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Accelerating particle swarm optimization algorithm based on MOOC framework for resource scheduling in physical teaching

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Abstract. In order to improve the rationality of the physical teaching resources scheduling, a new algorithm of particle swarm optimization based on MOOC framework is proposed. First of all, the physical teaching resources scheduling problem is studied, and the physical teaching resource scheduling model is described, and the model constraints are given; secondly, according to the proposed scheduling model, the particle swarm algorithm is applied to be optimized. At the same time, to improve the search performance of particle swarm algorithm, the self learning method of accelerating particle swarm optimization algorithm is adopted, and a kind of accelerating particle swarm optimization algorithm (APSO) is put forward. Finally, through the experimental design, the accelerating particle swarm optimization algorithm based on MOOC framework for resource scheduling in physical teaching is realized and the effectiveness of the proposed method is verified.

Key words. MOOC; Optimization algorithm; Particle swarm; Resource scheduling.

1. Introduction

The essence of college physical education curriculum problem is a multi objective and multi constraint NP hard combinatorial optimization problem [4]. There are many mature algorithms for solving such problems, such as branch and bound [5], grouping optimization decision [6], association rule algorithm [7], etc.. This kind of algorithm has achieved certain results in solving the NP hard combinatorial optimization problem, but there are some problems as follows: (1) in the solving process, the algorithm can solve a certain rather than a general sports timetabling method; (2) the standard of the pros and cons of curriculum criterion is less and the algorithm pays too much attention to the optimization of a certain direction instead

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of achieving the global optimization; (3)there are many problems that are hard to be obtained in the process by using the associated rules way, so the method is not universal and the solution is not ideal.

Particle swarm optimization algorithm (PSO) was proposed in 1995. The researches on the PSO algorithm is much more due to the performance advantages of the algorithm compared with the traditional optimization methods and other intelligent search method and the most important is the algorithm is easy to realize by computer. There are two key factors that can affect the performance of the algorithm: the algorithm exploration ability and development ability, the former affects the population diversity of the algorithm, benefiting the individual particles to find more food rich areas; the later helps the particles to fix the food enrichment area and then it can make deep development to accelerate the convergence. In order to make better use of the performance of PSO algorithm, some scholars have put forward a number of feasible improvement methods. In the paper, the document [1] is studied in detail, and the particle swarm acceleration model based on chaos algorithm is designed for the particle traversing the foraging space. According to the influence of learning factor and inertia weight on the performance of the algorithm, a parameter control machine is designed in document [2]. Based on complementary advantage of the algorithm, document [3] proposed a kind of improved hybrid PSO algorithm, adopting neighborhood search strategy to realize the diversity maintaining mechanism and the relationship between the global exploration "and" deep development "of algorithm is balanced.

In order to ensure the best point in the search area, a robust accelerating particles swarm optimization algorithm is adopted to realize the adaptive update of particle swarm search area. At the same time, the computational complexity of the algorithm is effectively reduced, and the speed of convergence is improved to improve effect of sports timetabling. At the same time, based on the MOOC framework, an online scheduling algorithm based on accelerating particle swarm optimization algorithm is designed.

2. Model of physical teaching curriculum

2.1. Description of the model of physical teaching curriculum

Assuming there are G teachers, L lesions, T course time and R playgrounds in the school is going to execute sports timetabling. Then its mathematical model is described as:

The class set for physical education class is $C = \{c_1, \cdots, c_C\}$: the set the number of the students in each class is $K = \{k_1, \cdots, k_C\}$. The set of the substitute teachers is $G = \{g_1, \cdots g_G\}$, the classes that teachers are responsible for is $Y = \{y_1, \cdots y_G\}$, the number of courses is $L = \{l_1, \cdots l_L\}$, the corresponding class number for each class is $Z = \{z_1, \cdots z_L\}$, the playground is described as $R = \{r_1, \cdots, r_R\}$: the number of students per teacher is $X = \{x_1, \cdots, x_R\}$:. The collection of playground used in each time period is $R = \{r_1, \cdots, r_R\}$.

By calculating the time and the Descartes product of the playground, then the problem of physical education curriculum is transformed into the model of the curriculum and the right time:

2.2. Model constraint

Constraint 1: At the same class, there can be no more than one course at the same time. The form of the constraint is:

$$\sum_{g=1}^{G}\sum_{l=1}^{L}\sum_{r=1}^{R} c_c g_g l_l r_r t_t \leq 1\,. \tag{1}$$

In the equation, $c = 1, 2, \cdots, C \quad t = 1, 2, \cdots, T$. If the class c_c is using the playground r_r, the teacher g_g is responsible for the class l_l in the time t_t, then the expression form is $c_c g_g l_l r_r t_t = 1$, or it is 0.

Constraint 2: The same teacher can only teach one courses at the same time. The form of the constraint is:

$$\sum_{c=1}^{C}\sum_{l=1}^{L}\sum_{r=1}^{R} c_c g_g l_l r_r t_t \leq 1\,. \tag{2}$$

In the equation, $g = 1, 2, \cdots, G \quad t = 1, 2, \cdots, T$. If the teacher g_g is teaching l_l for the class c_c in the playground r_r during the time t_t, then the expression form is $c_c g_g l_l r_r t_t = 1$ or 0.

Constraint 3: the same playground can only hold one course at the same time. The form of the constraint is:

$$\sum_{c=1}^{C}\sum_{g=1}^{G}\sum_{l=1}^{L} c_c g_g l_l r_r t_t \leq 1\,. \tag{3}$$

In the equation, $r = 1, 2, \cdots, R\ t = 1, 2, \cdots, T$. If the teacher g_g is teaching l_l for the class c_c in the playground r_r during the time t_t, then the expression form is $c_c g_g l_l r_r t_t = 1$ or 0.

2.3. Optimization goal

The essence of PE course scheduling system is a multi-objective optimization problem, and its optimization goal is as follows:

Goal 1: the important courses are arranged at the time of good teaching effect. If the 5 courses in the daily teaching are expressed as $a_i\,(i = 1, 2, 3, 4, 5)$, according to the actual teaching experience, the teaching effect of the 1st, 3rd and 5th course is best, expressed as $a_i = 1\,(i = 1, 3, 5)$, the teaching effect of the 2nd and 4th is poor expressed as $a_i = 0\,(i = 2, 4)$. The use of parameters $\beta_j = 1\,(j = 1, 2, 3, 4)$ represent the importance of the curriculum, such as the weight assignment to elective, basic, professional and degree courses is different, the optimization goal is

$$\max(f_1) = \sum (a_i \beta_j) . \tag{4}$$

$$\max(f_2) = \sum (\chi_i \delta_j) . \tag{5}$$

Goal 2: considering the teacher's class time and place, the title coefficient is $\chi_i (i = 1, 2, 3, 4)$, respectively for teaching assistants, instructors, associate professors and professors and other personnel. Willingness of teachers to give class in the set time can be expressed as $\delta_i = 0, 1, 2$, respectively represent no, yes and is willing to. Its optimization objective form:

$$\max(f_2) = \sum (\chi_i \delta_j) .$$

$$\max(f_3) = \sum (\beta_i \varepsilon_j) . \tag{6}$$

Goal 3: for the courses with more hours weekly (such as $n \geq 4$), the courses should be arranged every other day to ensure the teaching effect. The definition of $\beta_j = 1\, (j = 1, 2, 3, 4)$ is the same as goal 1, the definition of $\varepsilon_i\, (i = 1, 2, 3, 4)$ represents the teaching effect of curriculum that is arranged every the other day, then the goal of the optimization is:

$$\max(f_3) = \sum (\beta_i \varepsilon_j) .$$

Goal 4: resource utilization, the larger proportion of the number of students k_c taking the capacity of the playground means the higher the utilization rate, t the goal of the optimization is:

$$\max(f_4) = \sum (k_c / r_r) . \tag{7}$$

The above objective function is optimized by multi objective function, and the optimization scheme is not clear, and the scheme is not optimal. The problems of using single objective optimization is different magnitude, the traditional scheme using weight to synthesize, which need for a priori knowledge, the actual optimization process, the magnitude of each target is changed in real time. Fixed weight is obviously inappropriate. In this regard, the form of adaptive weights is as follows:

$$f = \max \left(\sum_{m=1}^{4} \frac{f_m - f_m^{\min}}{f_m^{\max} - f_m^{\min}} \right) . \tag{8}$$

In the equation, f_m is the Current individual fitness value of the m population, $f_m^{\max}$ is the maximum fitness of the population, $f_m^{\min}$ and is the minimum fitness of the population. This method can realize the weight adaptation, and can improve the accuracy of the search.

3. Accelerating factor self-learning particle swarm optimization

3.1. Behavior analysis of particle swarm optimization algorithm

Particle swarm optimization model is mainly composed of three parts [4∼5]:

$$v_{id}^{k+1} = v_{id}^{k} + c_1 r_1 \left(p_{id}^{k} - x_{id}^{k}\right) + c_2 r_2 \left(p_{gd}^{k} - x_{id}^{k}\right) . \tag{9}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} . \tag{10}$$

Referred to as "history" in the relevant literature, its main role is to reflect the inertia of the previous generations of individual trends, which is the last generation of particle flying speed, and the basis of particle velocity, playing the role of inertia.

$c_1 r_1(p_{id}^{k} - x_{id}^{k})$ is known as "cognitive" part, the main function of this part is the observation of particle for the evolutionary process to determine the next behavior tendency. When the value is increased, the particle will be close to the global optimum value.

$c_2 r_2(p_{gd}^{k} - x_{id}^{k})$ is known as the "social" part, through the comparison of the current particles with the neighbor particles, drawing on the good aspects of the neighborhood particle in the foraging process, inheriting and carrying forward the behavior trend of the population particles.

Through simple logic analysis, we know that, when flying particles tend to be "cognitive", indicating a population between tendency to stick to make self as the center to maintain the diversity of population; and particle flight tends to be "social", then particle swarm can accelerate the convergence to the global optimum value

3.2. c_1, c_2 mathematical analysis of self learning algorithm

Here we take the two-dimensional vector as an example to illustrate, such as the Vector superposition of $c_1 r_1(p_{id}^{k} - x_{id}^{k}) + c_2 r_2(p_{gd}^{k} - x_{id}^{k})$ shown as figure 1. It can be seen directly from the vector diagram, when the $r_1(p_{id}^{k} - x_{id}^{k}) r_2(p_{gd}^{k} - x_{id}^{k})$ is set, the vector angle β and $\theta_1 + \theta_2$ are set, then the Relative size change of θ_1, θ_2 will affect the impact of particle flight direction to be "cognitive or society. That is to change the relative size of θ_1, θ_2 can change the behavior tendency of development and exploration of PSO algorithm.

Theorem 1. Learning factor c_1 increases and c_2 keep unchanged, in-flight particle behavior is more "cognition", tending to explore independently, which helps to maintain diversity; learning factor c_1 is constant, c_2 increases, then the particles tend to be "social", which is good to speed up convergence.

Proof: as shown in Figure 1, according to the theorem:

$$\frac{a}{\sin\text{(A)}} = \frac{b}{\sin\text{(B)}} = \frac{c}{s\text{in (C)}} = 2R\,. \tag{11}$$

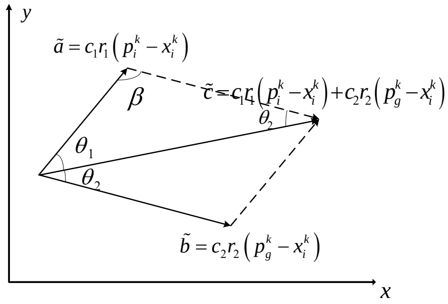


Fig. 1. Two-dimensional particle behavior vector

Among them a, b, c represents the side; A, B, C represent angle. Corresponding to the relations Among the Angles and Sides, according to the formula (3):

$$\frac{c_1 r_1 \left| p_i^k - x_i^k \right|}{\sin(\theta_2)} = \frac{c_2 r_2 \left| p_g^k - x_i^k \right|}{\sin(\theta_1)} = 2R\,. \tag{12}$$

It can be concluded that, when the learning factor c_2 is constant, c_1 is increased and θ_1 is reduced; similarly, learning factor c_1 is constant, c_2 is increased and θ_2 is reduced. Based on the above analysis, we can prove the theorem 1 is true.

Theorem 2. Particle being "cognitive" or "social" is partly determined by the direction change of c_1/c_2: when c_1/c_2 increasing, particle behavior tends to be "cognitive", which is good to keep the diversity of birds; when c_1/c_2 reducing, particle behavior tends to be "society", which is good for bird populations and individuals to quickly locate and find the optimal value.

Proof: according to equation (4):

$$\frac{c_1 \sin(\theta_1)}{c_2 \sin(\theta_2)} = \frac{r_2 \left| p_g^k - x_i^k \right|}{r_1 \left| p_i^k - x_i^k \right|}\,. \tag{13}$$

From the foregoing knowledge, it is known that the $r_2 \left| p_g^k - x_i^k \right| / r_1 \left| p_i^k - x_i^k \right|$ of k is fixed value, which is set as Δ_1, then $\theta_1 + \theta_2$ is fixed value, which is set as Δ_2, then the equation (5) can be transformed as:

$$\frac{c_1}{c_2} = \Delta_1 \frac{\sin(\Delta_2 - \theta_1)}{\sin(\theta_1)}\,. \tag{14}$$

$$\frac{c_1}{c_2} = \Delta_1 \frac{\sin(\theta_2)}{\sin(\Delta_2 - \theta_2)}\,. \tag{15}$$

For equation (6) and (7), it can be concluded that when the learning factor c_1/c_2 increases, θ_1 decreases. Similarly, the learning factor c_1/c_2 increases, the θ_2 will decrease. Based on the above analysis, we can establish the theorem 2.

3.3. c_1, c_2 *parameter adjustment design*

Through the above analysis and combined with particle swarm algorithm mechanism, we should know that good algorithm in the early stages of the search should be emphasis on "exploration", as far as possible to maintain the population diversity, and prevent the premature convergence of the algorithm, and in the later search, we should emphasis on the "development", speeding up the search and convergence to optimize target value. We port algorithm to each individual particle, when individual overly tends to be "exploration", we can adjust the relative value of c_1, c_2 in the evolutionary process, making it gradually tend to be "development", and vice versa. In the end, the individual particles can reach a state of equilibrium. Combining with fitness, we design parameter adjustment method are as follows:

$$\begin{cases} c_1 = a - prob_i \\ c_2 = b + prob_i \\ prob_i = fit_i / \max fit \end{cases} \tag{16}$$

Among them, $\max fit$ is the optimal value of the current PSO population, fit_i is the adaptive value of the i particle of current PSO population, so the range of values of $prob_i$ is between $[0, 1]$ (for the optimization problem of the maximum extreme value), a, b is constant value, $c_1 \in [a-1, a]$ $c_2 \in [b, b+1]$ can be obtained. The algorithm procedure of accelerating particle swarm optimization algorithm based on MOOC framework for resource scheduling in physical teaching is shown in figure 2.

In the figure, VTR is the Set end value of the objective function, $k_{\max}$ is the set maximal iterative algebra

4. Experimental analysis

4.1. Performance test of optimization algorithm

Griewank:

$$f2 = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1\,.$$

Rosenbrock:

$$f3 = \sum_{i=1}^{n} \left(100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right).$$

At first, the performance of the algorithm is simulated and compared based on the standard test function. The standard test function is as follows:

Griewank:

$$f2 = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1\,.$$

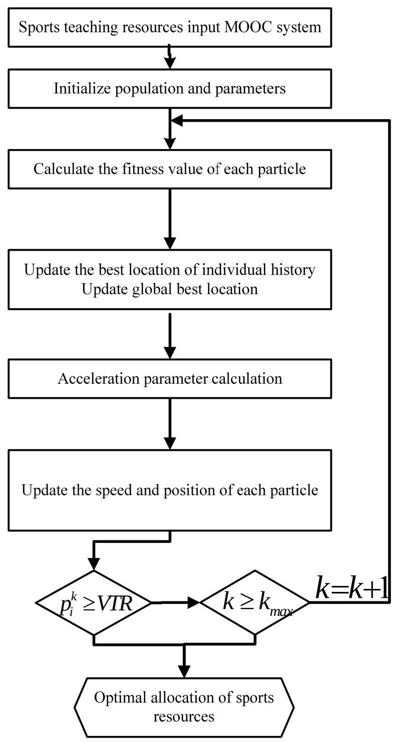


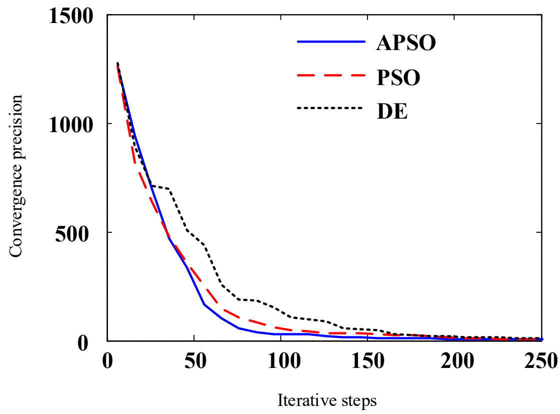
Fig. 2. Procedure of parameter self-adjusting particle swarm algorithm

Rosenbrock:

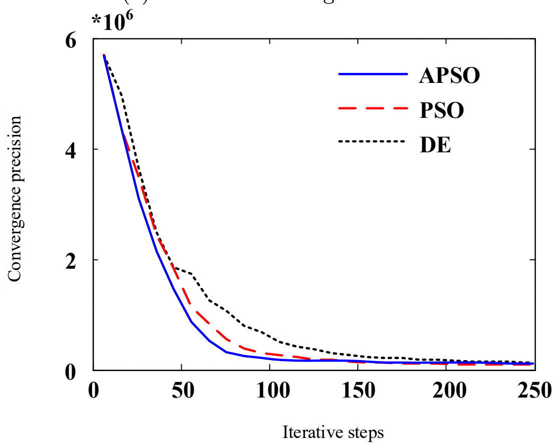
$$f3 = \sum_{i=1}^{n} \left(100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right).$$

Comparison algorithm selects differential evolution algorithm (DE), APSO algorithm and PSO algorithm. Simulation results of APSO algorithm and contrast algorithm in convergence speed and convergence accuracy (shown in Figure 3). Hardware equipment: CPU i3-2440, RAM 8G ddr3 1600. Simulation software: matlab2012a. In order to ensure the fairness of the results, the algorithm runs 20 times and the average value is obtained. Select the algorithm $T_{\max} = 250$ to terminate the number of iteration steps, water drop algorithm other parameter settings see literature [2].

Figure 3 (a), (b) respectively provides convergence curves of three kinds of contrast algorithm in the standard test functions. Although it can be seen in the early stage that the PSO algorithm is slightly better than the APSO algorithm, but the overall convergence rate of APSO algorithm is faster than the DE algorithm and particle swarm optimization (PSO) algorithm and PSO algorithm convergence speed is faster than the APSO algorithm. The convergence accuracy of the APSO algorithm is better than the other two kinds of contrast algorithm.



(a) Griewank convergence curve



(b) Rosenbrock convergence curve

Fig. 3. Comparison of convergence

4.2. Course scheduling system optimization

The subject is a university course table, the arranging elements of which are shown in table 1. The developed course scheduling system is implemented based on visual c++.

Table 1. class arrangement elements

Element	Student	Teacher	Class	Course	Playground	Task
Quantity	6200	387	125	669	168	669

The standard DE algorithm is selected as the contrast algorithm, and the evaluation index is selected as the target function value and the evolution time. Experiments were carried out for 20 times with evolutionary algebra every 100 times, querying and obtaining the optimal individual adaptation value of current population. Table 1 shows the average convergence curve of the optimal individual fitness value. In the same way, the operation time of the algorithm is compared with that of the algorithm, and some of the results are shown in Table 1.

Table 1 gives the APSO algorithm and the DE algorithm of the average convergence curve, it can be seen that the convergence rate of APSO algorithm is faster than the DE algorithm, and the convergence accuracy of APSO algorithm is higher. Figure 5 shows the APSO algorithm and DE algorithm in the course scheduling system running time comparison and it can be seen that the APSO algorithm is significantly less than the DE algorithm. Figure 6 is given based on the visual c++ and the algorithm of this paper to achieve the course scheduling system schematic. Table 2 is the comparison of the effect of course arrangement.

Table 2. Effect of class arrangement

Method	weekly class number of main subjects(day)	Interval of same class	average number of classes every day
DE	2.3	1.3	6.3
APSO	2.7	1, 5	4.8
Playground utilization(%)	Missing course Number	Teacher satisfaction	Course conflict rate(%)
89.5	18	86.4	16.3
99.3	0	99.5	1.2

Table 2 shows the comparison of class arrangement between APSO and DE algorithm. It can be seen from the table, the indicators of resources use rate, and course missing quantity, satisfaction of the playground, class arrangement conflict rate of APSO algorithm is better than the DE algorithm, reflecting the application effectiveness of APSO algorithm in class arrangement system.

5. Concluding

This paper provides an accelerating particle swarm optimization algorithm based on MOOC framework for resource scheduling in physical teaching, descriptions of sports teaching resources scheduling model the constraints of the model, then puts forward an accelerated particles swarm optimization algorithm, realizing the accelerating particle swarm optimization algorithm based on MOOC framework for resource scheduling in physical teaching. Finally, through the experiment the proposed method is proved to be effective.

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