J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 561--577

Journal of Combinatorial Mathematics
and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Research on Personalized Learning Path Optimization Strategy Assisted by Artificial Intelligence

Lai Lu[1], Xiaohua Chen[2,✉], Yuejun Li[1]

[1] School of Computer Engineering, Zhanjiang University of Science and Technology, Zhanjiang, Guangdong, 524000, China
[2] School of Foreign Languages, Zhanjiang University of Science and Technology, Zhanjiang, Guangdong, 524000, China

ABSTRACT
Aiming at the learning path recommendation problem, which is the key in personalized teaching, this paper takes the personalized learning path recommendation model as a guide, and researches and gives a method that combines the learning path recommendation model with the NFSBPSO algorithm. The learning path recommendation model based on the two-dimensional features of learners and learning resources is constructed, the population is initialized using the chaos strategy, and the optimal and worst particles in the iteration are optimized using the particle optimization strategy to obtain the optimal solution of the learning path. In order to verify the effectiveness of the personalized learning path recommendation optimization model in this paper, simulation experiments are carried out, and the teaching prototype system of a higher education institution in F city is seen as the experimental platform, and the model in this paper is applied to carry out personalized learning path recommendation practice. The first group of experimental subjects who learn according to the recommended path of this paper have an average test score of 83.6 and an average learning time of 371.7 minutes, which is better than the second group of experimental subjects who learn according to the default path. Most of the values of the recommended matching degree of personalized learning paths are between 0.64-0.9, and most of the adaptation degrees are between 0.11-0.21, which proves that the learning paths recommended by this paper's model to the users have a high degree of accuracy and adaptability.

Keywords: learning path recommendation model, NFSBPSO algorithm, chaos strategy, particle optimization strategy, personalized learning

1. Introduction

The rapid development of artificial intelligence has empowered in many fields and brought far-reaching impact on society, and its excellent processing effect, wide applicability and powerful

✉ Corresponding author.
E-mail address: cxh13590097995@163.com (X. Chen).
Received 25 March 2024; Revised 05 July 2024; Accepted 30 October 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-032

expansion ability provide a solid technical foundation for the informationization service of universities. With the continuous progress of science and technology, the application of AI technology in the field of education is becoming more and more widespread, which can not only optimize the teaching process, but also intelligently analyze the learning situation of students, so as to provide more personalized and accurate educational services for students [1-2].

Among them, machine learning algorithms play an important role in education data analysis, through the analysis of a large amount of education data, machine learning algorithms can reveal learners' learning behaviors and patterns, providing strong support for personalized teaching [3-6]. Meanwhile, deep learning also shows great potential in teaching content generation and recommendation, which can automatically generate and recommend relevant teaching content according to learners' needs and interests [7-9]. The realization of natural language processing technology in intelligent Q&A systems enables teaching assistants to understand learners' questions more accurately and provide precise answers and explanations [10-13]. In addition, AI technology enables intelligent analysis of students' learning outcomes. By collecting and analyzing students' learning data, the intelligent evaluation system is able to comprehensively assess students' learning achievements, habits, and attitudes, helping teachers to more accurately understand students' learning status, and thus provide more targeted teaching guidance [14-18]. This personalized learning experience ensures that students receive more help and attention in the areas they need, and at the same time encourages them to develop further in the areas they are good at.

In this paper, we first establish a personalized learning path recommendation model, parametrically represent learner characteristics and learning resource characteristics, including the learner's learner cognitive ability, learning resource information being studied, etc., and set decision variables to construct four objective functions: learner cognitive level objective, learner expectation objective, learning resource inter-expenditure objective, and learning time objective. Then, the SBPSO algorithm is improved from two aspects, namely, population initialization and change strategy of viscous weights, and the nonlinear factor-based viscous binary particle swarm algorithm (NFSBPSO) is proposed as an algorithm for learning path recommendation optimization.The NFSBPSO algorithm optimizes the viscous weights with the help of the nonlinear factors, and makes use of the chaotic strategy and the particle optimization strategy to initialize the population, to optimize the worst and the optimal particles to improve the quality of the population. Finally, the NFSBPSO algorithm is combined with the learning path recommendation model to realize the optimization of personalized learning path recommendation. Simulation experiments are carried out to verify the effectiveness of the model in personalized learning path recommendation. As for the practical utility test, this paper takes the teaching prototype system of a higher education institution in F city as the experimental platform, and uses the personalized learning path recommendation module of this model system to carry out application practice activities.

2. Personalized Learning Path Recommendation Model

With the continuous deep integration of artificial intelligence technology and educational applications, personalized learning path recommendation is becoming an important form of information service era, which is an effective way to alleviate learners' knowledge disorientation and enhance learning efficiency. However, the wide range of learning knowledge points and the many types of content resources lead to learners in the process of mastering knowledge is very easy to “learning lost” phenomenon, so that it is impossible for learners to recommend a learning path that meets their characteristics and needs. In this regard, in order to realize the personalized needs of learners for online learning resources, personalized learning path recommendation model also came into being, and has become the mainstream personalized learning path optimization strategy [19].

When constructing the personalized learning path optimization model, the personalized learning path optimization model considers two dimensions of learner characteristics and learning resource characteristics at the same time, and a two-dimensional recommendation model of learner (P) and learning resource (R) can be obtained. In this paper, we consider the learning resource difficulty water-half and the learner cognitive water-half, the learning resource time and the learning time range that the learner can afford, the knowledge covered by the learning resource and the learner's desired learning objectives, the learning resource to be the learning resource information and the learning resource information that the learner is learning, and the learning resource information parameters and the learning concept that the learner is going to learn as the personalized features of the two-dimensional model.

2.1. Parameter representation

Learner characteristic parameters and learning resource characteristic parameters representation is the prerequisite work of personalized learning path optimization problem, the purpose is to use mathematical symbols to represent each characteristic parameter of the two, and construct the function expression between the two, i.e., the personalized learning path optimization function, to complete the construction of the function of the personalized learning path optimization problem.

2.1.1. Learner Characterization Parameter Representation

1) Learner competency information. Learner $P=\{P_1,P_2,P_3,P_3,P_3,P_3..P_h\}$ denotes H learners, H denotes the total number of learners, P_h denotes the h rd learner, $1 \le h \le H$. Learner competence $C=\{C_1,C_2,C_3,C_h...C_h\}$ denotes the learning competence level of H learners, C_h denotes the learning competence level of learner P_h, $1 \le h \le H$.

2) Learning resource information expected by learners. Learner Expectation $W=\{W_1,W_2,W_3,W_n \dots W_H\}$ denotes H learning resources that the learner expects to learn, where each W_h has Q binary values, $W_h=\{W_{h1},W_{h2},W_{h3},W_{hq} \dots W_{hQ}\}$, if $W_{hq}=1, 1 \le h \le H, 1 \le q \le Q$, it means that the learning resource expected to be learned contains the knowledge points that need to be learned U_q, otherwise $W_{hq}=0$.

3) Information about the learning resources that the learner is studying. The learning resource that the learner is learning is ar_i, indicating that the ind learning resource is the learning resource that the learner is learning, which is corresponded by q knowledge points, $ar_i=\{ar_1 i, ar_2 i, \dots ar_{qi}\}, 1 \le q \le Q, 1 \le i \le N$; Q is the number of knowledge points, and N is the total number of learning resources.

4) Learner's expected learning time information. The upper limit of the learner's expected learning time is defined as Tu_h and the lower limit of the learner's expected learning time is defined as Tl_h, where $1 \le h \le H$, denotes the upper and lower limits of the learner's P_h expected learning time.

2.1.2. Characteristic parameter representation of learning resources

1) Learning resource information. Learning resource $R=\{R_1,R_2,R_3,\dots,R_n\}$ represents N learning resources, R represents the n rd learning resource, $1 \le n \le N$. Knowledge point $U=U_1,U_2,U_3,\dots,U_6$ represents Q knowledge points, U_q represents the q th knowledge point, $1 \le q \le Q$. $\{Y_1,Y_2,\dots,Y_n\}$ represents N knowledge points contained in the learning resource, each

$R_n, 1 \le n \le N$ with Q binary values, $Y_n = \{Y_{n1}, Y_{n2}, \ldots, Y_{n9}\}$, if the learning resource R_n contains the knowledge point U_q, $Y_{nq} = 1, 1 \le n \le N, 1 \le q \le Q$, otherwise $Y_{nq} = 0$.

2) Information about the learning resources that the learner will study. The learning resource that the learner will learn is br_j, which means that the j nd learning resource is the learning resource that the learner will learn. There are q knowledge points corresponding to $br_j = \{br_1 j, br_{2j}, \ldots, br_{aj}\}, 1 \le q \le Q, 1 \le j \le N$.

3) Difficulty information of learning resources. Difficulty of learning resources $D = \{D_1, D_2, \cdots, D_n\}$, D_n indicates the difficulty of the n th learning resource, $1 \le n \le N$. Learning resources are divided into learning resources that the learner is learning arr_i and learning resources that the learner is going to learn br_j, D_{sri} indicates the difficulty information of the i th learning resource that the learner is learning; D_{brj} indicates the difficulty information of the j th learning resource that the learner is going to learn.

4) Learning resource time information. Learning resource time information $T = \{T_1, T_2, \ldots, T_n\}$, T_n indicates the learning time of the n rd learning resource, $1 \le n \le N$. Learning resources are categorized into learning resources that the learner is learning ar_i and learning resources that the learner is going to learn br_j, T_{ari} indicates the learning time of the i th learning resource that the learner is learning, and T_{bj} indicates the learning time of the j th learning resource that the learner is going to learn.

2.1.3. Decision variables. Set the Learning Resource Recommended Paths variable to X_{sribrj}, and the value of variable X_{aribrj} is encoded in binary, where $1 \le i \le N, 1 \le j \le N$ the learning path is from the i th learning resource to the j th learning resource, then $X_{aribrj} = 1$; otherwise, $X_{aribrj} = 0$.

2.2. Personalized Learning Path Optimization Model Building

According to the parameterized representation of learner and learning resource features, a personalized learning path recommendation model (LEET model) is constructed.

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

The objective function f2 (Learner Expectation Objective) represents the difference between the knowledge points contained in the learning resource and the knowledge points that the learner expects to acquire, and the smaller the difference is, the more the knowledge points contained in the learning resource are in line with the knowledge points that the learner expects to acquire. As in formula (2):

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

The objective function f3 (Objective of Expenditure between Learning Resources) represents the information of expenditure between learning resources as in Eq:

$$f3 = \sum_{j=1}^{N} \sum_{i=1}^{N} x_{ar_i br_j} s_{ar_i br_j} \tag{3}$$

The objective function f4 (learning time objective) represents the difference between the learning time to complete the learning resource and the range of learning time that the learner can afford, as in equation (4):

$$f4 = \begin{cases} \sum_{n=1}^{N} T_n X_{nh} - T_{l_{hn}} > 0 \\ \qquad\qquad\qquad\qquad ,1 \le h \le H \\ \sum_{n=1}^{N} T_n X_{nh} - T_{u_{hn}} < 0 \end{cases} \tag{4}$$

These are the four sub-functions representing the characteristic parameters of learners and learning resources, which together construct the personalized learning path recommendation model. The smaller the values of the four objective functions, the more the generated personalized learning path meets the learner's requirements. The total optimization function of the learner and learning path is constructed by the sub-mapping function through the weighting coefficients, which is expressed by Equation (4), which is the function representation of the personalized learning path optimization problem, where ω_i represents the weighting coefficients:

$$\min F(x) = \sum_{i=1}^{4} w_i f_i \tag{5}$$

3. Personalized Learning Path Recommendation Optimization Model Based on NFSBPSO Algorithm

The algorithm used in the personalized learning path recommended by the traditional personalized learning path recommendation model has slow convergence speed and low convergence accuracy, which results in the personalized learning path recommended to the learner failing to meet the learner's needs. From the learning path recommendation model constructed in the previous chapter, it can be seen that the decision variables of this learning path recommendation problem are discrete, so for solving the discrete combinatorial optimization problem, a nonlinear factorized viscous binary particle swarm algorithm (NFSBPSO) is proposed to combine the learning path recommendation model with the NFSBPSO algorithm, and the learning path recommendation algorithm based on the two-dimensional feature model is proposed TDFM-LP.

3.1. Personalized learning path recommendation problem solving process

The learning path recommendation algorithm TDFM-LP based on 2D feature model is divided into two main parts.

1) Establishment of two-dimensional feature recommendation model for learning resources and learning resources

The premise of the personalized learning path recommendation model is to define the feature parameters, and then construct the learner's cognitive water half, the target knowledge point, learning style and learning time of the four daily standard function, weighted to get the final learning path objective function.

2) Optimize two-dimensional feature recommendation model using viscous binary particle swarm algorithm with nonlinear factors

The two-dimensional feature recommendation model is optimized by the NFSBPSO algorithm, and an optimal solution can be obtained in the end. It can be seen that when the value of the objective function of the learning path is smaller, the learning path recommended to the learner is better; on the contrary, when the value of the objective function is larger, it is not recommended to recommend the learning path to the learner. The flowchart for solving the personalized learning path recommendation problem is shown in Figure 1.

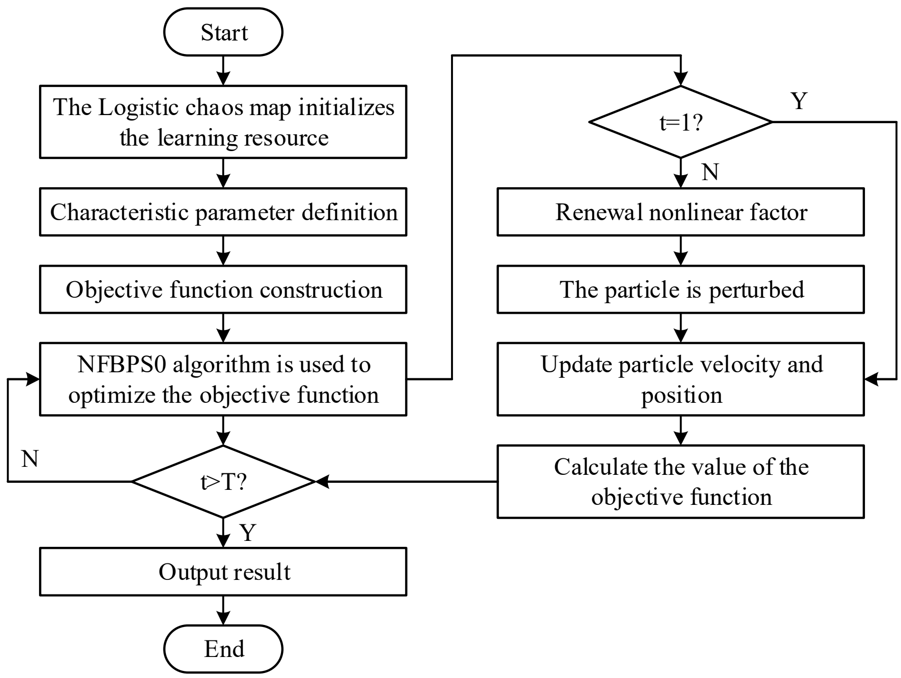


Fig. 1. Process of solving personalized learning path recommendation problem

3.2. *Personalized Learning Path Recommendation Algorithm*

3.2.1. Nonlinear factors. The magnitude of the nonlinearity factor i_s affects the ability of the algorithm to explore and develop [21]. When the value of i_s is large, it improves the probability of particle flipping and facilitates exploration; when the value of i_s is small, it reduces the probability of particle flipping and facilitates exploitation to avoid falling into local optimality. For viscous weight i_s, linear decreasing cannot effectively solve all the optimization search problems, and when the problem is more complex, the local search ability gradually decreases and the required optimal solution cannot be found.

This paper proposes a nonlinear i_s-factor (NF) as shown in Eq. (6) to balance the exploration and exploitation capabilities of the algorithm:

$$i_s = i_s\_l + (i_s\_u - i_s\_l) \times \exp(-20 \times (\frac{t}{T})^6) \tag{6}$$

3.2.2. Chaotic initialization strategy. The initial population of the viscous binary particle swarm algorithm is generated by a randomized strategy, and its population distribution is poor and of low quality. In order to improve the quality of the population, the NFSBPSO algorithm uses Logistic mapping for chaotic initialization as shown in Equation (7):

$$x_{t+1} = \mu x_t (1 - x_t), x_t \in (0,1) \tag{7}$$

where μ indicates the degree of chaos, the larger the value of μ, the higher the degree of chaos; the experiment concludes that when $\mu = 4$, the chaotic state of the system is optimal. In the mapping process, if $x_t \geq 0.5, x_t = 1$; if $x_t < 0.5, x_t = 0.5$.

3.2.3. Particle optimization strategy. SBPSO algorithm in the iterative process of all particles will move to the optimal particle position, resulting in the reduction of population diversity, which affects the particles jumping out from the local optimum. In this paper, we improve the NFSBPSO algorithm by drawing on the optimal particle perturbation strategy and the worst particle update strategy to improve the search ability of the algorithm in the later stage.

1) Worst Particle Update Strategy. In the particle swarm algorithm, has been adhering to the "survival of the fittest" law, in order to improve the quality of the worst particles, in the iterative process of its update operation. The worst particle update strategy is to improve the worst adapted particles in the population, in order to increase the diversity of the population, and then improve the search ability. The worst fitness particle improvement formulas are shown in equations (8), (9), and (10):

$$x_w orst(t) = \arg\max(fit(x_1(t)), fit(x_2(t)) \cdots fit(x_N(t))) \tag{8}$$

$$Eworst(t) = x_i(t) + rand(x_j(t) + x_k(t))(i \neq j \neq k \in 1, \cdots, N) \tag{9}$$

$$x\_worst(t) = \begin{cases} Eworst(t) & if\,(fit(Eworst) < fit(x_w orst)) \\ x\_worst(t) & otherwise \end{cases} \tag{10}$$

2) Optimal particle perturbation strategy. In the SBPSO algorithm, the global optimal solution of the population affects all the particles to move towards the direction of the optimal solution, which leads to the aggregation phenomenon in the later stage, so in this paper, according to the degree of aggregation of the population, the position of the global optimal solution is perturbed, so as to expand the global search ability of the population.

The formulas for determining the degree of aggregation of the population are shown in Eqs. (11) and (12):

$$avg_x(j) = \frac{1}{N}\sum_{i=1}^{N} x[i][j] \tag{11}$$

$$avg_r = \frac{1}{N}\sum_{i=1}^{N} | x_i - avg_x | \tag{12}$$

The perturbation strategy used in this paper is shown in Eqs. (13) and (14), and the size of the perturbation to the global optimal solution is determined by the exponential function in Eq. (13) and (14), while the above illustrates that the size of the perturbation is negatively correlated with avg_r, and therefore the exponential function is negatively correlated with avg_r:

$$Nbest(t) = (1 + sign(rand - 0.5)\exp(-avg_r)) \times Gbest(t) \tag{13}$$

$$Gbest(t) = \begin{cases} Nbest(t) & if\,(fit(Nbest(t)) < fit(Gbest(t))) \\ Gbest(t) & otherwise \end{cases} \tag{14}$$

3.2.4. NFSBPSO algorithm steps

The steps of NFSBPSO algorithm are as follows.

Step1, Logistic chaos strategy is used to initialize the population.

Step2, parameter initialization.

Step3, calculate the fitness value and update the historical optimal solution and global optimal solution for the individual population.

Step4, update the nonlinear factor i_s.

Step5, improve the particle with the worst fitness value.

Step6, perturb the global optimal position for the particle, and judge whether the global optimal solution needs to be replaced according to the adaptation of the particle after the perturbation.

Step7, update the velocity and position of the particle.

Step8, judge the termination condition of the algorithm, output the optimal solution if the condition is satisfied; if not, return to step 3.

4. Simulation Experiments on Personalized Learning Path Recommendation

In order to verify the effectiveness of the personalized learning path recommended by the method proposed in this paper, BPSO, RPSO based on random coefficients, LPSO based on linear coefficients, and VBPSO using V-shaped mapping function binary particle swarm optimization algorithm are applied in the field of online learning resources recommendation to carry out the simulation experiments of the personalized learning path recommendation and compare and analyze the recommendation model based on NFSBPSO algorithm with those of this paper's method. The recommendation model based on the NFSBPSO algorithm used in this paper is compared and analyzed. In order to be closer to the actual application of the learning scenario, the experiment is divided into five groups, and the group experimental parameters are listed in Table 1.

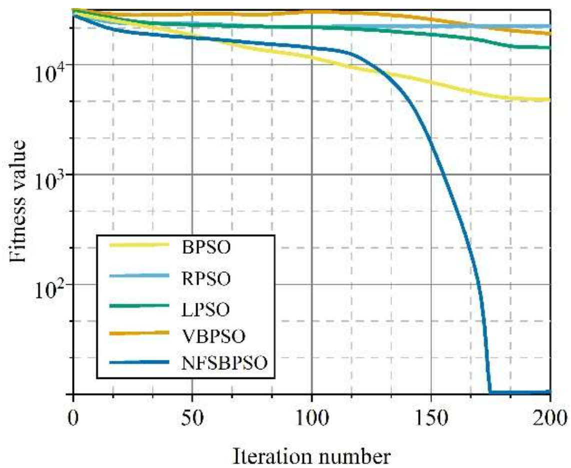
Table 1. Experimental group

	Experimental group 1	Experimental group 2	Experimental group 3	Experimental group 4	Experimental group 5
Number of learner's resource	50	100	150	150	150
Number of learners	40	40	40	50	60

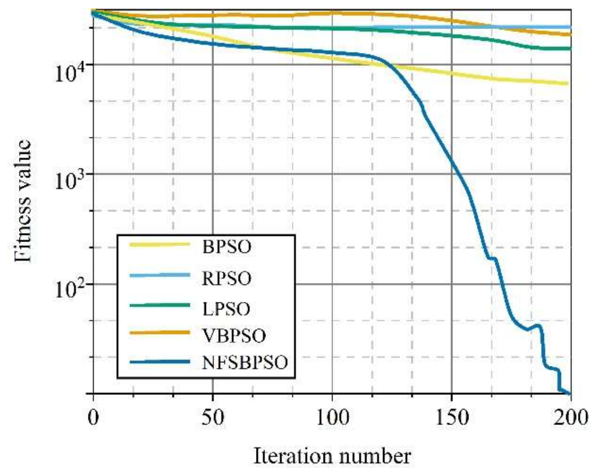
The environment for this simulation experiment is windows 7 operating system and the experimental platform is MATLAB R2012a. The hardware environment is Intel processor i5-4570 and the memory is 4GB.

4.1. *Comparative analysis of convergence*

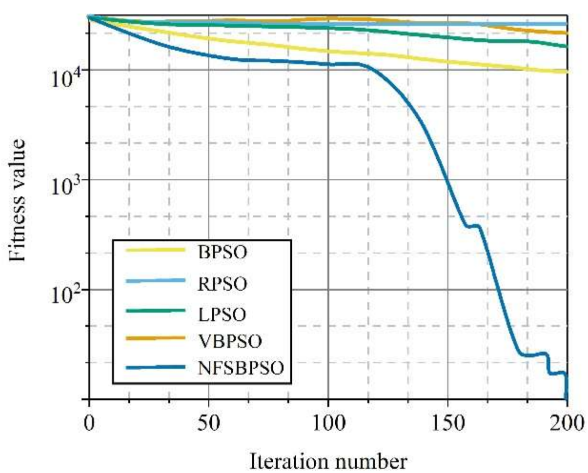
The convergence curves of this paper's personalized learning path recommendation optimization model with other comparative methods using different algorithms are specifically shown in Fig. 2, in which the model used in this paper is the NFSBPSO algorithm. Figures a~e show the convergence curves of different algorithms on experimental groups 1~5 in turn. From the convergence curves, it can be seen that all five particle swarm related algorithms have a tendency to converge, which indicates that the particle swarm algorithm to solve the personalized learning path recommendation model is feasible. By observing the convergence curves of experimental group 1, experimental group 2 and experimental group 3, NFSBPSO shows the best convergence speed in all 3 groups of experiments, which indicates that NFSBPSO has the optimal adaptive ability with the increase of learning resources. Then observe the convergence curves of experimental group 3, experimental group 4 and experimental group 5, with the increase of learners, NFSBPSO still has the best convergence speed and optimal adaptive ability. The model in this paper is able to accurately and quickly recommend personalized learning paths that satisfy learners' needs when learning resources and learners increase.



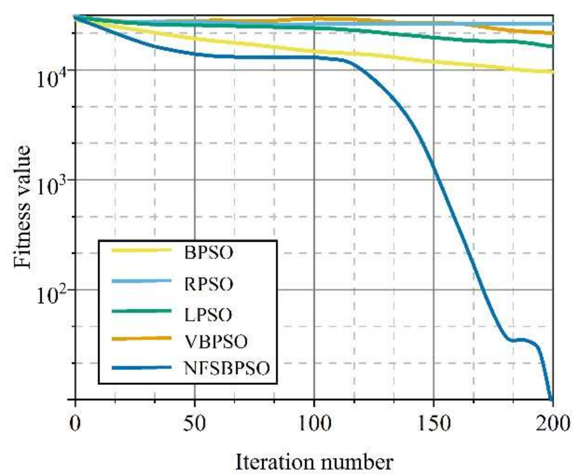
(a)Experimental group 1



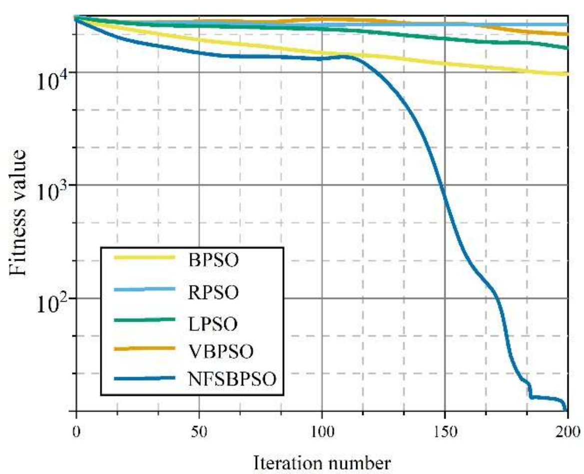
(b)Experimental group 2



(c)Experimental group 3



(d)Experimental group 4

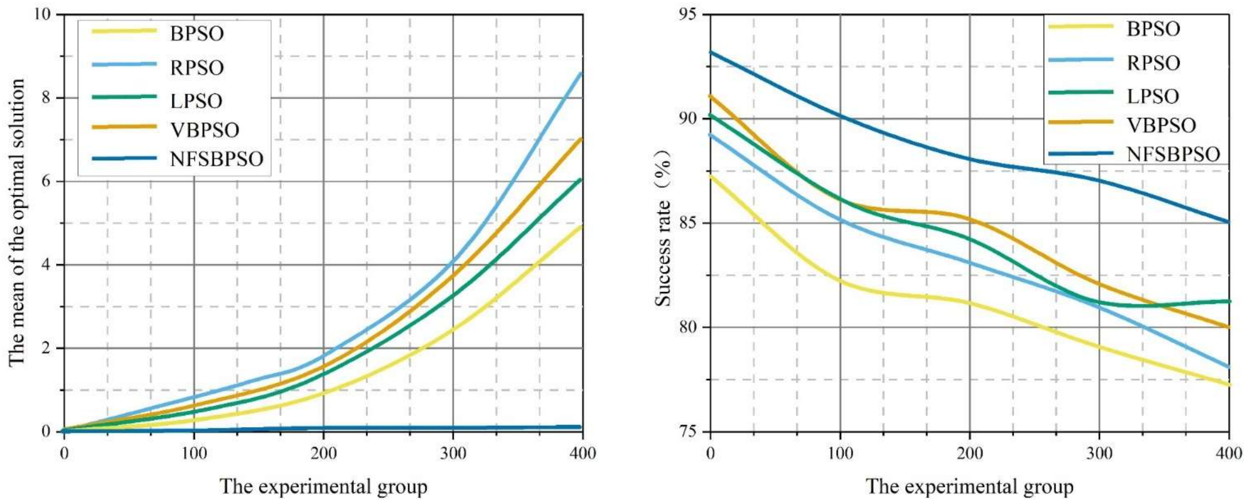


(e)Experimental group 5

Fig. 2. Convergence curve

4.2. Comparative analysis of accuracy

The accuracy comparison between this paper's model and other comparative methods is specifically shown in Fig. 3, where Fig. (a) shows the change curve of the mean value of the optimal solution of each algorithm, and Fig. (b) shows the change curve of the success rate of the algorithm converging to the global optimum. It can be clearly seen that with the increase of learning resources and learners, the solution accuracy and success rate of NFSBPSO are significantly better than other algorithms, and the personalized learning path recommended by the model in this paper has better accuracy and reliability than other methods.



(a)The mean of the optimal solution (b)success rate

Fig. 3. Accuracy contrast

The simulation data of this paper's model and the algorithms used by other methods performing 100 independent experiments are specifically shown in Table 2. Comparing the experimental group 1, experimental group 2 and experimental group 3, with the increase of learning resources NFSBPSO have the best convergence accuracy and stability, and then observing the experimental group 3, experimental group 4 and experimental group 5, NFSBPSO still have the best convergence accuracy and stability when the number of learners increases.

Table 2. Simulation data

Adopted algorithm	-	Experimental group 1	Experimental group 2	Experimental group 3	Experimental group 4	Experimental group 5
BPSO	Avg	2.5492×10^3	2.8993×10^4	9.2886×10^4	2.5194×10^5	4.954×10^5
	Var	1.359×10^3	7.8343×10^4	2.0882×10^4	5.6333×10^5	8.8109×10^5
RPSO	Avg	1.6633×10^3	7.6774×10^4	1.8913×10^4	4.2711×10^5	7.6942×10^5
	Var	4.7195×10^3	1.6056×10^4	3.9775×10^4	9.1758×10^5	1.2747×10^5
LPSO	Avg	8.555×10^3	5.0839×10^4	1.3833×10^4	3.3029×10^5	6.2222×10^5
	Var	2.845×10^3	1.2226×10^4	2.9561×10^4	7.0039×10^5	1.0649×10^5
VBPSO	Avg	1.2769×10^3	6.5776×10^4	1.6934×10^4	3.8692×10^5	7.0966×10^5
	Var	4.1692×10^3	1.4341×10^4	3.5481×10^4	8.2409×10^5	1.1448×10^5
NFSBPSO	Avg	1.1739×10^3	2.573×10^4	7.7233×10^4	2.7534×10^5	9.3287×10^5
	Var	1.7469×10^3	1.4897×10^4	5.3454×10^4	1.4331×10^5	2.2578×10^5

4.3. Comparative analysis of time performance

The mean value of the execution time for each algorithm to converge to the global optimum for each group of experiments is specifically shown in Figure 4. The execution time of each algorithm increases significantly as the complexity and size of the problem becomes larger with more learning resources and learners. In the same set of experiments, the execution time of NFSBPSO algorithm is slightly lower than other algorithms, because NFSBPSO algorithm integrates the fuzzy control optimization strategy, when other algorithms fall into the local optimum and are difficult to converge, NFSBPSO can converge to the optimal value quickly, especially when the control factor is less than 0.5, the advantage of fast convergence can be demonstrated, and the other NFSBPSO has a higher success rate. In addition, NFSBPSO has a higher success rate, and the average execution time is less than other algorithms, so in terms of time performance, the personalized learning recommendation optimization model based on the NFSBPSO algorithm constructed in this paper is also better than other methods.

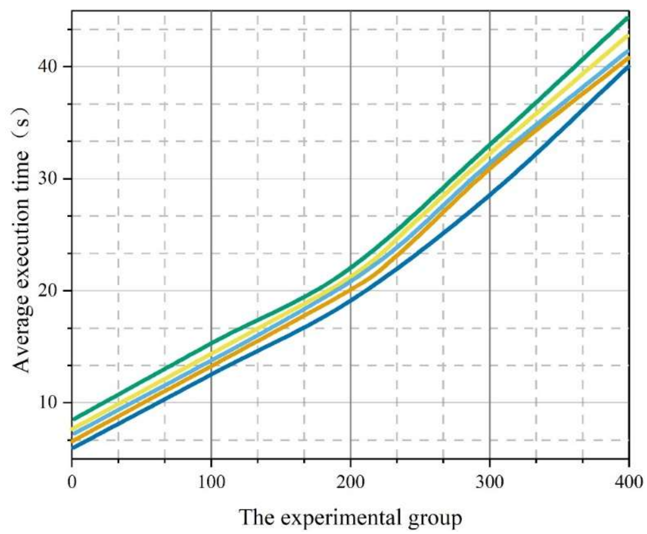


Fig. 4. Contrast of timeliness

5. Personalized Learning Path Recommendation Practices

In this paper, a teaching prototype system in a higher education institution in F city is used as an experimental platform to implement a personalized learning path recommendation module supporting schema knowledge using the model of this paper. The experiments in this paper are implemented on the teaching prototype system that supports schema knowledge, and the target knowledge domain and the set of learning objects are provided by this prototype system. Learning paths are recommended to all the experimental subjects, and the experimental subjects are arranged to learn the target knowledge domains. The experimental subjects are divided into two groups, the students in the "first group" follow the path recommended by the algorithm, and the students in the "second group" do not adopt the learning path although it is also recommended, but follow the default path. At the end of the experiment, we obtained feedback information from the experimental subjects and analyzed the effectiveness, accuracy and adaptability of the learning path recommendation algorithm NFSBPSO proposed in this paper with the experimental results.

5.1. Algorithm effectiveness analysis

The effectiveness of the algorithm examines whether the recommended paths are effective in improving students' performance and reducing their learning time. It is known from the experimental procedure that 30 subjects were divided into two groups of 15 each to learn the knowledge area of "C++ Data Representation". The subjects in the first group followed the path recommended by the algorithm, and the subjects in the second group followed the default path. The learning time and average test scores of the subjects in the two groups are shown in Table 3. As can be seen from the table, the average learning time of the experimental subjects in the first group is 371.7 minutes, and the average learning time of the experimental subjects in the second group is 392.1 minutes, and the learning time of the experimental subjects in the first group is overall less than that of the experimental subjects in the second group. The average test average score of the experimental subjects in the first group was 83.6, and the average test average score of the experimental subjects in the second group was 81, and the test average score of the experimental subjects in the first group was larger than that of the experimental subjects in the second group on the whole. From the results, it can be seen that the average score of the experimental subjects who learn according to the recommended path is better than the average score of those who learn according to the default path, and the time spent on learning is also shorter. It can be seen that the algorithm proposed in this paper has good effectiveness.

Table 3. Learning time and average score of the test

First group			Second group		
Number	Learning time (min)	Average score of the test	Number	Learning time (min)	Average score of the test
1	393	77.5	1	405	76.6
2	384	85.9	2	383	82.4
3	361	87.5	3	371	84.3
4	355	82.2	4	391	78.7
5	399	86.2	5	411	89.2
6	346	87.2	6	429	82.9
7	361	80.2	7	380	81.6
8	343	82.7	8	363	78.8
9	352	82.6	9	408	74.9
10	396	84.1	10	370	79.8
11	380	77.2	11	377	77.2
12	389	86.3	12	388	81.6
13	391	79.1	13	379	73.9
14	367	83.8	14	421	87
15	358	91	15	405	85.4
Average	371.7	83.6	Average	392.1	81.0

5.2. Algorithm accuracy analysis

Algorithm accuracy analysis mainly examines whether the learning path given by the recommendation algorithm matches the user's needs. This experiment analyzes the accuracy of the algorithm from the perspective of recommendation matching degree. Recommended Matching Degree (RMD) refers to the ratio of the number of repeated sections between the learning path recommended to the user and the user's favorite learning path to the number of all sections in the path. The recommended matching degree of the experimental subjects is shown in Table 4.

Table 4. Recommended matching degree

Number of the experimental object	RMD	Number of the experimental object	RMD
1	0.8921	16	0.7421
2	0.6895	17	0.6895
3	0.6668	18	0.6589
4	0.6263	19	0.8495
5	0.5842	20	0.8821
6	0.7695	21	0.7142
7	0.5037	22	0.7295
8	0.8447	23	0.9047
9	0.5616	24	0.7168
10	0.6468	25	0.8495
11	0.7621	26	0.8321
12	0.7216	27	0.6489
13	0.6742	28	0.7742
14	0.8432	29	0.7095
15	0.7995	30	0.7195

The data in the above table is converted into a graph, as shown in Figure 5. From the figure, it can be intuitively seen that the minimum value of the recommended matching degree of the experimental subjects is 0.5037, the maximum value is 0.9047, and most of the values are between 0.64 and 0.9, which indicates that there is a high degree of similarity between the learning paths recommended by the algorithm in this paper and the students' favorite learning paths. Therefore, the learning path recommendation algorithm proposed in this paper has good accuracy.

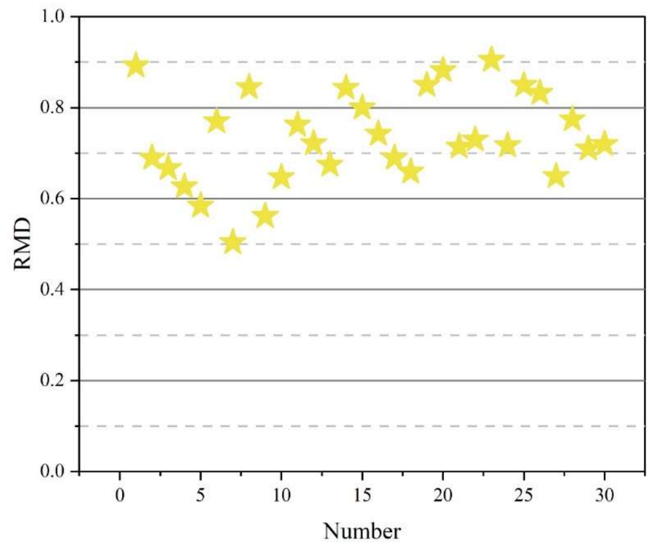


Fig. 5. Recommended matching degree graph

5.3. Algorithm adaptation analysis

Algorithm adaptation analysis mainly examines whether the characteristics of the learning objects on the learning path given by the recommendation algorithm match the learning characteristics of the user. The knowledge domain of this experiment contains a total of 19 knowledge points, and this paper utilizes the mean value of the degree of matching between the 19 learning objects in the recommended learning path and the learning characteristics of the experimental subjects, i.e., the degree of adaptation, to measure the adaptability of the algorithm. Therefore, the formula for the algorithm adaptation degree can be obtained as follows:

$$S = \frac{\sum_{j=1}^{19} Match(s_0, k_j)}{19} \tag{15}$$

The interval of S value is $[0, \sqrt{2}]$. From the formula of Euclidean distance, it can be seen that the smaller the value of S is, the more the characteristics of the learning object on the learning path match with the learning characteristics of the user, i.e., the better the adaptability of the learning path recommended by the algorithm. The experimental results are shown in Table 5.

Table 5. Suitability

Number of the experimental object	S	Number of the experimental object	S
1	0.1404	16	0.1161
2	0.1863	17	0.2155
3	0.2143	18	0.3087
4	0.1036	19	0.1965
5	0.2189	20	0.1155
6	0.1422	21	0.2019
7	0.3034	22	0.2195
8	0.1594	23	0.1728
9	0.1941	24	0.3018
10	0.1134	25	0.3126
11	0.1917	26	0.2091
12	0.2763	27	0.0854
13	0.1283	28	0.1725
14	0.09	29	0.1991
15	0.1551	30	0.1806

The data in the above table is converted into a graph, as shown in Figure 6. From the figure, it can be intuitively seen that the fitness of the recommended paths are all below 0.35, and most of them are between 0.11 and 0.21. It can be seen that the learning objects on the recommended learning paths are more in line with the user's learning characteristics, so the learning paths recommended to the user by the NFSBPSO algorithm proposed in this paper have a high degree of adaptability.

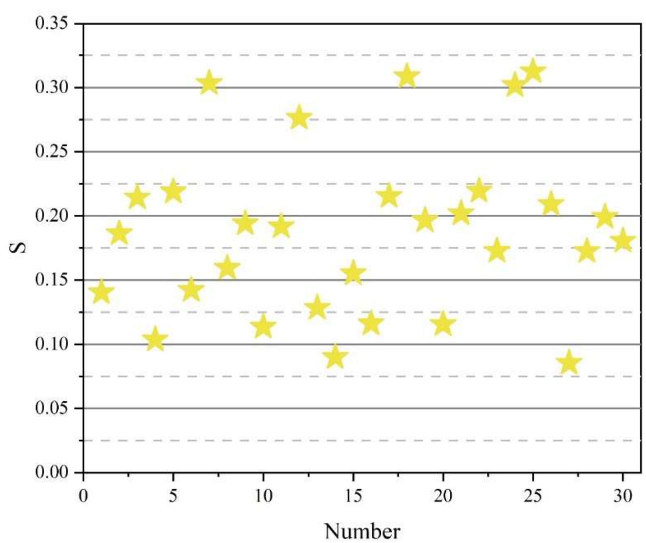


Fig. 6. Suitability comparison chart

6. Conclusion

This paper constructs a personalized learning path recommendation model as an optimization strategy for personalized learning paths, and for the problems of slow convergence speed and low convergence accuracy of the algorithm used for the personalized learning paths recommended by the traditional model, it proposes a viscous binary particle swarm algorithm with nonlinear factors (NFSBPSO), and builds up a personalized learning path recommendation model by adopting a chaotic strategy to optimize the initial population and other ways. Optimization model. In order to verify the effectiveness of the personalized learning path recommended by the model in this paper, BPSO, RPSO, LPSO and VBPSO algorithms are selected as comparison objects to carry out personalized learning path simulation experiments. On experimental groups 1~5, the NFSBPSO algorithms applied by this paper's model all show the best convergence speed with the best convergence speed and the best adaptive ability. With the increase of learning resources and learners, the NFSBPSO algorithm also significantly outperforms the other comparative algorithms in terms of solution accuracy and success rate, and the average execution time of the NFSBPSO algorithm will be less than the other algorithms when the execution time of all algorithms increases significantly. Obviously, in the simulation experiments, the personalized learning path recommended by the model in this paper has better accuracy and reliability than other methods, and also has a slight advantage in time performance.

Finally, the effectiveness, accuracy and adaptability of the NFSBPSO algorithm used in the personalized learning path recommendation optimization model of this paper are discussed in the application practice. The teaching prototype system of a higher education institution in F city is used as an experimental platform, and the model of this paper is adopted to support the personalized learning path recommendation module of this system. In terms of the effectiveness of the algorithm, the subjects in the first group learn according to the path recommended by the NFSBPSO algorithm, while the subjects in the second group maintain learning according to the default path. The average learning time of the first group of experimental subjects is 371.7 minutes, which is lower than the average learning time of the second group of experimental subjects, which is 392.1 minutes, but the first group of experimental subjects performs better in terms of learning performance, with an average test score of 83.6 points, which is 2.6 points higher than that of the second group of experimental subjects. Obviously, the NFSBPSO algorithm proposed in this paper has good effectiveness. As for the accuracy performance of the algorithm, most of the values of the recommended matching degree of the experimental subjects are between 0.64-0.9, and the learning paths recommended by the algorithm in this paper have a high degree of similarity with the students' favorite learning paths, presenting good accuracy. In addition, the adaptability of the recommended paths of the NFSBPSO algorithm are all lower than 0.35 and are mainly between 0.11-0.21, and the learning objects on the recommended learning paths can be more in line with the user's learning characteristics, showing a high degree of adaptability.

References

[1] Pratama, M. P., Sampelolo, R., & Lura, H. (2023). Revolutionizing education: harnessing the power of artificial intelligence for personalized learning. Klasikal: Journal of education, language teaching and science, 5(2), 350-357.

[2] Hashim, S., Omar, M. K., Ab Jalil, H., & Sharef, N. M. (2022). Trends on technologies and artificial intelligence in education for personalized learning: systematic literature. Journal of Academic Research in Progressive Education and Development, 12(1), 884-903.

[3] Shawky, D., & Badawi, A. (2019). Towards a personalized learning experience using reinforcement learning. Machine learning paradigms: Theory and application, 169-187.

[4] Chen, W., Shen, Z., Pan, Y., Tan, K., & Wang, C. (2024). Applying Machine Learning Algorithm to Optimize Personalized Education Recommendation System. Journal of Theory and Practice of Engineering Science, 4(01), 101-108.

[5] Essa, S. G., Celik, T., & Human-Hendricks, N. E. (2023). Personalized adaptive learning technologies based on machine learning techniques to identify learning styles: A systematic literature review. IEEE Access, 11, 48392-48409.

[6] Raj, N. S., & Renumol, V. G. (2022). A systematic literature review on adaptive content recommenders in personalized learning environments from 2015 to 2020. Journal of Computers in Education, 9(1), 113-148.

[7] Zhou, Y., Huang, C., Hu, Q., Zhu, J., & Tang, Y. (2018). Personalized learning full-path recommendation model based on LSTM neural networks. Information sciences, 444, 135-152.

[8] Taylor, R., Fakhimi, M., Ioannou, A., & Spanaki, K. (2024). Personalized learning in education: a machine learning and simulation approach. Benchmarking: An International Journal.

[9] Kundu, S. S., Sarkar, D., Jana, P., & Kole, D. K. (2021). Personalization in education using recommendation system: an overview. Computational Intelligence in Digital Pedagogy, 85-111.

[10] McHugh, D., Shaw, S., Moore, T. R., Ye, L. Z., Romero-Masters, P., & Halverson, R. (2020). Uncovering themes in personalized learning: Using natural language processing to analyze school interviews. Journal of Research on Technology in Education, 52(3), 391-402.

[11] Wang, Z. (2023). Online language education recommendation based on personalized learning and edge computing. Internet Technology Letters, e408.

[12] Pal, S., Pramanik, P. K. D., & Choudhury, P. (2024). Learner's intention analysis to mitigate the cold start problem in personalized learning recommendation systems. Multimedia Tools and Applications, 1-55.

[13] Xu, G., & Wong, C. U. I. (2024). Deep Learning-Based Educational Image Content Understanding and Personalized Learning Path Recommendation. Traitement du Signal, 41(1).

[14] Berondo, R. (2023). Harnessing the power of artificial intelligence for personalized learning in education. European Chemical Bulletin, 12(10), 1243-1251.

[15] Iqbal, M. (2023). AI in education: Personalized learning and adaptive assessment. Cosmic Bulletin of Business Management, 2(1), 280-297.

[16] Yu, H., Wang, J., Murugesan, M., & Rahman, A. S. (2022). Artificial intelligence-based quality management and detection system for personalized learning. Journal of Interconnection Networks, 22(Supp02), 2143004.

[17] Chang, J., & Lu, X. (2019, August). The study on students' participation in personalized learning under the background of artificial intelligence. In 2019 10th International Conference on Information Technology in Medicine and Education (ITME) (pp. 555-558). IEEE.

[18] Katiyar, N., Awasthi, M. V. K., Pratap, R., Mishra, M. K., Shukla, M. N., & Tiwari, M. (2024). Ai-Driven Personalized Learning Systems: Enhancing Educational Effectiveness. Educational Administration: Theory and Practice, 30(5), 11514-11524.

[19] Guoli Xu & Cora Un In Wong. (2024). Deep Learning-Based Educational Image Content Understanding and Personalized Learning Path Recommendation. Traitement du Signal(1).

[20] Kazim Issraa Jwad,Tan Yuegang & Li Ruiya. (2022). Comparison Study of the PSO and SBPSO on Universal Robot Trajectory Planning. Applied Sciences(3),1518-1518.

[21] Kutateladze Varlam. (2022). The kernel trick for nonlinear factor modeling. International Journal of Forecasting(1),165-177.