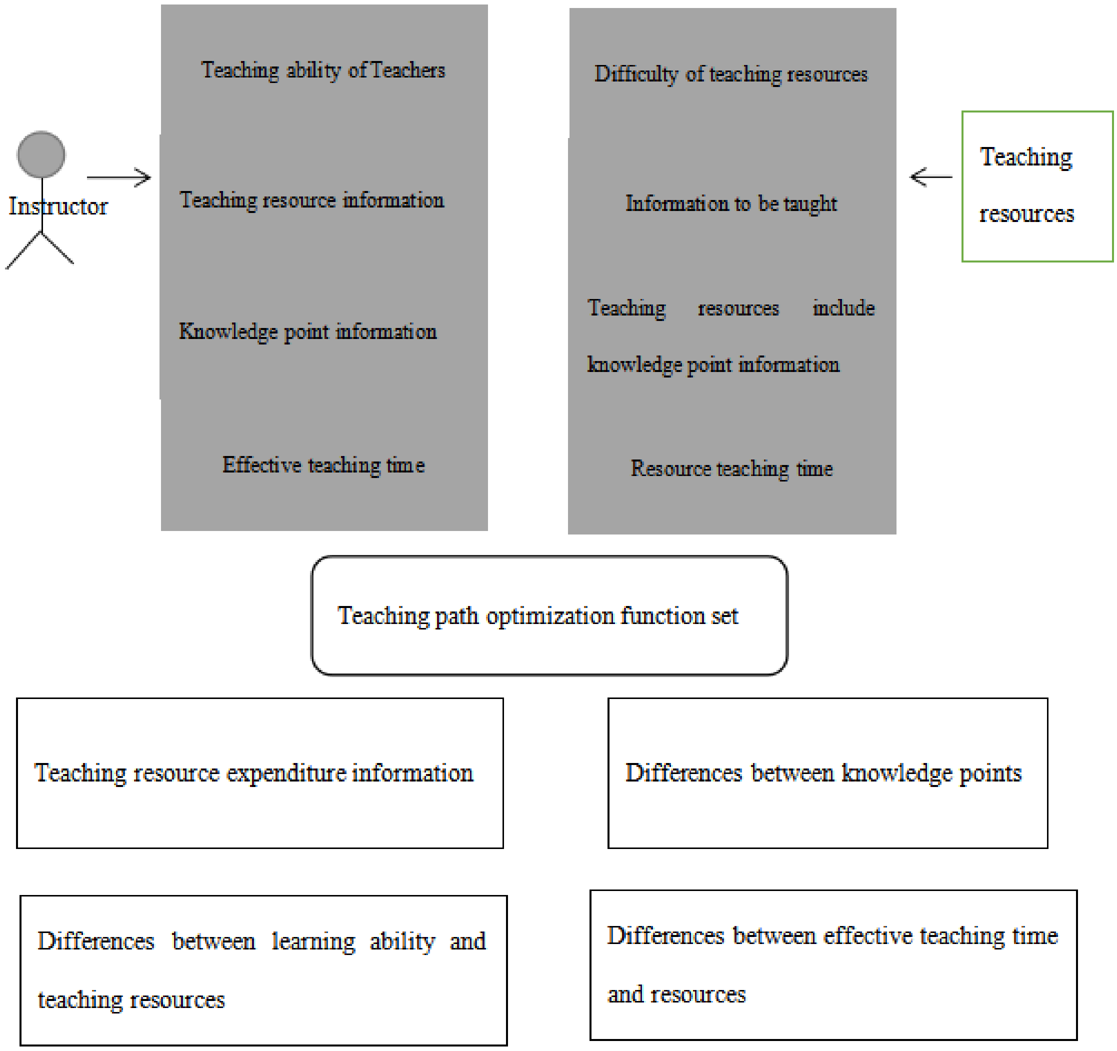

Figure 1: LEET model

In the model shown in Fig. (C.-M. Chen, 2008)1, the characteristics of the teaching staff include the cognitive , the information of the resources being taught, the information of the expected target knowledge points of the teaching staff and the effective teaching time of the teaching staff; The characteristics of teaching resources include the difficulty of teaching resources, the information of teaching resources to be taught, the information of knowledge points contained in teaching resources and the teaching time of teaching resources (Strand, Egeberg, & Mozumdar, 2010; Tao & Ma, 2021). Path optimization set formed in the teaching process includes there are many, which are respectively represented by F1, F2, F3 and F4.

The objective function F1 (the cognitive level objective of the teaching staff) indicates the gap between the two levels the teaching resources. The smaller the difference, the more the difficulty of the teaching resources in the recommended teaching path conforms to the cognitive level of the teaching staff. Such as equation 1.(Lin, Yeh, Hung, & Chang, 2013)

$$f1 = \sqrt{\sum_{j=1}^{N} \left| \frac{\sum_{i=1}^{N}[X_{ar_i br_j}(dar_j - c_h) + X_{ij}(dar_j - c_h)]}{2\sum_{i=1}^{N} ar_i br_j} \right|}, \quad 1 \le h \le H \qquad (1)$$

The objective function F2 (expected goal of the teacher) represents the difference the gap between two kinds of knowledge points expected to be obtained by the teacher. The smaller the difference, the higher the acquisition rate of knowledge points, as shown in formula 2.

$$f2 = \frac{\sum_{q=1}^{Q}\sum_{n=1}^{N} X_{nh}|Y_{nq} - W_{nq}|}{\sum_{n=1}^{N} X_{nh}}, \quad 1 \le h \le H \qquad (2)$$

The meaning represented by the objective function F3 (teaching objective) is shown in Formula 3.

$$f3 = \sum_{j=1}^{N}\sum_{i=1}^{N} x_{ar_i b_{rj}} s_{ar_i br_j} s_{ar_i br_j} \qquad (3)$$

The objective function F4 (teaching time objective) represents the specific gap between the specified teaching time and the time acceptable to teachers as shown in formula 4.

$$f4 = \begin{cases} \sum_{n=1}^{N} T_n X_{nh} - T_{i_{hn}} > 0 \\ \sum_{n=1}^{N} T_n X_{nh} - T_{u_{hn}} < 0 \end{cases} \qquad (4)$$

In the function, dar_j and db_{rj} respectively represent the difficulty level of the ith teaching resource that the teacher is teaching and the difficulty level of the jth teaching resource that the teacher will teach, $1 \le i \le H$,$1 \le j \le N$; c_h indicates the cognitive ability level of the teacher h. (Overdevest, Theodorescu, & Lee, 2009) for different teaching resources, the cognitive ability level of the teacher h is different;Y_{nq} represents the q-th knowledge point of the n-th teaching resource, $1 \le n \le N$,$1 \le q \le Q$,W_{hq} represents the knowledge point q,$1 \le h \le H$ that the H-th teacher expects to teach, and $1 \le q \le Q$,$s_{ar_i br}$ represents the teaching expenditure between the teaching resource being taught and the teaching resource to be taught; $T_{i_{hn}}$represents the lower limit of teaching time of the H-th teacher for the n-th teaching resource, $T_{u_{hn}}$ represents the upper limit of teaching time of the H-th teacher for the n-th teaching resource, $1 \le h \le H$,$1 \le n \le N$.

These are the four sub functions that represent the characteristic parameters of teachers and teaching resources. If the obtained data value is not high, it determines that the personalized teaching path generated is more in line with the requirements of teachers. Combined the sub functions into the total objective function by using four weights.(Kaput & Rodriguez, 2006) Formula 5 which is the functional expression of the personalized teaching path optimization problem, where the weighting coefficient is expressed.

$$minF(x) = \sum_{i=1}^{4} w_i f_i \qquad (5)$$

3.2 Analysis of binary particle swarm optimization algorithm

Particle swarm optimization (PSO) is an adaptive swarm intelligence search algorithm proposed by American psychologist James Kennedy and electrical engineer Rus 5 e 11 EB erhart in 1995 by observing the predatory.(C. M. Chen, 2009) Because this method requires fewer parameters to be adjusted, the not too complicated, so it has successfully solved many complex optimization problems.

In view of the fact that many problems in practical application are not continuous problems, but discrete problems, Jame: Kennedy and Russell Eberhart proposed a binary particle swarm optimization algorithm (binary particle swarm) in 1997 to solve the discrete optimization combination problem (Lang, 2015; Yang, 2021).

The traditional particle swarm optimization (PSO) algorithm has a poor effect in solving the problem of order constraints.(Hall, 2008) However, the problems studied in this paper are not aggregated enough, Therefore, according to the current situation abroad, researchers usually use BPSO to solve this problem, and the final results are quite remarkable. In BPSO algorithm, particle renewal is closely related to speed and teaching objectives. The position of particles in T + 1 is determined by the speed, as follows:

$$v_{ij}^{t+1} = \omega v_{ij}^{t} + c_1 r_1 (p_{ij} - x_{ij}^{t}) + c_2 r_2 (g_{ij} - x_{ij}^{t}) \qquad (6)$$

$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \qquad (7)$$

In the formula, i denotes particles; j denotes the dimension of the particle; ω denotes an inertia weight; t denotes the number of iterations; c_1 and c_2 are normal numbers, generally c_1=c_2=2, c_1 represents self teaching factor, c_2 represents social teaching factor, and r_1 and r_2 are random numbers distributed between [0, 1]; p_{ij} denotes the optimal solution of the particle; g_{ij} denotes finding the global optimal solution in the population.(da Silva, de Souza Baptista, de Menezes, & de Paiva, 2008; Smith, 1970). In this method, the state of particles cannot be generalized, and there is a certain probability. In this range, 0 and 1 vij represent the final value of each particle, explain the probability that x_{ij} takes 1. The formula is as follows:

$$X_{ij} = \begin{cases} 1 & rand() < S(V_{ij}) \\ 0 & rand() < S(V_{ij}) \end{cases} \quad (8)$$

$$S(v_{ij}) = \frac{1}{1+e^{-v_{ij}}} \quad (9)$$

Where, Rand () is a random number distributed in [0,1], and formula 4 represents the sigmoid function.

3.3 Mabpso design of personalized teaching path recommendation algorithm

In this paper, an adaptive inertia weight binary particle swarm optimization algorithm (mabpso) with mutation operator is proposed by improving PSO algorithm. Firstly, according to the population iteration, the inertia weight is adaptively adjusted in a nonlinear gradually increasing manner, so that the algorithm has a large inertia weight at the later stage of the iteration, improving the global optimization ability and enhancing the ability to escape from the local optimization; (Okubo, 2004; Pan et al., 2022).

At the same time, the mutation operator is added to explore the unknown space, the velocity formula is improved, the particle's exploration of the unknown space is increased, the particle's search space is expanded, and the mabsp is increased. The diversity of algorithms can improve the probability of binary particle swarm optimization algorithm jumping out of local optimization (Hamilton, 2012; Jin & Li, 2021).

3.3.1 Nonlinear Increasing Strategy of Inertia Weight

In the binary particle swarm optimization algorithm, the smaller inertia weight improves the exploration ability, while the larger inertia weight focuses on development. Although this algorithm has strong advantages in performance improvement, it also has obvious disadvantages and cannot achieve the final goal and cannot achieve an effective balance between development and search performance.(Graham, Borup, Short, & Archambault, 2019; Xie et al., 2016) In order to make the research method more accurate, the formula of inertia weight has been listed below:

$$w = \begin{cases} \omega_{min} + \frac{2}{\pi} arctan\left(\pi * \frac{t(\omega_{max}-\omega_m)}{T}\right) & 0.4 < \omega \le 0.9 \\ \omega_{max} & \omega > 0.9 \end{cases} \quad (10)$$

It can be seen from formula 10 that the number of iterations changes. T represents the normal number, and T represents the maximum number, When W_{max}=0 .9,W_{min}=0 .4is taken,see Figure 2 for details:

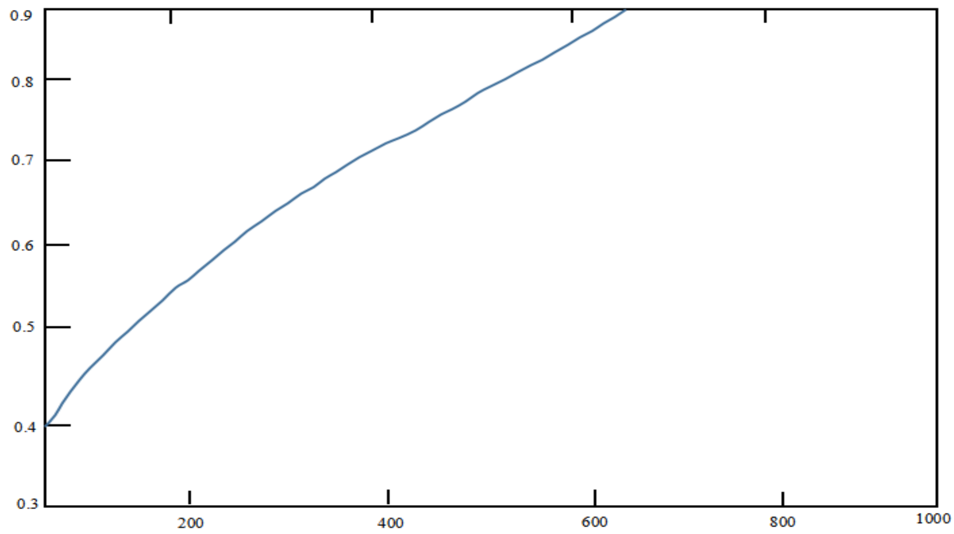

Figure 2: inertia weight change curve

It can be seen from Fig. 2 that can be clear improved method has a small w in the early stage of optimization, and has a strong local exploration ability; In the later stage of optimization, it has a large W and a strong global exploration ability.

3.3.2 Mutation operator

As the mutation operator has significant performance in improving the convergence performance of the algorithm, this paper integrates the mutation operator into the binary particle swarm optimization algorithm based on the mutation idea of the genetic algorithm to prevent premature convergence of the algorithm. The improved formula of the binary particle swarm optimization algorithm is as follows:

$$v_{ij}^{k+1} = wv_{ij}^{k} + c_1 r_1 \left(p_{ij} - x_{ij}^{k}\right) + c_2 r_2 \left(g_{ij} - x_{ij}^{k}\right) + pr_3 \left(Random - x_{ij}^{k}\right) \quad (11)$$

Where random is the random position in the solution space; p is the curiosity coefficient of the unknown world. After a large number of experimental observations,p=2 can get the best effect. r_3 is a random number distributed in [0, 1] Due to the mechanism of exploring unknown space, the search range of particles is expanded, the population diversity is increased, and the premature convergence of the algorithm to a certain extreme value is prevented (Shi, 2012; Stephens, 2020).

3.4 MABPSO process of personalized teaching path recommendation algorithm

By improving particle swarm optimization algorithm from two aspects of inertia weight and mutation operator setting, a more effective and accurate method mabpso is proposed. The steps of personalized teaching path recommendation algorithm mabpso are as follows:

1) Initialize the particle parameters of the mabpso algorithm, including speed, position, individual historical optimum before iteration and global optimum of the population; 2) Update the inertia weight with formula 5; 3) The particle velocity and position are updated by formula 6, formula 3 and formula 4; 4) Calculate particle fitness values; 5) The particle updates the individual optimal and global optimal according to the fitness value; 6) If the algorithm reaches the termination condition, output the optimal value; otherwise, return to step 2.

Complexity analysis of mabspo algorithm: suppose the population size is n and the number of iterations is t. The complexity at initialization is 0 (n); The complexity when calculating the particle fitness value is 0 (NT). So the responsibility of mabpso algorithm is 0 (NT).

4. Test of personalized teaching path recommendation algorithm on benchmark function

In order to determine whether the performance of mabpso is sufficiently perfect, tests were carried out on three unimodal functions sphere, step, Rosen Brock and three complex multimodal functions rastrigrin, Ackley and Griewank. (M. Jiang et al., 2023) The BPSO algorithm with W linear decreasing, the upbpso algorithm with W linear increasing and the binary particle swarm optimization algorithm (mbpso) with unknown space exploration mutation operator proposed in this paper are compared.

4.1 Test function

The three unimodal functions sphere, step and Rosenbrock and the three complex multimodal functions rastrigrin, Ackley and Griewank the details are as follows:

Table 1(a): test functions

FUNCTION NAME	EXPRESSION	EXTREMUM
SPHERE（F1)	$F_1(x)=\sum_{i=1}^{D} x_i^2$	0
STEP（F2）	$F_2(x)=\sum_{i=1}^{D} (x_i+0.5)^{\ 2}$	0
ACKLEY（F3）	$F_3(x)=-20epx\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - exp\left(\frac{1}{D}\sum_{i=1}^{D} cos(2\pi x_i)\right) + 20 + e$	0

Table 1(b): test functions

FUNCTION NAME	EXPRESSION	EXTREMUM
RASTRIGIN（F4）	$F_4(x)\sum_{i=1}^{D}[x_i^2-10cos(2\pi x_i)+10]$	0
GRIEWANK（F5）	$F_5(x)=1/400\sum_{i=1}^{D}x_i^2-\Pi_{i=1}^{D}cos\frac{x_i}{\sqrt{i}}+1$	0
ROSENBROCK（F6）	$F_6(x)=\sum_{i=1}^{D}(1-x_i)\ ^2+100(x_{i+1}-x^2)\ ^2$	0

4.2 Experimental parameter setting

The maximum number of iterations of the four algorithms is 1000, the population size is 30, and they run in 300 dimensions. In the four algorithms BPSO, UPBPSO, MBPSO and MABPSO, the initial value of inertia weight is 2, the maximum value is 0.9, the minimum value is 0.4, the C1 and C2 values are 2, and the p value in mabpso algorithm is set to 2.

4.3 Evaluation criterion

1）Mean value of fitness: the mean value of the results of 30 optimal solutions. 2）Fitness variance: variance of the results of the 30 times optimal solution. 3）Fitness optimal value: the best of the 30 optimal values. 4）Worst fitness: the worst of the 30 best values.

5. Experimental Results and Analysis

5.1 Data analysis

The experimental methods adopted by the following algorithms are as follows: 1) 30 times of operation are adopted respectively; 2) The best results were obtained; 3) Then collect the best results and list a series of values, as shown in Table 3:

Table 2(a): data when the test function is 300 D

FUNCTION	ALGORITHM	BEST VALUE	WORST	MEAN VALUE	STANDARD DEVIATION
F1	BPSO	6.1E+01	7.6E+01	6.93667+01	3.1457E+00
	UPBPSO	5E+01	6.3E+01	5.80333E+01	2.7852E+00
	MBPSO	1.4E+01	2.3E+01	1.91667E+01	2.0356E+00
	MABPSO	1.1E+01	1.4E+01	1.26333E+01	9.6431E-01
F2	BPSO	2.01E+02	2.23E+01	2.13067E+02	5.343E+00
	UPBPSO	1.79E+02	2.01E+01	1.89867E+02	5.1644E+00
	MBPSO	1.07E+02	1.21E+01	1.13733E+01	3.7686E+00
	MABPSO	9.3E+01	1.03E+01	9.84E+01	2.634E-00

Table 2(b): data when the test function is 300 D

FUNCTION	ALGORITHM	BEST VALUE	WORST	MEAN VALUE	STANDARD DEVIATION
F3	BPSO	1.7515E+00	1.9033E+00	1.8318E+00	3.3575E-02
	UPBPSO	1.6125E+00	1.7648E+00	1.6831E+00	4.1957E-02
	MBPSO	8.7472E-01	1.1E+00	9.9547E-01	4.8829E-02
	MABPSO	7.5146E-01	8.7472E-01	8.0348E-01	3.399E-02
F4	BPSO	8.97058E+05	8.97074E+05	8.97068E+05	3.3107E+00
	UPBPSO	0.97051E+05	8.97066E+05	8.97058E+05	3.4833E+00
	MBPSO	8.97016E+05	8.97021E+05	8.97019E+05	1.4499E+00
	MABPSO	8.97009E+05	8.97015E-05	8.97012E+05	1.4559E+00
F5	BPSO	2.8021E-01	3.2892E-01	3.0051E-01	1.2605E-02
	UPBPSO	2.3249E-01	2.7367E-01	2.5647E-01	9.7287E-03
	MBPSO	7.3791E-02	1.0507E-02	8.794E-02	7.3989E-03
	MABPSO	4.3721E-02	6.422E-02	5.3927E-02	5.8385E-03
F6	BPSO	8.847E+03	1.0147E+04	9.58153E+03	3.09499E+02
	UPBPSO	8.149E+03	9.446E+03	8.95893E+03	3.44979E+02
	MBPSO	3.22E+03	4.326E+03	3.73267E+03	2.75589E+02
	MABPSO	2.01E+05	3.374E-03	2.522E+03	3.66129E+02

The unimodal function has only one global optimal solution and no local optimal solution, which is suitable for the convergence accuracy of the detection algorithm. It can be seen from table 2 that in the unimodal functions F1, F2 and F6, the compared with the traditional method, the three values obtained by mbpso are higher those obtained by BPSO and upbpso algorithms, indicating that the convergence accuracy of mbpso is higher than that of BPSO and upbpso algorithms, while the three values mabpso are better than that of mbpso, indicating that the convergence accuracy of mabpso is higher than that of mbpso and is the best among the four algorithms. There are many problems in the multimodal function, of which the local optimal solution is the main one. (BOESCH & BOESCH, 2015; Strand et al., 2010) The degree of change of such problems is high, but the advantages are also obvious. It can identify the local optimal solution in different algorithms in time and play a role in testing. From the above table that in the multimodal functions F3, F4 and F5, the three values mbpso stronger than those obtained by BPSO and upbpso algorithms, which indicates that mbpso has a stronger ability to avoid falling into the local optimal solution than BPSO and upbpso. Meanwhile, three values mabpso on all test functions are better than mbpso, which indicates that mabpso has a stronger ability to avoid falling into the local optimal solution than mbpso and. It is the most accurate of the above algorithms.No matter how multimodal function or a unimodal function, three values mbpso are better than those obtained by BPSO and upbpso algorithms, and greatly improves the convergence efficiency of the algorithm. On FL, F2 and FS, mabpso has the best standard deviation. On

F3, F4 and F6, mabpso's standard deviation is slightly larger than that of BPSO and mbpso. It shows that mabpso algorithm does not damage the stability of the algorithm while improving the convergence accuracy and enhancing the ability of the algorithm to jump out of the local optimal solution (Y. Jiang, Liu, Huang, & Wu, 2010; Peng, Ling, & Wu, 2010).

5.2 Convergence Curve Analysis

The convergence diagram of the algorithm can clearly show the its progress. The following figure lists the final convergence results of the six test functions in detail. In order to ensure their accuracy, each value has 30 runs, as shown in Figure 2:

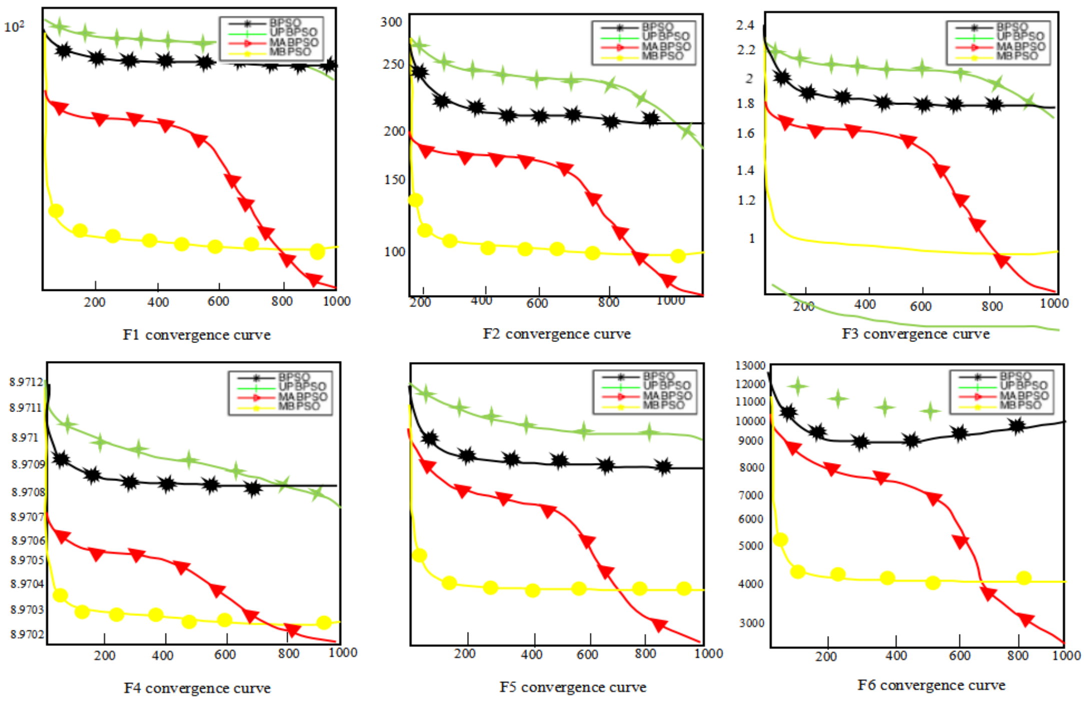

Figure 3: convergence curves of four algorithms on six test functions

It can be seen from Fig. 2 that the final convergence accuracy of the BPSO algorithm is inferior to that of the upbpso algorithm on the functions F1, FZ, F3, F4, F5 and F6; Compared with the BPSO algorithm and the upbpso algorithm, the mbpso designed by adding mutation operator to the basic BPSO algorithm has significantly improved the convergence speed and accuracy. The final results can show that the mutation operator has strong advantages and fewer disadvantages. The advantage is that it can enhance the accuracy and speed of the algorithm. The reason is that it can exert the search range to the strongest state as possible. The disadvantage is that its ability to solve local optimization is not perfect, and there is still a large risk. However, compared with other algorithms, the accuracy and performance of this algorithm are relatively high, and the motion law is more regular.

5.3 Box Whisker Diagram Analysis

In order to more intuitively see the distribution of solution sets, the solution set box whisker diagram of four algorithms on six test functions is given, as shown in Figure 3.

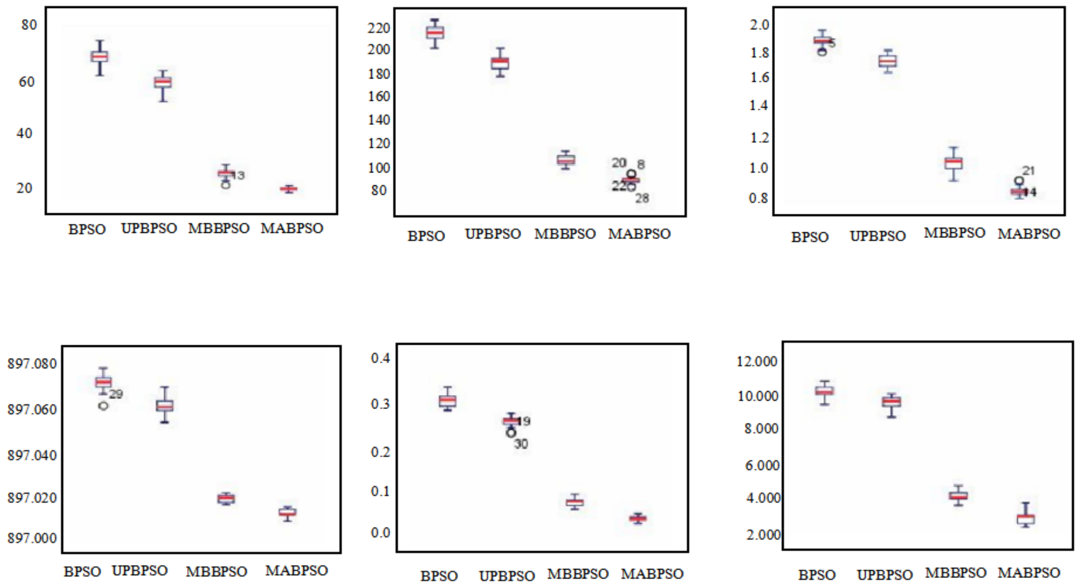

Figure 4: four algorithms in different test functions

It can be seen from Fig. 3 that in the three unimodal functions (a), (b) and (f), the data obtained by the mabpso algorithm is closer to the abscissa axis than the data obtained by other algorithms, indicating that the solution obtained by the data mabpso algorithm is better than the comparison algorithm. On the sphere function and step function, the data range obtained by the data mabpso which indicates that mabpso has better stability. On the three multi peak functions (c), (d) and (E), the data obtained by the mabpso less difference from the horizontal axis, and the numbers obtained is also not only good convergence performance but also good stability. Therefore, the mabpso algorithm proposed in this paper has good convergence performance in both simple unimodal functions and complex multimodal functions (Meng et al., 2010; J. Zheng, Wu, & Song, 2007).

6. Conclusion

Based on the improved particle swarm optimization algorithm, this paper studies the current online teaching path of physical education, brings more personalized methods and more persuasive theories to universities, and finally obtains mabpso. The specific research contents are as follows: firstly, W is obtained from the evolution of this method, mainly in the form of non-linear increment, and more accurate algorithms are used to explore the search performance. In order to maximize its search ability, mutation operator method is also introduced, and finally it is proved that its effect is remarkable, making the accuracy of this method higher and having certain accuracy. Finally, the experimental results obtained by testing on six benchmark functions show that the optimization of the binary particle swarm optimization algorithm in this paper has better ability to escape from the local optimal solution than the other three algorithms, and improves the convergence accuracy and convergence speed of the algorithm. Finally, the prototype system developed in this paper is not yet perfect and mature. Developing a more mature teaching system to provide personalized teaching path services for teachers is the place that needs attention in the next step. Building a mature and stable personalized teaching recommendation platform to provide better user experience is an important way to promote personalized teaching for teachers.

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