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A Smart Algorithm based Teaching Model for Optimizing Language Education Using PSO-DE Intelligence

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ABSTRACT

This paper proposes a smart algorithm based teaching model for language education, leveraging a hybrid intelligent algorithm that combines Particle Swarm Optimization (PSO) and Differential Evolution (DE). The model aims to enhance teaching effectiveness by optimizing classroom content and adapting to students' diverse learning needs. The study identifies 18 effective teaching behaviors through expert consultation and applies the hybrid algorithm to analyze and improve linguistics instruction. Experimental results show the hybrid PSO-DE algorithm outperforms traditional methods like genetic algorithms and ant colony optimization in convergence speed and solution accuracy. The research highlights that expert teachers' strategies follow a pyramid shaped effectiveness structure, emphasizing the importance of tailored, data driven instruction. Findings suggest that integrating adaptive algorithms can significantly boost learning efficiency, student satisfaction, and overall educational quality in language teaching. The authors advocate for broader adoption of such intelligent systems to support teacher development and modernize linguistics education in the digital era.

Keywords: Smart Algorithms, Language Teaching, Hybrid Intelligent Algorithm, Particle Swarm Optimization (PSO), Differential Evolution (DE), Teaching Effectiveness, Adaptive Learning, Educational Optimization

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1. Introduction

As society advances, the effectiveness of teaching is increasingly put to the test, particularly for college students. Essentially, youngsters are shifting from hands on experiences to more abstract thought processes. They have yet to cultivate a communal awareness, a sense of social duty, and strong ethical principles. Additionally, shifts in family dynamics mean their education leans more heavily on conventional teaching methods. However, due to the rigorous standards set by linguistics education assessments, undernourishment, and an overload of homework, many current teaching practices have become pointless and inefficient [1]. The concept of a sports teaching management information system, grounded in hybrid intelligent algorithms, aims to facilitate improved oversight and enhancement of teaching practices, ultimately enhancing educational quality. Utilizing hybrid intelligent algorithms can significantly boost teaching effectiveness [2]. This approach can effectively refine traditional genetic algorithms and enhance ant colony algorithms. These goals can be accomplished through the creation of mathematical models for hybrid intelligent algorithms. This research concentrates on linguistics education courses and investigates how hybrid intelligent algorithms can optimize classroom materials. We will examine the optimization of classroom content from various angles and derive insights from it. Additionally, we will present a series of reform proposals to enhance our classrooms' intelligence and facilitate the seamless execution of classes.

2. Related Work

In today's world, owing to the swift evolution of computer technology, intelligent test paper generation has become a vital resource for managing educational quality. Numerous researchers have dedicated themselves to exploring more adaptable and efficient computations suitable for a range of applications [3]. The use of hybrid intelligent algorithms has seen considerable advancements globally, with many firms creating specialized examination systems, such as Adobe and Cisco certification assessments [4]. In China, a multitude of universities and experts have recognized the importance of question bank management and the development of hybrid intelligent algorithms. In the academic sphere, a number of researchers have adopted self management theory and the Reggio Emilia approach to early childhood education as theoretical frameworks for teaching behaviors. They have investigated various teaching phenomena under the influence of these theories, yielding valuable insights. Fu J. suggested that hybrid intelligent algorithms can assist linguistics education instructors in implementing more effective teaching strategies, thereby deepening their comprehension of the learning process and actively engaging language learners [5]. Dekun Jiang et al. argue that hybrid intelligent algorithms can aid individuals in enhancing their personalities, fostering intrinsic motivation, and better adapting to their social environments, thus achieving their personal development objectives [6]. Li H posits that three fundamental psychological needs competence, autonomy, and relatedness form the cornerstone for effective linguistics education as well as mental and linguistic well being [7]. Hence, it is essential to consider students' autonomous and regulated motivation in predicting their learning outcomes, performance, experiences, and mental health. Moreover, we should also pay attention to students' preferences for teaching methods and their expressions of experiential learning behavior in linguistics activities to better address their needs. WuS examined the teaching practices of linguistics education educators by employing hybrid intelligent algorithms.

The findings revealed that such conduct could employ diverse teaching techniques based on different student traits, encouraging them to engage more actively, assisting them in completing tasks more effectively, and improving their social skills to accomplish tasks more cohesively [8]. Zong Xingxing and colleagues utilized hybrid intelligent algorithms to investigate the significance of educators' beliefs and classroom activities on students' cognitive abilities [9]. Their findings suggested that students' cognitive capacities might be constrained by their classroom experiences, indicating the necessity to thoroughly examine how to support them in grasping and mastering classroom material from a theoretical stand point. To optimize the use of hybrid intelligent algorithms, educators must adopt the roles of proactive learners and inquisitors, attentively listen, comprehend students' perspectives, uncover their potential, and harness this potential for effective classroom instruction instead of simply offering basic safety measures. Although China initially trails behind

Western developed nations in digital education, the traditional educational framework has been influenced by digital learning due to the swift advancement of global information technology and ongoing developments in China's internet sector. Innovative education and digital learning have garnered broader attention and play a vital role in advancing educational and teaching reforms [10]. Based on the characteristics of the audience, we classify the teaching activities of linguistics education instructors into two categories: the instructor conveying knowledge and the instructor receiving guidance. With technological advancements, numerous researchers have created various approaches to assess educators' teaching activities, including TBAS, FIAS, and 3C-FIAS. Employing these approaches enables a deeper understanding of teachers' instructional activities and provides valuable insights.

Smart algorithm based teaching models for language education are demonstrably effective and feasible, with multiple studies showing significant improvements in learning outcomes and student satisfaction**.**

The evidence base comprises six primary studies that implement various AI/ML approaches in language teaching. Congcong Wang et al. [11] provide the strongest quantitative evidence, analysing over 5 million learning data points and demonstrating a 30% increase in learning efficiency for business English learners. Xiaohua Zhang et al., [12] reported 80% student satisfaction with their AI powered college English smart classroom model. Wang Li et al. [13] showed that machine learning algorithms had a "certain effect" in improving linguistic teaching efficiency through optimised root cause analysis algorithms and layered pruning strategies.

Additional supporting evidence comes from Liu Yan et al., [14] demonstrating system efficacy in enhancing learning through auto grading and pronunciation feedback features, and I. Kolegova et al., [15] proving their AI based foreign language teaching model effective with high student interest and satisfaction. The models consistently employ machine learning, natural language processing, and adaptive algorithms to create personalized, data driven learning experiences.

3. Hybrid Intelligent Algorithm Techniques

3.1 Particle Swarm Optimization (PSO) Algorithm

The Particle Swarm Optimization (PSO) algorithm seeks to effectively derive valid models through a range of algorithms such as iterative methods, model based methods, neural network techniques, etc., and convert them into a set of efficient models for addressing specific challenges. It can significantly enhance model performance. Drawing inspiration from the coordinated behavior of birds, fish, and other creatures, this mathematically oriented optimization technique has been introduced. It aids us in gaining a clearer understanding of various linguistic phenomena within the field of linguistics and accurately forecasting shifts in these phenomena. PSO assists in identifying the core of linguistic phenomena while also facilitating the understanding of their fluctuations. The speed 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 formula, "w" signifies a value associated with inertia that can modify the system's dynamics, referred to as the inertia weight. "r" denotes a uniformly distributed random value between [0, 1], which aids the system in broadening the exploration of the search space. The variables "c" and "c2" are both positive, where "c" indicates the minor deviation that the entire system can detect, known as the cognitive factor, while “c2” represents the overall quality perceived by the whole system. By fine tuning these parameters, the algorithm can achieve the optimal outcome with greater precision. The significance of parameter tuning is paramount, as it not only enhances the overall functionality of the system but also boosts its stability, which in turn increases the overall efficiency of the information system. Consequently, parameter tuning has emerged as a crucial area in contemporary technological progress. Over time, society’s perception has experienced notable transformations. From solitary particle swarms to clusters of particles, individuals are exploring methods to alter their movement traits, collectively termed global particle swarms or local particle swarms. Regardless of the developmental phase of particle swarm algorithms, they are perpetually shaped by individuals, groups, and communities, forming the essence of collective intelligence. Figure 1 illustrates the flowchart of the Particle Swarm Optimization (PSO) algorithm.

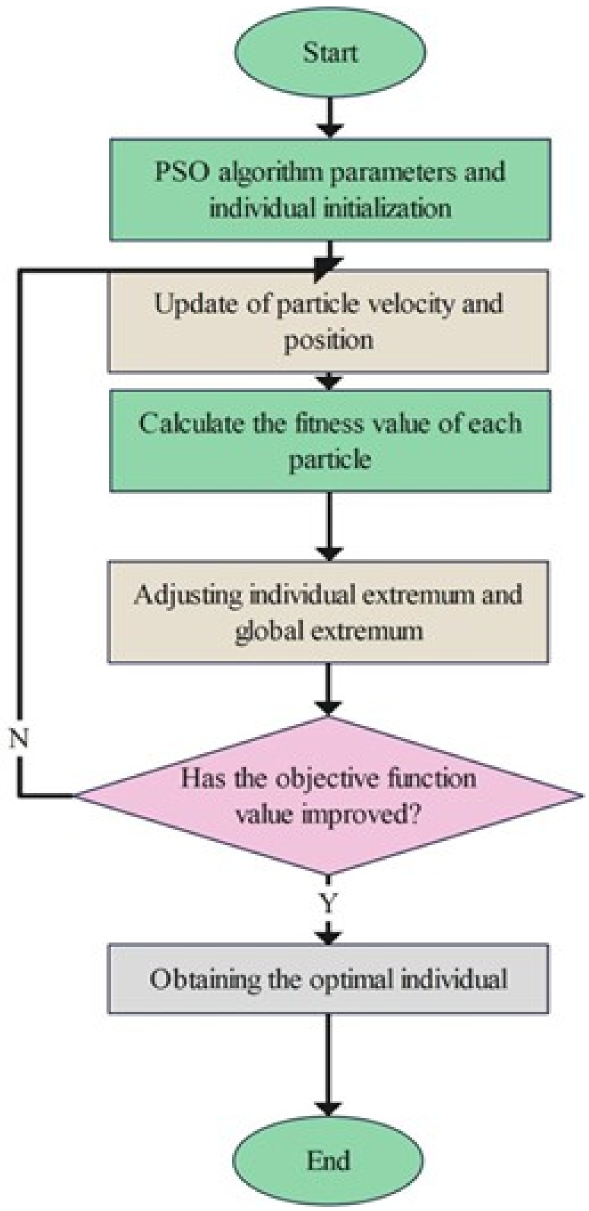

Figure 1. Flowchart of the PSO Algorithm

3.2 Differential Evolution (DE) Algorithm

The Differential Evolution (DE) algorithm is a robust and model driven evolutionary algorithm that can efficiently and accurately execute tasks. It leverages the model's features and computations to complete tasks efficiently without requiring intricate inputs. Furthermore, its performance exceeds that of traditional evolutionary algorithms in several practical evaluation outcomes. The DE algorithm can be viewed as a stochastic algorithm with multiple capabilities, allowing it to perform various tasks concurrently and seek optimal solutions to enhance search precision further. Similar to the Particle Swarm Optimization (PSO) algorithm, the DE algorithm can initialize a population with NP dimensions in a D dimensional space. Following a series of iterations, each participant can discover a valid set of parameters to identify the optimal search space. This process does not depend on the number of participants; instead, it utilizes a group of participants who randomly draw parameters from the existing participant data set as a reference. Over time, the newly refined DE algorithm can concentrate more data on areas with higher probabilities, facilitating better multidimensional analysis to adapt to ever evolving requirements and improve overall performance and dependability. When NP vectors are evenly distributed in D dimensions, each individual can be represented in the following manner:

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

By specifying the number of participants "*i*," the number of iterations "*g*," and the overall population size "NP," the differential algorithm can extract these variables from the outset and ensure their consistency throughout the entire evolutionary process. Additionally, the differential algorithm can generate the initial population through random selection. To accurately assess the performance of each individual within the population, it is necessary to establish a suitable evaluation function based on particular conditions to carry out the corresponding operations effectively.

Compared to traditional evolutionary algorithms, a notable feature of the differential evolution algorithm is its use of various differential operations, which allow individuals to undergo mutations. For instance, given a target vector *x*1, *g*, selecting individuals *Xr1, g-Xr2, g, Xr3, g (r1#, r2#, r3=i*) 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 equation, F>0 [0,2], where *FE* is commonly referred to as the mutation coefficient or scaling factor. This coefficient adjusts for the difference between two individuals, minimizing minor discrepancies 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

While the Particle Swarm Optimization (PSO) algorithm is straightforward in concept and easy to operate, allowing it to discover optimal results quickly, it has a limitation: it can rapidly iterate, resulting in the convergence of the population's diversity, which impacts the overall efficiency of the algorithm. In contrast, the differential evolution algorithm offers greater adaptability. It can swiftly explore the variation trends within the population, thereby improving the algorithm's overall efficiency and accurately forecasting the changes in the population. The fundamental principle of the PSO-DE hybrid algorithm can be summarized as follows: 1) Implement a random algorithm to create a particle swarm within the solution space. 2) Evaluate the fitness value of each particle to assess its performance and adherence to established constraints. 3) Adjust the positions and motions of particles in the swarm according to formulas (2) and (3) to generate new particles. 4) Continuously update cognitive experiences to identify the optimal individual. 5) If a change occurs in P(t), we can apply the differential evolution method to evolve this particle for ongoing improvement of "p," encompassing evolution, exchange, optimization, etc. 6) Define the termination condition for the algorithm. If it is satisfied, deliver the result; if not, revert to step (2) to recalculate the fitness values of the particles and repeat the procedure.

4. Experimental Design and Results Analysis

4.1 Predictive Measurement of Teaching Behavior

We formulated preliminary measurement hypotheses utilizing the hybrid intelligent algorithm to implement practical teaching actions. The panel of experts was composed of 10 specialists, including two sports statisticians, two curriculum theorists, three sports measurement evaluators, and three distinguished linguistics education teachers from the field. The measurement criteria were categorized into two models: one created by the research team and another devised by professional experts. Following three rounds of consultations with experts, 18 effective teaching actions were identified. The expert authority coefficient was 0.93, with a positive coefficient of 100%. Each effective action received an average score of E=4.6 (on a scale of 5), and the percentage of actions rated at 5 points was k=87%. The internal consistency of the results was w=0.68, and the coefficient of variation was 0.23 (representing the average fluctuation rate for each item). Using the hybrid intelligent algorithm, we identified 18 proposed effective teaching behaviors.

4.2 Analysis of Experimental Results

Through assessment, we discovered that the objective function value of the hybrid algorithm was more aligned with that of the traditional algorithm, suggesting that this method is more applicable. In this discussion, we define the objective function as a value that signifies the likelihood of the algorithm's success. After 40 iterations of the hybrid algorithm, the objective function value saw a notable decline, and as time progressed, this reduction became increasingly apparent. Consequently, we analyzed their advantages and disadvantages. As illustrated in Figure 2, the objective function value curves of the three algorithms are displayed.

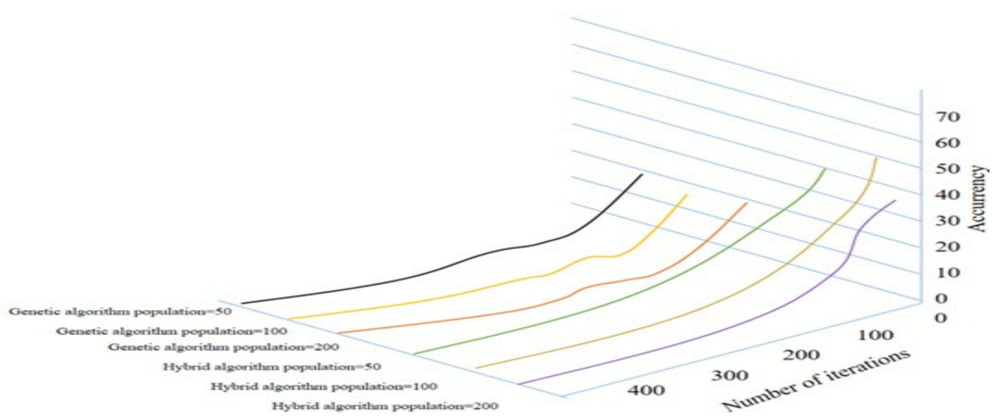

Figure 2. Comparison of Objective Functions

Through thorough investigation, we observed that the objective function value of the genetic algorithm significantly exceeds that of the ant colony method, a finding corroborated by the three dimensional line graph. Figure 2 reveals that the objective function value of the genetic algorithm is closer to the optimal solution, indicating a quicker convergence rate. Conversely, the objective function value of the ant colony method is higher, suggesting a slower convergence rate. While the objective function value of the hybrid algorithm surpasses that of the genetic algorithm, it is even closer to the optimal solution. This finding may be attributed to its benefits. After 200 iterations of evolution, we observed that although the genetic algorithm exhibits a slower convergence rate, the convergence efficiency of the hybrid algorithm significantly exceeds it, and its final convergence result is also substantially lower than that of the genetic algorithm. Thus, we concluded that the convergence rate of the hybrid algorithm is considerably higher than that of the genetic algorithm, and in some cases, it even exceeds it. With an increase in evolution iterations, the convergence rate of the hybrid algorithm will also enhance. However, even after surpassing 300 iterations, the convergence rate remains relatively stable with minor fluctuations. Nevertheless, the hybrid algorithm remains the best in terms of final outcomes. It not only retains the high efficiency of genetic algorithms but also incorporates the flexibility of the ant colony method. Following processing by the hybrid algorithm, the accuracy of test questions improved significantly, surpassing that of traditional algorithms such as genetic algorithms and ant colony methods. Through the research and analysis of the teaching behavior model of linguistics education teachers using the hybrid intelligent algorithm, we found that the establishment of classroom objectives comprises eight-factor items. According to the five point scoring conversion rules, we can determine that if the overall effectiveness score of classroom objectives exceeds 32, it is deemed frequently effective. Conversely, a score below 24 indicates lesser effectiveness. Based on the data presented in Figure 3, the IRW-PSO algorithm demonstrated significant advantages, as it can swiftly and accurately address complex unimodal functions. After 400 iterations, the convergence rate of the random walk algorithm becomes more pronounced, and the standard deviation of its results increases significantly, indicating the reliability of this approach.

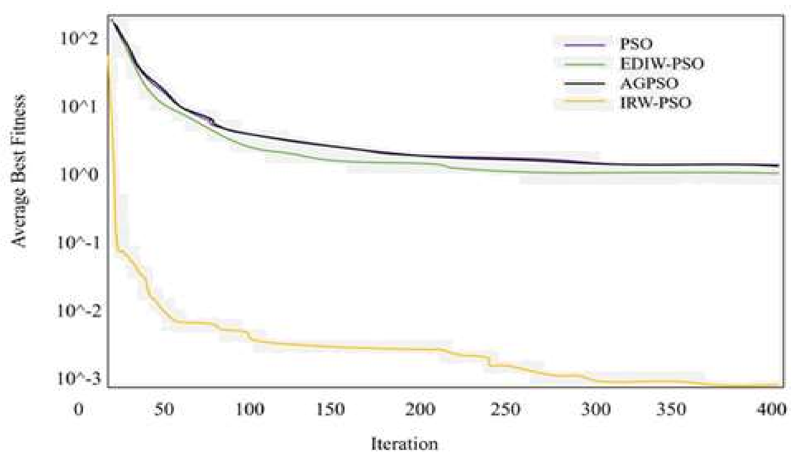

Figure 3. Convergence Chart of F7 Linguistics Education Teacher's Classroom Plan Value

The above Figure illustrates that successful teaching strategies for exceptional linguistics educators typically adhere to a pyramid shaped structure. As the number of iterations increases, the average optimal fitness of the four algorithms steadily declines. The PSO, EDIW-PSO, and AGPSO methods display significantly superior average optimal fitness compared to IRW-PSO. Effective classroom activities in linguistics education influence teachers' capabilities and lead to variability among them. The findings suggest that discrepancies in teaching skills and levels of experience among linguistics education instructors play a vital role in impacting the overall quality of linguistics education programs. Furthermore, the 14 distinct behaviors identified in this study are more varied than those in earlier research, encompassing a broader range of domains, thus more accurately representing the current teaching landscape.

5. Conclusion

The proficiency level of exceptional linguistics educators is a key factor in a school's competitiveness. Therefore, it is essential to thoroughly comprehend their teaching methodologies, principles, and approaches to support their work and help foster a more productive classroom environment, ultimately enhancing the overall quality of linguistics education in the school. Previous research has often overlooked this aspect, making it challenging to achieve genuine educational progress. Through our analysis of the hybrid intelligent algorithm, we found that effective teaching methods are crucial in the field of linguistics education. The significance of these methods is represented in the ratio of 6.7:5:4.2:3, forming a progressively ascending pyramid. Based on this insight, we recommend that professionals conduct a more thorough evaluation of the strengths and weaknesses of this approach and utilize it to enhance their skill levels.

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