Teaching Decision Optimization for Sustainable Development of Students

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Abstract—With the shift of the global education view to humanism, more and more scholars and experts have gradually deepened their research on sustainable development ability of students in higher vocational colleges. As for sustainable development of students, the core and basic point is to develop their personality and teach them in accordance with their aptitude. As a bridge and link between teaching thinking and practice of teachers, their teaching decisions need to fully take into consideration the sustainable development of students, which is of great significance to future employment, job transfer and promotion of students. Therefore, this paper studies the teaching decision optimization (TDO) for the sustainable development of students. First of all, a related teaching decision model is constructed. Then this paper proposes the particle swarm optimization algorithm (PSO) of teaching decision path based on progress rate, gives the principle of selecting TDO template, designs three different optimization models for ordinary particles, high-quality particles and progress particles and represents the optimization strategy of teaching decision path. Finally, experimental results verify the effectiveness of the optimization model.

Keywords—sustainable development of students, teaching decisions of teachers, decision optimization

1 Introduction

Teaching decisions of teachers refer to a series of dynamic processes of determining the most effective teaching plans, in which teachers play their subjective ability [1–4], through prediction, analysis and reflection on teaching practice and in accordance with their own beliefs, knowledge and constantly formed practical wisdom, thus achieving teaching objectives and completing teaching tasks [5–10].

With the shift of global education view to humanism, more and more scholars and experts have proposed that recessive quality is the key support for students to achieve success in the long run, and gradually deepened their research on the sustainable development ability of students in higher vocational colleges [11–15]. However, the existing relevant research lacks a unified standard, which cannot give a targeted and feasible overview and description of the sustainable development ability [16–20], because the core and basic point of sustainable development of students is to develop their personality and teach them according to their aptitude. As a bridge and link between teaching thinking and practice of teachers, their teaching decisions need to fully taken into consideration the complex and dynamic time-varying characteristics of teaching subjects and learning subjects in the classroom, with the goal of making students fully understand the process of knowledge generation and development, thus enabling the students to obtain the learning effects of improving their good aspects and filling in the gaps in the whole teaching, which is of great significance to the future employment, job transfer and promotion of students.

Zhang et al. [21] constructs a decision model for the quality evaluation system of practical teaching, which is composed of five first-level evaluation indicators, namely, objectives, design, resources, implementation and effects of practical teaching, and 17 second-level evaluation indicators, such as clear teaching objectives and so on. The evaluation system has the characteristics of strong operability and comprehensive coverage of indicators, which can effectively improve the quality of practical teaching. In order to provide direct and reliable decision support for the promotion of personalized learning resources (PLR), the current research urgently need to overcome several problems of PLR recommendation, such as the recommended PLR not meeting requirements, no dynamical analysis of learning behavior, and no good prediction of learning intention. In order to solve these problems, Huiji [22] discusses big data-assisted PLR recommendation and teaching decision support. Take oral and written language education in the process of exploration as an example, which introduces the flow of the algorithm in detail and proves its effectiveness in experiment. Distance education requires teachers to make innovative teaching decisions. Therefore, it is of great significance to optimize the elements of distance education, improve the quality of teaching activities and achieve sustainable development. Zhao [23] aims to study the optimization of teaching decisions based on teaching data of distance education platform. First of all, a hybrid neural network, combining bidirectional long and short term memory (Bi-LSTM) model with convolutional neural network (CNN), is introduced into TDO model, which aims to capture the bidirectional time series characteristics of teaching decisions and build a feature space with stronger expression ability. Effectiveness and superiority of the model are verified in experiment.

Success of education for sustainable development (ESD) requires training of necessary specific skills to cope with the highly emotional background after epidemic. In this regard, Guillén et al. [24] focuses on the ability of college students to understand and manage their emotions, which is considered to be the key factor of ESD. The study aims to show how students' emotional intelligence affects their resilience and the influence on their participation and subsequent academic performance. A model is provided to link the classical variables of education and positive psychology research with ESD during COVID-19. Awotunde and Westhuizen [25] investigates the impact of applying systematic action learning and action research (SALAR) on entrepreneurial self-efficacy (ESE) of students, and determines the relationship between ESE development, entrepreneurial intention and action. A structured and self-managed 7-point Likert scale survey was conducted on students from a selected university in South Africa for 9 months by using quantitative design and retest method. The research results put forward a flexible social technology model (SHAPE) and method (SALAR), which can be used by other higher education institutions to promote the development of youth entrepreneurship education.

Existing research usually studies the teaching decisions of teachers in specific subjects and analyzes the factors that affect the teaching effects. TDO is usually divided into two aspects, namely, teaching subject and learning subject. However, most scholars have not done relevant research on how to optimize teaching decisions for the sustainable development of students. Some scholars emphasize the teaching feedback function of students, however, as for the guidance and demonstration of teachers in the future vocational education process of students in higher vocational colleges, their research lacks this comprehensive consideration. Therefore, this paper studies TDO for students' sustainable development. In chapter 2, the paper constructs a related teaching decision model. In chapter 3, the paper proposes PSO of teaching decision path based on progress rate, gives the principle of selecting TDO template, designs three different optimization models for ordinary particles, high-quality particles and progress particles, and presents the optimization strategy of teaching decision path. Finally, experimental results verify effectiveness of the optimization model.

2 Construction of TDO

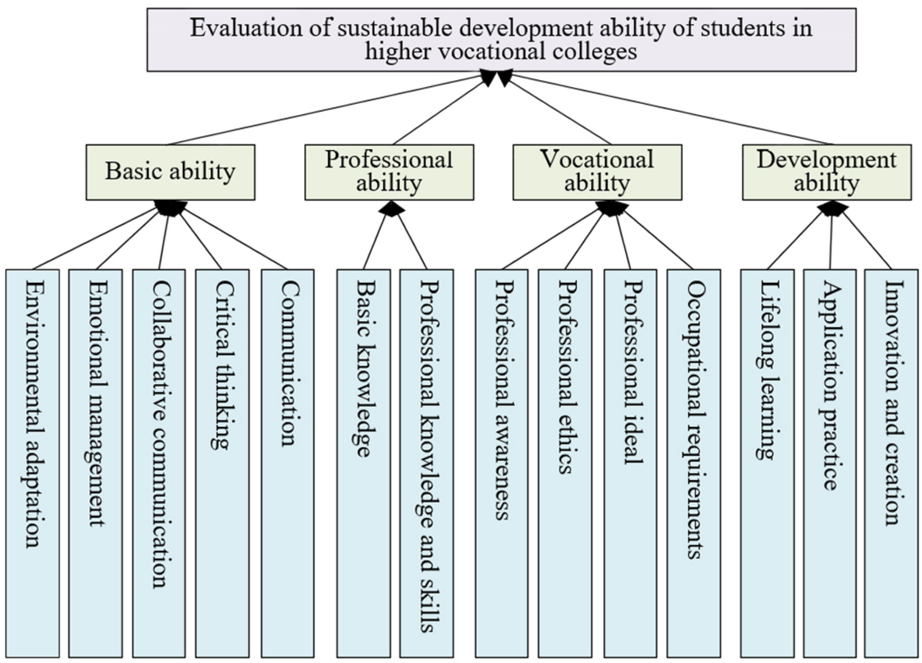

Fig. 1. Evaluation of sustainable development ability of students in higher vocational colleges

Under the guidance of sustainable development theory, by drawing on the concepts of career planning, long-term development of students in higher vocational colleges and modern vocational education, this paper summarizes the development directions of sustainable development ability of those students based on existing research results, which is shown in Figure 1.

In the research scenario of this paper, by considering current learning and future sustainable development of students as a whole, teachers make centralized teaching decisions. Based on the principle of maximizing the overall learning energy efficiency of students, teaching links in the teaching system of teachers determine the degree of TDO, with centralized teaching decision situation represented by subscript D. It is assumed that z represents the unit learning energy efficiency benefits of students in each teaching link, A represents the sustainable development demand of students, $g(a)$ and $G(a)$ represent the cumulative probability density function and distribution function respectively, K represents the teaching ability level of teachers, c represents the random output factor in terms of the degree of teaching decisions satisfying students' sustainable development needs, d represents the difficulty degree of TDO, r_1 represents the missing cost of all teaching links meeting the sustainable development need of students, r_2 represents the unit punishment of each teaching link when the sustainable development need of students cannot be met, and u represents the unit disposal residual value of the remaining TDO ability. As for centralized teaching decisions, the expected benefits of the overall teaching system of teachers are as follows:

$$\Psi_D = z\min(a, cK_D) - dK_D - r_1(a - cK_D)^+ + u\,(cK_D - a)^+ \tag{1}$$

As for the centralized teaching decisions, the expected payoff function of the whole teaching system can be simplified as follows:

$$P(\Psi_D) = \int_x^y \int_0^{rK_D} (z + r_1 - u)(a - cK_D)g(a)\psi(c)dadc - r_1\lambda_a - dK_D + (z + r_1)\lambda_c K_D \tag{2}$$

In the above formula, the optimal student learning energy efficiency improvement K_D^*, which is caused by the centralized teaching decisions, satisfies the equation:

$$\int_x^y c\left[1 - G(cK_D^*)\right]\psi(c)dc = \frac{d - u\lambda_c}{z + r_1 - u} \tag{3}$$

The first derivative of expected payoff function $P(\Psi_D)$ by using K_D is as follows:

$$\begin{aligned} \frac{\partial^2 P(\Psi_D)}{\partial K_D^2} &= (z + r_1)\lambda_c - d - \int_x^y \int_0^{rK_D} (z + r_1 - u)\, cg(a)\,\psi(c)\, dadc \\ &= (z + r_1)\lambda_c - d - \int_x^y (z + r_1 - u)\, cG(cK_D)\,\psi(c)\, dc \end{aligned} \tag{4}$$

The second derivative of expected payoff function $P(\Psi_D)$ by using K_D is as follows:

$$\frac{\partial^2 P(\Psi_D)}{\partial K_D^2} = -\int_x^y (z + r_1 - u)\, c^2 g(cK_D)\,\psi(c)\, dc \tag{5}$$

Value of the above formula is less than zero, which can be inferred that $P(\Psi_D)$ is the concave function of K_D. Therefore, when the value of formula 4 is 0, the learning energy efficiency improvement of students K_D^* is obtained.

Based on implicit function theorem, sensitivity analysis of TDO model can be made to reach the following conclusions:

$$\frac{\partial K_D^*}{\partial z} > 0, \frac{\partial K_D^*}{\partial r_1} > 0, \frac{\partial K_D^*}{\partial u} > 0, \frac{\partial K_D^*}{\partial d} < 0 \tag{6}$$

In a centralized teaching decision context, as for the optimal student learning energy efficiency improvement value, which optimizes all teaching links in the whole teaching system, it increases with the increase of z (the unit student learning energy efficiency benefits of all teaching links), r_1 (the missing cost of all teaching links meeting the sustainable development need of students) and u (the unit disposal residual value of the remaining TDO ability), and decreases with d (the increase of the difficulty degree of TDO).

3 PSO of teaching decision path based on progress rate

3.1 Teaching decision optimization template

In the TDO process by using heuristic algorithms, how to maintain the diversity of decision optimization strategies is a key issue. In fact, in the process of continuous optimization of teaching plans, teachers often have multiple optimization templates, which helps students extract different knowledge or experience conducive to their sustainable development in each teaching link of the teaching system.

This paper uses PSO to optimize the centralized teaching decision of each teaching link in the teaching system. The individual particles of particle swarm represent the learning energy efficiency of students. From the perspective of contour map, it can be found that there are dense contours near the local optimal value of individual particles, which is a common feature of centralized TDO. Therefore, if the fitness value of a particle changes sharply in two consecutive iterations in the search process, the particle may have found a local optimal solution, that is, a teaching strategy optimization path which significantly improves the learning efficiency of students. Considering that the global optimal solution is also a local optimal solution, the above particles are likely to be near the local optimal solution. In this paper, these particles, which are defined as progress particles effectively improving learning efficiency of students, are regarded as learning objects of other particles.

Inspired by the learning phenomenon of human society and the optimization contour map, this paper evaluates the advantages and disadvantages of particles of traditional PSO through progress rate. Specifically, three particles with the highest fitness values and particles with the top 10% progress rates in the population are selected as high-quality particles and progress particles separately, and recorded in the corresponding sets separately. That is, if the population size is represented by M, the number of high-quality particles and progress particles in each iteration is 3 and 10% M separately. It is assumed that $g(a_i^o)$ represents the fitness value of the oth generation of the ith particle, and $|A_i^{o+1} – A_i^o|$ represents the Euclidean distance of position changes of the particle in two consecutive iterations. Change rate of fitness value of a particle within unit distance is defined as progress rate of the particle, and the specific calculation formula is as follows:

$$ZS\,(i) = \frac{g(a_i^{o+1}) - g(x_i^o)}{p^{\left|A_i^{o+1} - A_i^o\right|}} \tag{7}$$

According to the above formula, if the progress rate of a particle is large, it means that the position changes of the particle are little and its fitness value is greatly improved.

It should be noted, with maximization of the overall learning energy efficiency of students being discussed in this paper, the high-quality particles need to be arranged in descending order according to the fitness values, that is, particles with larger fitness values are in the front, and those with smaller fitness values in the back. However, the progress particles are arranged in ascending order according to their progress rates, that is, the particles with smaller progress rates are in the front, and those with larger progress rates in the back. In this paper, the high-quality particles and progress particles are recorded based on their current positions instead of historical optimal positions. The expressions of high-quality particle set R_h and progress particle set R_i at o time are as follows:

$$R_h^o = \{A_1^o, A_2^o, A_3^o \mid g\,(A_1^o) \le g\,(A_2^o) \le g\,(A_3^o)\} \tag{8}$$

$$R_i^o = \{A_1^o, A_2^o, \cdots, A_j^o \mid g(A_1^o) \ge g(A_2^o) \ge \cdots \ge g(A_j^o)\} \tag{9}$$

In addition, it is possible for a particle to exist in both high-quality particle set and progress particle set, which is worth noting. Of course, due to different selection indicators adopted by the two sets, the possibility of this situation is quite small.

3.2 Optimization strategy of teaching decision path

After introducing progress particles as the additional optimization template of particles, as for TDO path for maximizing the whole learning energy efficiency of students, its search by using the algorithm will be jointly affected by two kinds of particles and the historical optimal locations of the individual particles, because progress particles do not have good fitness values. Therefore, this paper designs three different optimization models for ordinary particles, high-quality particles and progress particles.

Since high-quality particles represent the best teaching decision path in the particle swarm, this paper constructs a confidence model for them as their way of optimization and improvement. In this model, as for the high-quality particles in the traditional PSO, they optimize according to their own experience instead of learning from the progress particles. However, in the PSO taking progress rate into consideration, in order to improve the optimization diversity of high-quality particles, a high-quality particle need to optimize other two high-quality particles apart from optimizing based on its own experience. This paper introduces a perturbation term into the confidence model, which can help high-quality particles jump out of the local optimal trap. It is assumed that s_1 and s_2 represent a random number obeying uniform distribution within (–1,1), $s_1 \times u_i^o$ represents the perturbation term that helps high-quality particles improve their fitness values, and WE^o represents the weighted average positions of high-quality particles. The following formula shows the speed update method of the confidence model:

$$u_i^{o+1} = s_1 \times u_i^o + \theta \times u_i^o + s_2 \times (WE^o - a_i^o) \tag{10}$$

Assuming that WE_i represents the ith high-quality particle in the high-quality particle set, the weighted average position WE^o can be calculated by the following formula:

$$WE^o = \frac{1}{6}(3 \times WE_1 + 2 \times WE_2 + WE_3) \tag{11}$$

According to the above formula, the particles with the best fitness values have a significant impact on other high-quality particles. This optimization and progress way ensures that the best TDO experience in the particle swarm can be effectively shared among high-quality particles.

The ordinary particles in the particle swarm need to learn from the high-quality particles and the progress particles. An ordinary particle will randomly select a particle from two particle sets, namely, high-quality particle set and progress particle set, in accordance with different probabilities as its optimization template. Of course, particles with better fitness values or progress rates in the sets will have a higher probability of being selected. Assuming that N represents the length of the set, the probability of the lth particle being selected in the set can be calculated by the following formula:

$$z = \frac{N - l + 1}{\sum_{i=1}^{N} i} \tag{12}$$

The following discusses two cases of progress particles being superior or inferior to individual historical optimal locations of current particles. In the former case, by ignoring their own historical optimal positions, the particles choose to learn from the selected progress particles and high-quality particles only instead of optimizing based on their own experience. Assuming that TG_i^o and WE_i^o represent progress particles and high-quality particles selected by the ith particle at o time respectively, then:

$$u_i^{o+1} = \theta \times u_i^o + s_1 \times (TG_i^o - a_i^o) + s_2 \times (WE_i^o - a_i^o) \tag{13}$$

In the latter case where the optimization experience of the progress particles does not influence the current particles any longer, the particles' search track for the TDO path will be determined by its historical optimal positions and high-quality particles:

$$u_i^{o+1} = \theta \times u_i^o + s_1 \times (zbest_i^o - a_i^o) + s_2 \times (WE_i^o - a_i^o) \tag{14}$$

Based on different types of particle optimization models, particles in particle swarm can choose different optimization strategies at different evolution stages. Figure 2 shows the flow chart of PSO.

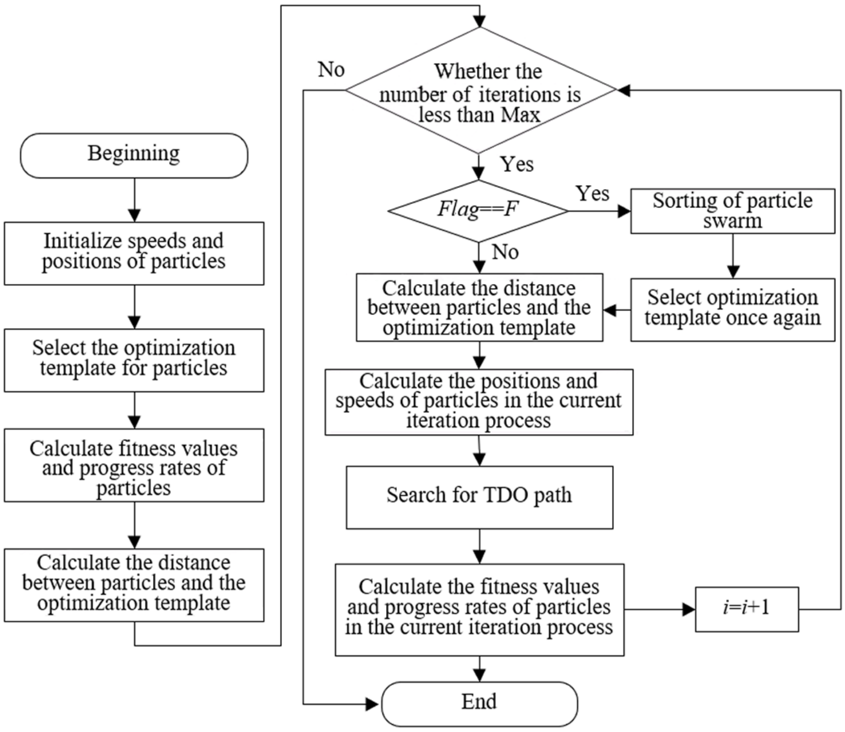

Fig. 2. Flow chart of PSO

3.3 Particle motion boundary constraint strategy

In traditional PSO, based on the particle positions in the previous iteration process and the particle speeds in the current iteration process, the particle positions in the current iteration process are updated. Therefore, as for particles whose positions exceed the solution space boundary of target problem, their speeds in the current iteration process will be damaged, and some of the speeds will suddenly disappear. At this time, the speeds of current particles lose their original influence on the update of their positions, and the particles will be tied by force to the solution space boundary of the target problem. At the same time, in the next iteration process, in terms of speed update in the dimension of the solution space of the target problem, the particles will move in the direction beyond the solution space boundary because of inertia. In order to solve the above problem, this paper sets the solution space elastic boundary for the target problem. As a result, when the particles move to the positions of solution space boundary, they rebound elastically without their speeds being damaged.

$$a_{i,j}^{o+1} = \begin{cases} a_{\max,j} - (a_{i,j}^{o+1} - a_{\max,j}), if \quad a_{i,j}^{o+1} > a_{\max,j} \\ a_{\min,j} - (a_{\min,j} - a_{i,j}^{o+1}), if \quad a_{i,j}^{o+1} < a_{\min,j} \\ a_{i,j}^{o+1}, other \end{cases} \tag{15}$$

At this time, speeds of the particles will change. The following formula gives the expression of the speeds:

$$u_{i,j}^{o+1} = \begin{cases} -u_{i,j}^{o+1}, if \quad crash \\ u_{i,j}^{o+1}, other \end{cases} \tag{16}$$

4 Experimental results and analysis

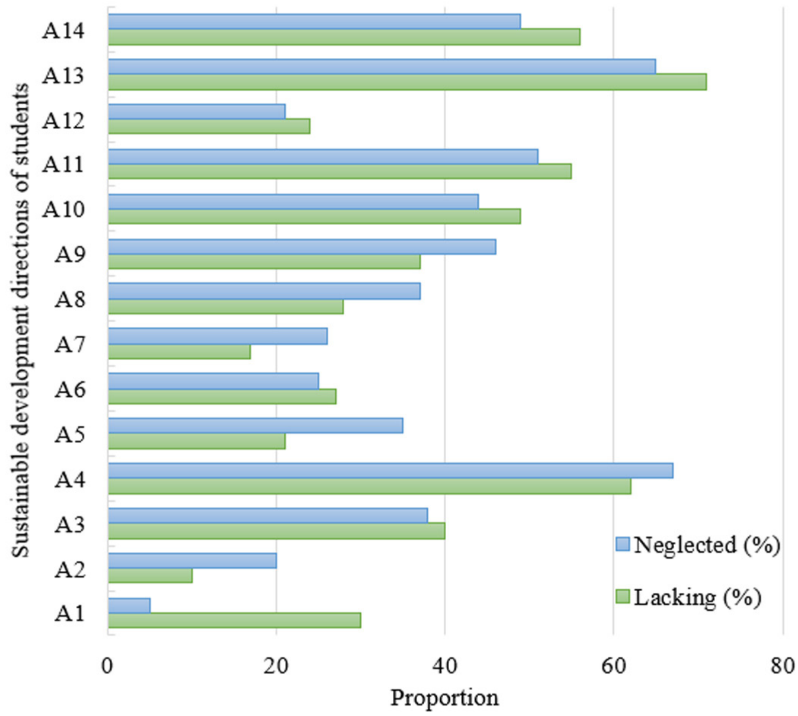

Fig. 3. Histogram of sustainable development directions of students in higher vocational colleges

Corresponding to the development directions of sustainable development ability of students in higher vocational colleges in Figure 1, the histogram of each direction is shown in Figure 3. According to the figure, the proportion of 14 sustainable development directions is different. As the statistical results shows, as for the ability of innovation, team cooperation and interpersonal communication and basic professional quality, which can help sustainable development, the students are lacking in those abilities. At the same time, lack of basic professional knowledge and skills can also be seen intuitively. Therefore, when teachers optimize their teaching decisions, they need to pay attention to the cultivation of practical ability of students and avoid focusing on theoretical education.

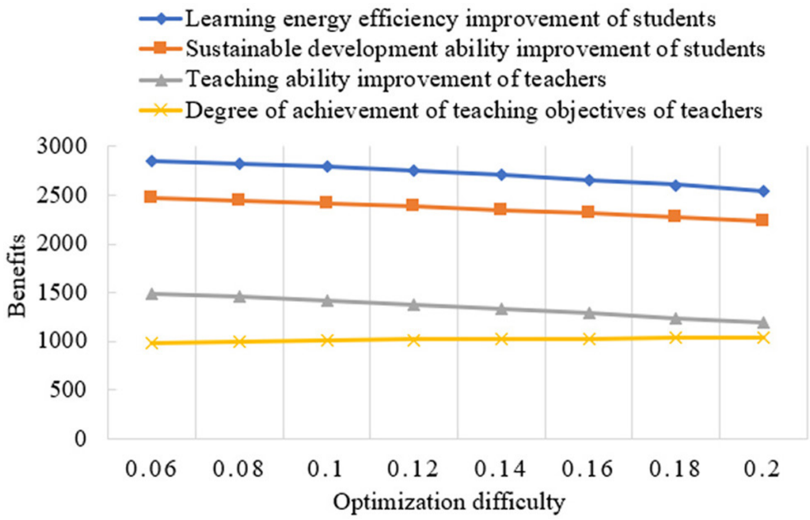

Fig. 4. The impact of the difficulty of TDO on TDO benefits

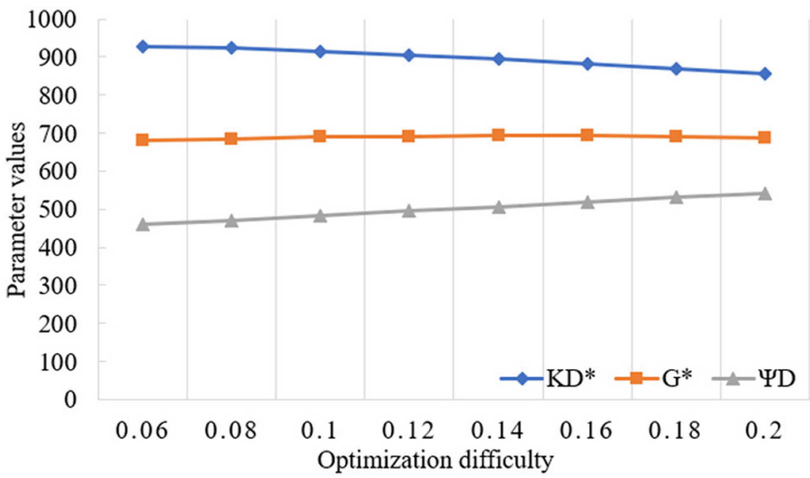

Fig. 5. Influence of TDO difficulty on the parameter values of the decision model

Figure 4 shows the impact of TDO difficulty on TDO benefits. According to the figure, when the average value of TDO difficulty is fixed, with increase of its fluctuation range (that is, with more discrete TDO difficulty), as for the overall teaching system of centralized decisions, four TDO benefits will decrease accordingly, namely, learning energy efficiency and sustainable development ability of students, teaching ability of teachers and the degree of achievement of teaching objectives of teachers. This verifies that when TDO difficulty changes within a certain range, teachers are more inclined to meet the need of learning energy efficiency improvement of students by improving their teaching ability. Being the leader of teaching activities, as for the uncertainty of sustainable development of different students, teachers need to improve the quality of TDO in order to meet the need of students for future development.

Figure 5 shows the influence of TDO difficulty on the parameter values of the decision model. According to the figure, when the average value of TDO difficulty is fixed, no matter what decision optimization strategy the teachers adopt, with increase of the volatility of learning energy efficiency of students in each teaching environment, the TDO benefits will decline for the overall knowledge system.

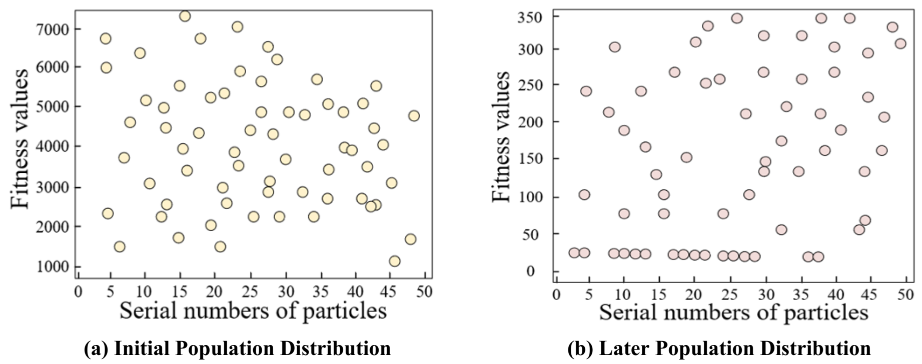

Fig. 6. Distribution of population fitness values of PSO

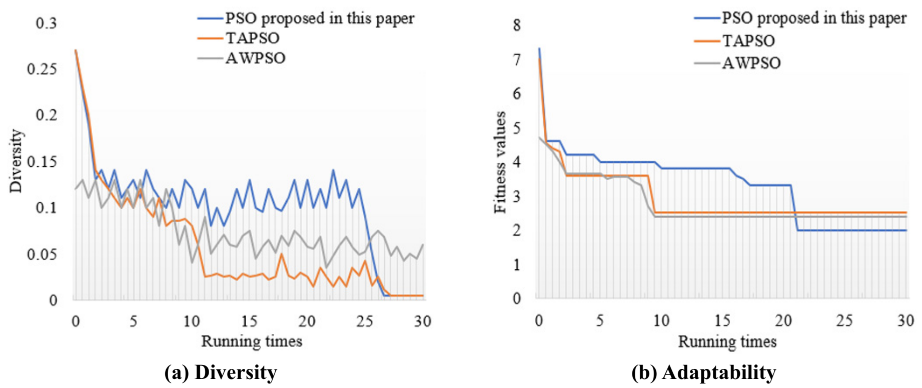

Fig. 7. Comparison of optimization and diversity maintenance of different algorithms

In order to more intuitively describe the impact of the three optimization models designed on the population diversity of PSO, Figure 6 shows the distribution of population fitness values of PSO. According to the figure, the particles are distributed relatively evenly when PSO proposed in this paper is initialized; when PSO remains relatively high diversity at the later stage of iteration, the particles have strong evolutionary ability.

Figure 7 shows the comparison of optimization and diversity maintenance of different algorithms. According to the figure, compared with TAPSO and AWPSO, where population diversity slowly decreases in the process of optimization, the population diversity of PSO proposed in this paper is better. In addition, as for PSO proposed in this paper, there are more particles converging near the global optimal particles, and the search accuracy of all optimal decision optimization paths is better. However, as for TAPSO and AWPSO algorithms, the particle populations are relatively scattered at the end of their operation, and it is difficult to obtain high-quality solutions. In general, PSO proposed in this paper has better convergence performance and richer population diversity, and the population can converge near the global optimal position, which is more suitable for the optimization of teaching decision path.

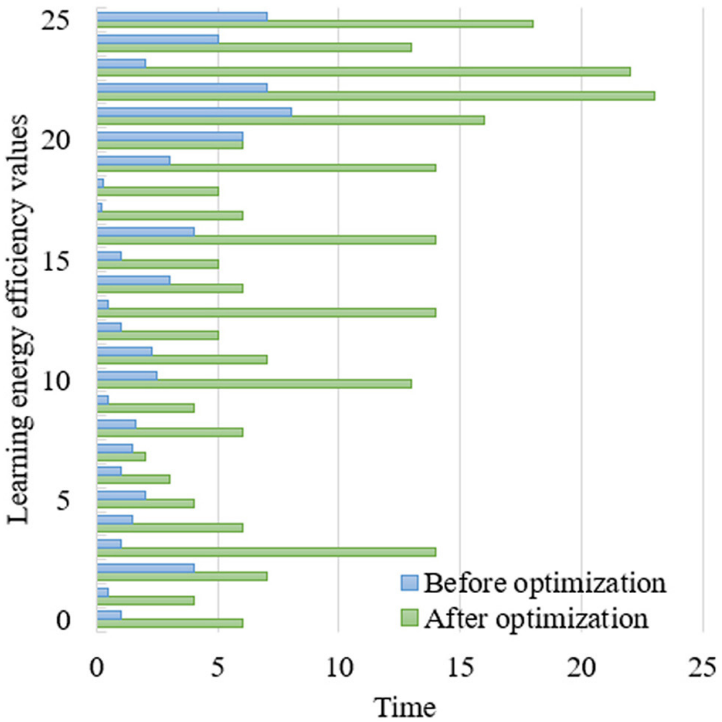

Fig. 8. Comparison of learning energy efficiency values of students before and after the optimization of teaching decision path

Figure 8 shows the comparison results of learning energy efficiency values of students within 5 weeks before and after implementation of TDO. It clearly shows that the learning energy efficiency values of students have greatly improved after implementation of TDO, which verifies the effectiveness of TDO, which takes into consideration the sustainable development of students in this paper.

5 Conclusion

This paper studies TDO concerning sustainable development of students. First of all, a teaching decision model for the sustainable development is constructed. This paper proposes PSO of teaching decision path based on progress rate, gives the principle of selecting TDO template, designs three different optimization models for ordinary particles, high-quality particles and progress particles, and elaborates the optimization strategy of teaching decision path. Combined with experiment, this paper gives a histogram of sustainable development directions of students in higher vocational colleges, emphasizing that teachers should pay attention to the cultivation of practical ability of students when optimizing their teaching decisions, and avoid focusing on theoretical education. In addition, this paper analyzes the influence of TDO difficulty on TDO benefits, gives distribution of population fitness values of PSO, and analyzes the influence of the three optimization models designed on the population diversity of PSO. Finally, this paper compares optimization and diversity maintenance of different algorithms, which verifies that PSO proposed in this paper is more suitable for optimization of teaching decision path because it has better convergence performance and richer population diversity, and the population can converge near the global optimal position.

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