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The Effective Teaching Behavior Model of Linguistics Teachers Based on Hybrid Intelligent Algorithms

Chao Zhou
School of Linguistics Education
Hunan University of Arts and Science
415000, Changde, Hunan, China
13873644129@huas.edu.cn

ABSTRACT

Currently, research on effective teaching behavior of linguistics education teachers could be more substantial, severely hindering linguistics education's high-quality development. Therefore, this study focuses on exploring the effective teaching behavior of linguistics education teachers based on hybrid intelligent algorithms to help them achieve teaching objectives more effectively. Hypotheses of effective teaching behavior are constructed using the Delphi method, and advantageous teaching behaviors of expert linguistics education teachers are identified through comparison. Pearson correlation analysis is employed to validate effective teaching behavior. At a macro level, there are 14 types of effective teaching behavior for linguistics education teachers. Through deep data analysis and interpretation, these 14 effective teaching behaviors can be clustered into four deeper dimensions: evaluative teaching behavior, student-oriented teaching behavior, teacher-student integration teaching behavior, and classroom organization and construction teaching behavior. They present a pyramid model with proportions of 6.7:5:4.2:3 from the base to the top. Conducting effective teaching based on this pyramid model can achieve significant results. The teaching level of outstanding linguistics education teachers determines the competitiveness of a school. Therefore, it is necessary to understand their teaching methods, principles of work, and ways of expression further to guide their work and help them establish a more efficient classroom atmosphere, thus improving the overall level of linguistics education in the entire school.

Keywords: Hybrid Intelligent Algorithms, Linguistics Education Teachers, Effective Teaching Behavior

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1. Introduction

With society's progress, teaching effectiveness is increasingly challenged, especially for college students.

Fundamentally, children are transitioning from practical activities to abstract thinking processes. They have not yet developed a collective consciousness, a sense of social responsibility, and good moral values. Moreover, due to changes in the family environment, their training relies more on traditional teaching methods. However, due to the strict requirements of linguistics education exams, malnutrition, and excessive homework, many current teaching activities have become meaningless and inefficient [1]. The concept of a sports teaching management information system based on hybrid intelligent algorithms aims to help us better control and improve teaching activities to enhance teaching quality. Using hybrid intelligent algorithms can greatly improve teaching efficiency [2]. It can effectively modify traditional genetic algorithms and improve ant colony algorithms. These objectives can be achieved by constructing mathematical models of hybrid intelligent algorithms. This study focuses on linguistics education courses and explores how to use hybrid intelligent algorithms to optimize classroom content. We will discuss optimising classroom content from multiple perspectives and draw lessons from it. We will also propose a series of reform suggestions to make our classrooms more intelligent and promote the smooth operation of classes.

2. Related Work

Today, due to the rapid advancement of computer technology, intelligent examination paper composition has become an essential tool for education quality management. Many researchers have been devoted to studying a more flexible and efficient computation to adapt to various types of applications [3]. The application of hybrid intelligent algorithms has made significant progress worldwide, with many companies developing specialized examination programs, such as Adobe and Cisco certification exams [4]. In China, numerous universities and experts have widely recognised questions bank management and the development of hybrid intelligent algorithms. In academia, many researchers have used self-management theory and Reggio Emilia's early childhood education theory as theoretical frameworks for teaching behaviour. They have explored various phenomena in teaching under the guidance of these theories and gained beneficial conclusions. Fu J. proposed that hybrid intelligent algorithms can help linguistics education teachers implement better teaching practices, thus enhancing their understanding of the learning process and effectively motivating language learners [5]. De-kun Jiang et al.believe that hybrid intelligent algorithms can help individuals improve their personalities, promote internal motivation, and help them better adapt to the social environment, thereby achieving their development goals [6]. LiH believes that three basic psychological needs of humans - competence, autonomy, and relatedness - are the foundation for effective linguistics education and mental and linguistics health [7]. Therefore, we should consider students' autonomous and controlled motivation to predict learning, performance, experience, and mental health. Furthermore, we should also focus on students' choices of teaching activities and expressions of perceptual teaching behavior in linguistics activities to meet their needs better. Wu S explored the teaching behavior of linguistics education teachers by applying hybrid intelligent algorithms. The results showed that such behaviour couldadopt different teaching strategies according to various student characteristics and motivate them to explore more actively, help them complete tasks more efficiently, and enhance their social abilities to complete tasks more harmoniously [8]. Zong Xingxing, et al. used hybrid intelligent algorithms to explore the importance of teachers' beliefs and classroom activities in learners' cognitive abilities [9]. Their results indicated that learners' cognitive levels may be limited by their classroom activities, so it is necessary to seriously discuss how to help them understand and master classroom content from a theoretical perspective. To better utilize hybrid intelligent algorithms, teachers need to play the roles of effective learners and inquirers, listen carefully, understand students' thoughts, tap into their potential, and use this potential for effective classroom education rather than merely providing certain safety precautions. Although China initially lags behind Western developed countries in informationized education, the traditional education model has been impacted by informationized education due to the rapid progress of global information technology and continuous updates in China's internet industry. Innovative education and informationized education have received more extensive attention and play a critical role in promoting educational and teaching reforms [10]. According to the audience's characteristics, we categorise linguistics education teachers' teaching activities into two types: the teacher imparting knowledge and the teacher receiving guidance. With the development of technology, many scholars have developed various methods to measure teachers' teaching activities, such as TBAS, FIAS, and 3C-FIAS. Using these methods, we can better understand teachers' teaching activities and gain valuable experience.

3. Hybrid Intelligent Algorithm Techniques

3.1 Particle Swarm Optimization (PSO) Algorithm

The Particle Swarm Optimization (PSO) algorithm aims to effectively extract valid models using a series of algorithms such as iterative methods, model methods, neural network methods, etc., and transform them into a group of effective models for solving specific problems. It can effectively improve the performance of models. Inspired by the ordered behavior of birds, fish, and other organisms, this mathematically-based optimization method has been proposed. It helps us better understand various linguistics phenomena in the linguistics world and accurately predict changes in these phenomena. PSO helps us determine the essence of linguistics phenomena but also aids in comprehending their variations. The velocity and position of particles are defined as follows:

$$V_i(t+1) = wV_i(t) + c_1 r_1 \left(P_i(t)\right) \qquad (1)$$

In this equation, "w" represents a quantity related to inertia that can adjust the system's movement, known as the inertia weight. "r" represents a uniformly distributed random number in the range [0, 1], which helps the system expand the coverage of the search space. "c" and "$c2$" are both greater than zero, where "c" refers to the small deviation that the entire system can perceive, known as the cognitive factor, and "$c2$" represents the overall quality that the whole system can perceive. By adjusting these parameters, the algorithm can achieve the optimal result more accurately. The importance of parameter adjustment cannot be ignored, as it not only improves the system's overall performance but also enhances its stability, thereby increasing the overall efficiency of the information system. Therefore, parameter adjustment has become an important topic in current technological development. Over time, people's understanding of society has undergone significant changes. From individual particle swarms to groups of particles, people are seeking ways to change their movement characteristics, collectively called global particle swarms or local particle swarms. Regardless of the stage of development of particle swarm algorithms, they are constantly influenced by individuals, groups, and communities, forming the core of collective intelligence. Figure 1 shows the flowchart of the Particle Swarm Optimization (PSO) algorithm.

3.2 Differential Evolution (DE) Algorithm

The Differential Evolution (DE) algorithm is an effective and model-based evolutionary algorithm that can quickly and accurately complete tasks. It utilizes the characteristics of the model and computation to swiftly accomplish tasks without adding any complex inputs. Moreover, its performance surpasses traditional evolutionary algorithms in some practical measurement results. The DE algorithm can be seen as a random algorithm with multiple functionalities, enabling it to conduct various tasks simultaneously and seek the best solutions to enhance search accuracy further. Like the Particle Swarm Optimization (PSO) algorithm, the DE algorithm can initialize the population with NP dimensions in D-dimensional space. After a series of iterations, each participant can find a set of valid parameters to locate the best search space. This process does not involve the number of participants; it only has a group of participants who randomly extract parameters from the current participant data set as a reference. Over time, the new basic DE algorithm can focus more data on more probable areas, enabling better multidimensional analysis to meet constantly changing demands and improve overall performance and reliability. When NP vectors have a uniform distribution in D dimensions, each individual can be represented in the following form:

$$x_{i,\,g} \quad (i = 1, 2, \cdots, NP) \tag{2}$$

By providing the number of individuals "*i*," the iteration count "*g*," and the total population size "*NP*," the differential algorithm can obtain these parameters from the beginning and maintain their stability throughout the entire evolutionary process. The differential algorithm can also get the initial population through random selection. To accurately evaluate the performance of each individual in the population, we must determine a reasonable evaluation function based on specific circumstances to implement corresponding operations effectively. Compared to traditional evolutionary algorithms, a notable feature of the differential evolution algorithm is its adoption of various differential operations, allowing individuals to undergo mutations. For instance, given a target vector *x*1, *g*, selecting individuals *Xr1*, g-*Xr2*, g, *Xr3*, g (r1≠ r2≠r3≠ι) and using the following formula, a new mutated individual can be obtained:

$$v_{i,\,g+1} = x_{r1,\,g} + F\left(x_{r2,\,g} - x_{r3,\,g}\right) \tag{3}$$

In this formula, F>0 [0,2], where *FE* is commonly referred to as the mutation coefficient or scaling factor. This coefficient adjusts the difference between two individuals, avoiding excessive minor differences during the search process. Furthermore, it also regulates the convergence speed of the algorithm. The correct choice of *F* is crucial, as an incorrect selection may significantly degrade the performance of the differential algorithm, reducing its search range. The size of *F* is also critical as it will control whether the algorithm effectively seeks the best results, ensuring its effectiveness. Before conducting the analysis, ensuring that the number of individuals NP≥4 is crucial. Therefore, before the analysis, it must be ensured that the range of the three individuals is approximately consistent with that of the target vector, i.e., *r1≠r2≠r3≠i*.

3.3 PSO-DE Hybrid Intelligent Algorithm

Although the Particle Swarm Optimization (PSO) algorithm has a clear concept and convenient operation, enabling it to find the best results quickly, it also has a drawback: it can soon iterate, leading to the convergence of the population's variation and affecting the overall efficiency of the algorithm. On the contrary, the differential evolution algorithm is more flexible. It can quickly explore the population's variation trend, thereby enhancing the overall efficiency of the algorithm and accurately predicting the population's changes. The core principle of the PSO-DE hybrid algorithm can be expressed as follows: 1) Use a random algorithm to construct a particle swarm in the solution space. 2) Measure the fitness value of each particle to evaluate its performance and compliance with predefined constraints. 3) Update the positions and movements of particles within the swarm based on formulas (2) and (3) to obtain new particles. 4) Continuously update cognitive experiences to obtain the optimal individual. 5) If there is a change in P(t), we can use the differential evolution method to evolve this particle to achieve continuous improvement of "*p*," including evolution, exchange, optimization, etc. 6) Determine the algorithm's termination condition. If met, produce the result; otherwise, return to step (2) to recalculate the fitness values of particles and repeat the process.

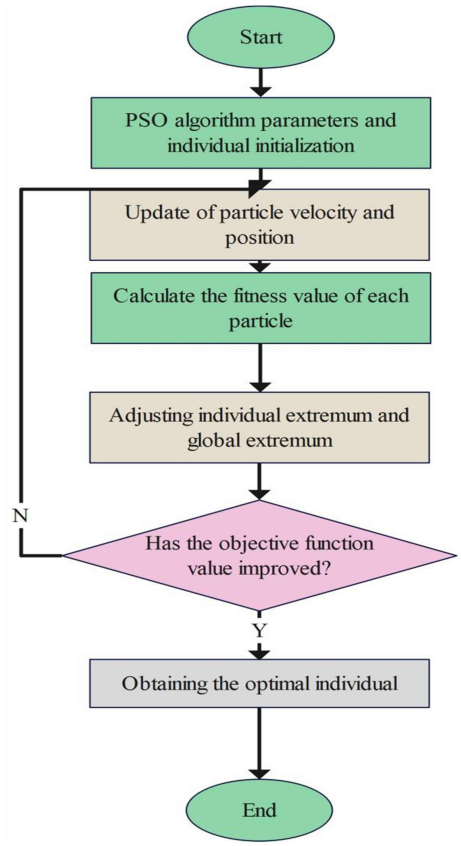

Figure 1. Flowchart of the PSO Algorithm

4. Experimental Design and Results Analysis

4.1 Predictive Measurement of Teaching Behavior

We constructed preparatory measurement hypotheses using the hybrid intelligent algorithm to carry out effective teaching actions. The expert group consisted of 10 experts, including two sports statisticians, two curriculum theorists, three sports measurement evaluators, and three outstanding linguistics education teachers from the frontline. The measurement items were divided into a model provided by the research team and a model provided by professional experts. After three rounds of expert consultations, 18 effective teaching actions were obtained. The expert authority coefficient was 0.93, and the positive coefficient was 100%. Each effective action had an average E=4.6 (out of 5 points), and the rate of scoring 5 points was k=87%. The internal consistency of the results was w=0.68, and the coefficient of variation was =0.23 (average fluctuation rate for each item). Based on the hybrid intelligent algorithm, we identified 18 assumed effective teaching behaviors.

4.2 Analysis of Experimental Results

Through evaluation, we found that the objective function value of the hybrid algorithm was closer to that of the traditional algorithm, indicating that this algorithm is more practical. In this discussion, we define the objective function as a value that represents the probability of success of the algorithm. After 40 iterations of the hybrid algorithm, the objective function value significantly decreased, and over time, this decrease became more prominent. Therefore, we compared their merits and shortcomings. As shown in Figure 2, the objective function value curves of the three algorithms are reflected.

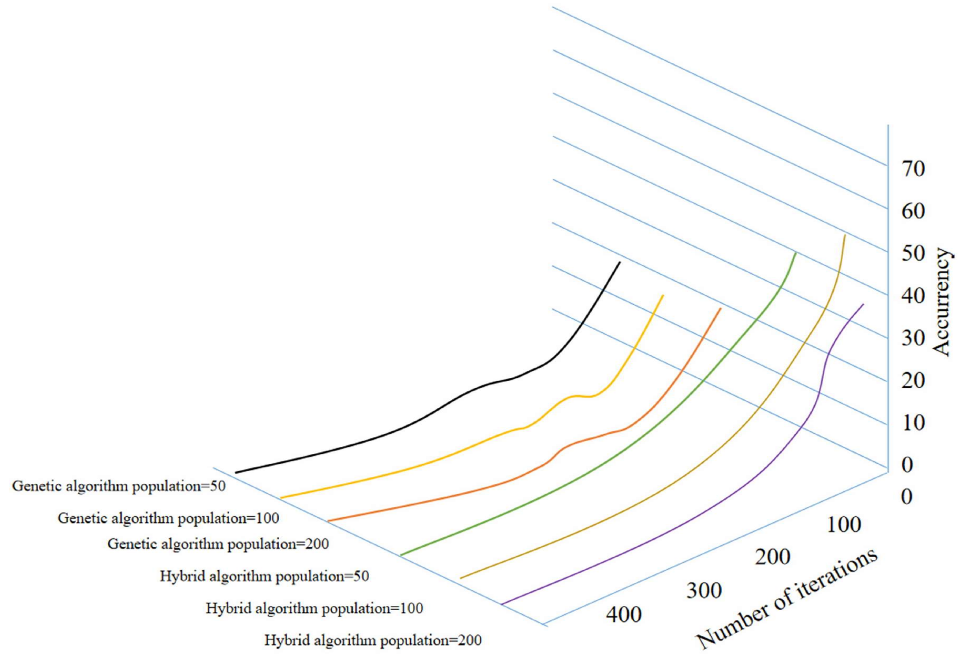

Figure 2. Comparison of Objective Functions

Through systematic research, we found that the objective function value of the genetic algorithm significantly outperforms that of the ant colony calculation, a conclusion verified by the three-dimensional line graph. Figure 2 shows that the genetic algorithm's objective function value is closer to the optimal solution, indicating a faster convergence rate. On the other hand, the objective function value of the ant colony calculation is higher, implying a slower convergence rate. Although the objective function value of the hybrid algorithm surpasses that of the genetic algorithm, it is even closer to the optimal solution. This conclusion may be determined by its advantages. After 200 iterations of evolution, we found that despite the genetic algorithm's slower convergence rate, the hybrid algorithm's convergence efficiency far exceeds it, and its final convergence result is also significantly lower than that of the genetic algorithm. Therefore, we concluded that the convergence rate of the hybrid algorithm is much higher than that of the genetic calculation, even surpassing it. With the increase of evolution iterations, the convergence rate of the hybrid algorithm will also improve. However, even after more than 300 iterations, the convergence rate remains relatively stable with slight variation. Nonetheless, the hybrid algorithm remains the best in terms of final results. It not only maintains the high efficiency of genetic calculation but also possesses the flexibility of the ant colony algorithm. After being processed by the hybrid algorithm, the accuracy of test questions significantly improved, far surpassing traditional algorithms such as genetic algorithms and ant colony algorithms. Through the research and analysis of linguistics education teacher's teaching behavior model using the hybrid intelligent algorithm, we found that the setting of classroom objectives consists of eight-factor items. According to the five-point scoring conversion rules, we can conclude that if the overall effectiveness score of classroom objectives is greater than 32, it is considered frequently effective. At the same time, less than 24 indicates less effectiveness. Based on the data in Figure 3, the IRW-PSO algorithm showed significant superiority, as it can quickly and accurately solve complex unimodal functions. After 400 iterations, the convergence rate of the random walk algorithm is more remarkable, and the standard deviation of its results is more prominent, indicating the stability of this method.

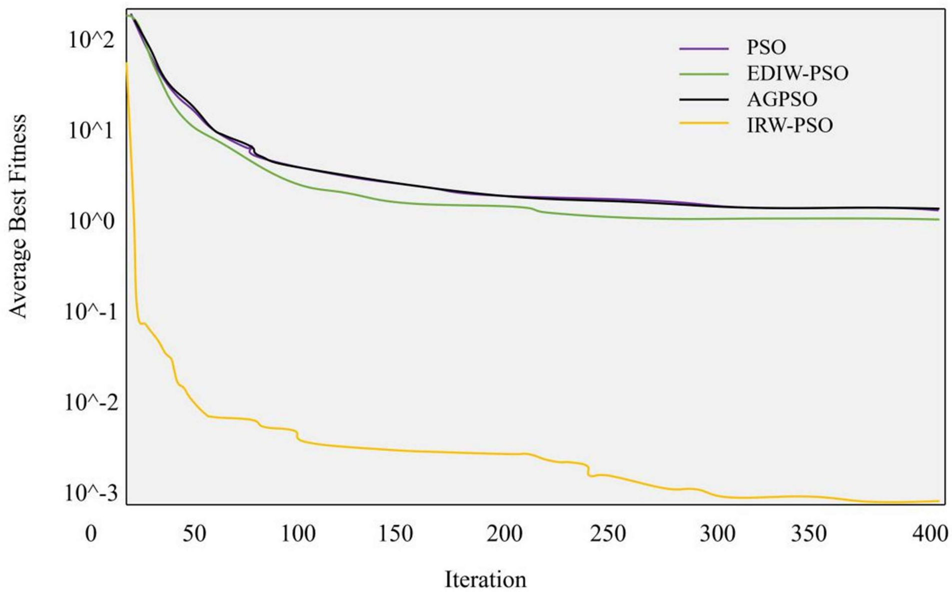

Figure 3. Convergence Chart of F7 Linguistics Education Teacher's Classroom Plan Value

Figure 3 shows that effective teaching methods for excellent linguistics education teachers usually follow a pyramid-shaped pattern. With the increase in iteration numbers, the average best fitness of the four algorithms gradually decreases. PSO, EDIW-PSO, and AGPSO have significantly higher average best fitness than IRW-PSO. Effective linguistics education classroom activities affect teachers'abilities and lead to teacher differences. The results indicate that the inconsistency in teaching skills and experience levels among linguistics education teachers is crucial in influencing the overall quality of linguistics education courses. Moreover, the 14 different behaviors in this study are more diverse than in previous research, covering a wider range of areas, thus better reflecting the current teaching situation.

5. Conclusions

The teaching level of outstanding linguistics education teachers determines the competitiveness of a school. Therefore, we must deeply understand their teaching patterns, principles, and expressions to guide their work and help them establish a more efficient classroom atmosphere, thereby improving the entire school's overall level of linguistics education. Past studies often overlooked this point, making it difficult to achieve real educational achievements. Analyzing the hybrid intelligent algorithm, we discovered that effective teaching methods are essential in linguistics education teaching. The importance of these methods is in the ratio of 6.7:5:4.2:3, forming a gradually increasing pyramid. Based on this, we suggest that our professionals better evaluate the advantages and disadvantages of this method and use it to improve their ability level.

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