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RESEARCH ARTICLE

Maximizing English Teaching Efficacy With Particle Swarm Optimization-Driven Neural Network Training

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ABSTRACT This study investigates the potential of Particle Swarm Optimization (PSO)-based Neural Network (NN) training to enhance the efficacy of English language instruction. Recognizing English as a global language vital for international communication and economic interaction, effective language training is imperative. Leveraging PSO as a guiding mechanism for NN training presents a novel approach to refine instructional strategies. This study critically examines existing literature and identifies shortcomings in conventional algorithms employed in English teaching methodologies. Subsequently, a sophisticated algorithmic framework integrating PSO with NN is proposed to address these deficiencies and augment instructional outcomes. The adaptability of this methodology to conventional teaching models in English language education is explored. Experimentation and simulation validate the effectiveness of this innovative approach, illustrating its potential to revolutionize English education by optimizing learning outcomes. The findings underscore the significance of PSO-driven NN training in enhancing teaching effectiveness, paving the way for advancing English language education methodologies.

INDEX TERMS English teaching, neural network, particle swarm optimization, algorithmic enhancement.

I. INTRODUCTION

Nowadays, English is regarded as a lingua franca, the global language of diverse nationalities. Teaching the English language is crucial worldwide, as it facilitates international communication, collaboration, and the interchange of cultures [1]. English has become the dominant language in diplomacy, science, technology, and commerce, with a worldwide population of over 1.5 billion English learners [2], [3]. Mastery of the English language surpasses linguistic barriers, allowing persons from various linguistic origins to participate in an ordinary conversation [4]. The increasing interdependence of economies and civilizations worldwide enhances the significance of English as a universal means of communication for commerce, diplomacy, and academics [5]. In addition to its practical usefulness, English is an entry point to an extensive repository of information, literature, and cultural legacy. Proficiency in language grants access to educational prospects, fosters intercultural comprehension, and augments one's marketability on the global platform [6]. Hence, proficient instruction in the English language transforms from a simple educational endeavor to a crucial facilitator of worldwide civic participation, assisting individuals to effectively traverse and make valuable contributions to the intricate, interrelated global society [7], [8].

Education is classified into two main modes: conventional and distant education. Conventional methodology involves educators presenting lectures on a platform while students physically attend courses [9]. In distant education, computer technologies facilitate learning across geographical barriers [10]. Both strategies contribute to the proficiency of English learners. Nevertheless, accurately assessing English learners' proficiency levels is essential to enhance instruction effectiveness [11], [12]. Regardless of the educational method used, conventional teaching, featuring direct interaction between instructors and learners, is preferable for

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evaluating and analyzing students' learning capabilities [13], [14]. On the other hand, distant education lacks direct contact, which challenges teachers in comprehending students' personalities and learning capacities [15]. Successfully tackling this issue is crucial for fostering precise evaluation of students' skills and optimizing learning efficacy in English instruction [16].

Thanks to technological advancements, distant learning in English studies has grown significantly, encompassing a nationwide English education [17], [18]. The field of English teaching has been impacted greatly by the use of distant education in multiple educational institutions [19]. Distant education offers unique benefits compared to traditional methods despite its challenges in maintaining constant learning time [20]. Networks and media resources are used to overcome geography limitations, partially addressing local concerns [21]. It may be challenging for learners to maintain regular communication with their teachers in distance education, which may restrict effective monitoring and diminish learning effectiveness. Tackling these challenges is essential for improving teachers' knowledge of English learners [22].

Utilizing current technological resources to precisely evaluate students' learning levels and adjusting teaching approaches to match individual learning circumstances are important considerations [23], [24]. Our methodology addresses several key limitations in English teaching and provides unique solutions to improve teaching effectiveness. Traditional methods of assessing student learning levels often rely on standardized or subjective assessments that may not capture the full range of individual learning circumstances. In contrast, our approach leverages advanced technological resources, particularly Neural Networks (NNs) and the Particle Swarm Optimization (PSO) algorithm, to analyze students' distance learning English skills with unprecedented accuracy and granularity.

One of the main advantages of our approach is its ability to collect real-time data about learners' unique characteristics during the teaching process. By using NNs to process this data, educators can gain deeper insights into student learning, preferences, and progress. For example, rather than using a one-size-fits-all teaching approach, our methodology allows teachers to customize their lessons based on individual learning styles, linguistic backgrounds, and ability levels. This level of individualization maximizes the effectiveness of teaching activities by ensuring that they are tailored precisely to the needs and abilities of each student.

Additionally, our approach allows educators to adjust their teaching strategies in real-time based on ongoing feedback and assessments. For example, if a student is struggling with a particular concept or skill, teachers can quickly identify opportunities for improvement and adjust their instruction accordingly. This dynamic and responsive approach increases learning effectiveness and promotes a supportive and inclusive learning environment where every student can succeed. Additionally, our methodology has the potential to revolutionize traditional English teaching by bridging the gap between remote and conventional learning environments. By combining the strengths of both approaches, educators can leverage the benefits of technology to improve instructional quality and student engagement in diverse educational environments. Ultimately, by leveraging the power of NNs and PSO algorithms, our approach has the potential to advance English teaching and enable educators to deliver more effective and impactful lessons.

II. LITERATURE REVIEW

This section examines and compares several studies related to incorporating cutting-edge technologies into language instruction. Studies on teaching English are examined comprehensively, with each offering distinct perspectives and approaches to overcoming the inherent difficulties. Table 1 summarizes the key aspects of the related works, including their focus areas, key technologies employed, datasets used, outcomes/applications, method evaluation, and the results achieved

Cho and Kim [25] implemented a cutting-edge text interface with deep learning on mobile platforms. The primary design emphasizes a handwritten text interface with a straightforward framework, utilizing touch-based input methods typically used in mobile applications. This strategy provides improved simplicity and convenience in contrast to conventional Graphical User Interfaces (GUI), where users frequently travel through menus and buttons repeatedly. The suggested interface also presents an interaction methodology that establishes a natural connection between input text, actions, and cognitive processes involved in decision-making. This involves utilizing a convolutional neural network (CNN) framework and the Extended Modified National Institute of Standards and Technology (EMNIST) dataset to recognize handwritten text. The identified text is linked to actions. English language education applications are created using the suggested interface during the last phase. These applications specifically emphasize promoting the efficient acquisition of alphabet writing and vocabulary through handwriting. User satisfaction with the interface throughout the instructional procedure is comprehensively examined and confirmed by experiments conducted with participants.

Artificial Intelligence in Education (AIEd) integrates artificial intelligence into education. Numerous AIEd-driven applications are being used in modern educational settings. Sun et al. [26] designed an online English teaching platform to compare with conventional auxiliary teaching systems, including an AI module integrated with knowledge recommendation. A variety of factors are investigated in this English teaching method to determine if there is any correlation between evaluation outcomes and them. With this system, students can enhance their English language proficiency based on their knowledge mastery and personality characteristics through deep learning-enabled interactive intelligent English teaching. Decision tree algorithms and

NNs were incorporated into a decision tree assessment model for English teaching. By analyzing extensive information, the system identifies valuable insights, formulates rules, and summarizes data, assisting teachers in enhancing their educational methods and improving students' English abilities. Expert systems based on artificial intelligence are used in this system. The efficacy and relevance of the system have been verified through test applications. The system also provides a reference point for future implementations of similar methods.

Chen [27] developed a data-driven multi-dimensional corpus English teaching framework. Research focuses on the principles of data-driven modeling, the computation procedure, and the features of the generated corpus. An artificial intelligence algorithm is used to overcome the limitations of data-driven modeling, specifically the inability to correlate quality variables with process variables. The method is thoroughly analyzed regarding its principles, computational processes, advantages, and disadvantages. The study introduces the autoregressive latent structure projection algorithm to handle the dataset's complexities and lack of orthogonal decompositions. This algorithm combines autoregressive concepts with artificial intelligence to enable orthogonal decomposition of sample data space and streamline modeling. The autoregressive latent structure projection approach and fuzzy C-means clustering algorithm are combined to evaluate the results of the English teaching model. Each category of sample data is categorized, and affiliation functions are calculated. Fuzzy comprehensive assessment is then used to evaluate the results of online calculations. The study uses simulations to validate the model's effectiveness in teaching junior students English. Research findings indicate that corpus-based English flipped classroom models enhance learning strategies, increase language proficiency, and improve students' ability to learn independently, providing a practical foundation for further study.

Zhang [28] proposed an innovative approach incorporating the Internet of Things (IoT), PSO algorithm, and NNs to address the challenges in teaching and evaluating English language translation, particularly in countries like China that highly value English proficiency. Teachers can use this approach to evaluate students' translation abilities more effectively. An application model measures students' abilities to learn English translation. By gathering information on learning progress, the PSO algorithm develops tailored teaching resources and learning plans for different learning styles, facilitating rapid advancements in English translation education. The paper also presents a model for practical translational application in English. The PSO-powered NN can handle translations and teaching data by minimizing training errors. The efficacy of the approach is assessed by measuring the mean discrepancies between test and training samples using varying particle counts. The results exhibit a notable level of precision in assessing students' translation skills.

Blended teaching, which combines online and conventional teaching techniques, provides a holistic learning strategy. Wu [29] developed a technique for evaluating the efficiency of College English blended teaching using data mining techniques. The approach involves gathering materials for College English blended instruction, building online and offline teaching support, improving the teaching environment, and eventually developing an integrated teaching model using data mining techniques. The experimental results indicate that this strategy greatly improves students' reading proficiency in College English, highlighting its practical significance in real-world situations.

Hui and Aiyuan [30] developed an instructional methodology incorporating artificial intelligence, specifically adopting a NN framework. The authors defined many dimensions appropriate for evaluating data-related indications, including resource search, cooperation, testing, learning, demographic background information, learning capacity, and attitude. The researchers sought to collect a comprehensive array of indicators. The researchers suggested an audio-visual fusion technique using a Convolutional Neural Network (CNN). This method includes creating different CNN structures to simulate audio-visual perception independently and transmit asynchronous information. A collective, completely linked architecture captures enduring interconnections in multi-dimensional domains. The experimental findings demonstrate that the audio-visual fusion approach employing CNNs greatly improves the effectiveness of the Audio-Visual Speech Recognition (AVSR) process, resulting in a reduction in the recognition error rate by around 15%. In addition, the cross-domain adaptive training technique significantly enhances the voice recognition system, with a reduction of over 10% in the recognition error rate compared to the baseline system.

Text-to-speech synthesis is a crucial tool for teaching and translation systems, essential to English education and progress. Nevertheless, the current text-to-speech translation encounters challenges due to specific inherent features. To optimize the effectiveness of this translation procedure, Li [31] enhanced conventional machine learning techniques and presented an advanced system that incorporates Support Vector Machines (SVM), factor analysis, and statistical language. The system consists of several training and testing modules integrating statistical and rule-based techniques in a cohesive framework. This framework utilizes English language characteristics to automatically convert phonetic properties and alphabetic characters. Furthermore, the study develops a framework model for transforming English text into sound. It assesses the model's performance and conducts experiments to determine its efficacy. The research findings indicate that the suggested approach has a beneficial effect on converting text into speech.

III. METHODOLOGY

This section introduces the methodology for addressing limitations in traditional algorithms. The proposed approach integrates the PSO algorithm with NNs, optimizing training using the collective intelligence of swarms. The complexity of the algorithmic framework is outlined, emphasizing its advantages over conventional methods. PSO and NN are explored in detail to comprehensively understand the novel methodology employed to enhance English language teaching effectiveness.

The PSO algorithm is a popular swarm-based stochastic algorithm inspired by the flocking behavior of birds. This algorithm uses particles resembling birds' flocks to explore the problem space [32]. In the collective, each particle disseminates its most optimal position and associated fitness measure while introducing random disturbances. This information exchange affects the particle's decision on its next movement inside the search space. The decision-making process considers each individual particle's past trajectory and the entire group's overall movement [33]. Once the particles update their locations in the current iteration, the next iteration of the search process begins, focusing on areas close to the perceived best solution. The iterative nature of this approach, driven by historical data and swarm dynamics, attempts to direct the swarm toward the optimal outcome of the goal function. The rate at which the entire swarm comes together is closely linked to the particular variation of PSO used and the values supplied to its control parameters [34].

The simplicity and effective performance of PSO have led to its widespread recognition and attraction in numerous academic disciplines and diverse applications. The algorithm's capacity to combine, specialize, and demonstrate emergent behavior in search spaces with many dimensions has made it a favored option. Although the original PSO version, which includes both the fundamental and inertia models, has advantages, it also encounters difficulties such as velocity explosion and a tendency towards early convergence. Premature convergence occurs when the algorithm reaches a local optimum without sufficiently investigating the full search space. The convergence behavior of inertia PSO depends on the supplied values of control parameters. The particles can either come together or move apart and even when they come together, it may not result in a single best point but rather a condition of balance when the particles stop moving. The issue lies in finding a balance between exploration and exploitation since algorithms that prioritize exploration may have difficulties exploiting opportunities and vice versa. PSO often necessitates several rounds focused on investigation before moving to exploitation, which may affect the solution's quality.

The PSO algorithm explores the search space for the optimal solution through populations of particles. Particles move within this multi-dimensional domain, characterized by velocity and position (represented by V and X matrices), as described in [35]. Two components influence particle movement: social and cognitive (individual). In the animal realm, the social aspect assumes that animals adapt to the behavior of others in proximity. At the same time, the cognitive component implies that individuals act under previous knowledge, disregarding nearby individuals. The PSO algorithm incorporates cognitive and social features to modulate individual particles' movements, modifying their positions in the search space. Although PSO is typically applied to continuous variables, Kennedy and Eberhart [36] introduced PSO using discrete binary variables. Mixed-integer programming using PSO has been thoroughly

TABLE 1. Overview of research in technological integration for english language teaching.

Research aspect	Cho and Kim [25]	Sun, et al. [26]	Chen [27]	Zhang [28]	Wu [29]	Hui and Aiyuan [30]	Li [31]
Focus area	Mobile text interface	Online English teaching	Corpus English teaching model	IoT, PSO, NN in English translation	Blended teaching efficiency	Audio-visual fusion using CNN	Text-to-speech conversion
Key technologies	Deep learning, Handwritten text, CNN	Deep learning, Decision tree, Neural Networks	Data-driven modeling, AI algorithm	IoT, PSO, NN	Data mining, Blended teaching model	Neural Network model, CNN, Audio-visual fusion	Statistical language, Factor analysis, Support Vector Machines
Datasets used	EMNIST dataset	Not specified	Autoregressive latent structure projection algorithm	EFLT, ELLC, EMPC	Not specified	Not specified	Not specified
Application	English education applications	AIEd-driven online English teaching system	Enhanced English teaching model	PSO-NN for English translation education	Improved College English reading proficiency	Improved AVSR system	Advanced text-to-speech conversion
Method evaluation	User satisfaction survey	Correlation analysis	Simulation and validation	PSO-enabled NN assessment	Data mining experimental results	AVSR system effectiveness	Performance assessment and control experiment
Results achieved	Improved simplicity and convenience	Enhanced language proficiency	Enhanced teaching methods, improved proficiency	Tailored learning strategies	Improved reading proficiency	Significant reduction in recognition error rate	Beneficial effect on text-to-speech conversion

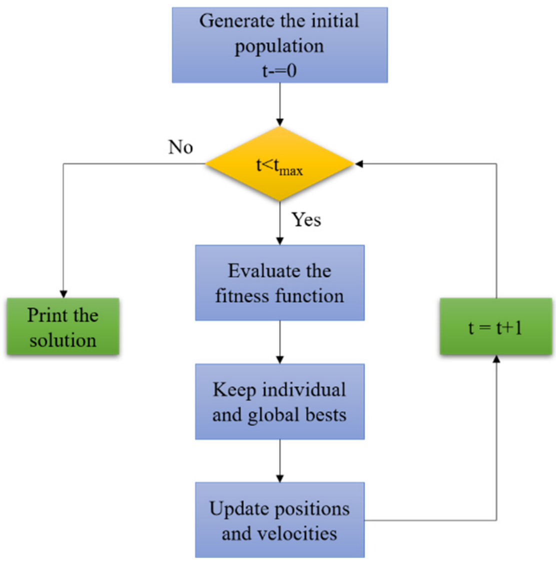

FIGURE 1. Workflow of the PSO algorithm.

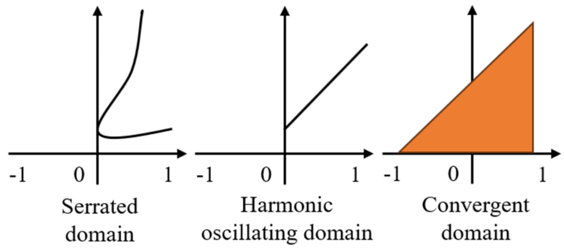

FIGURE 2. Particle states in different dynamic regions.

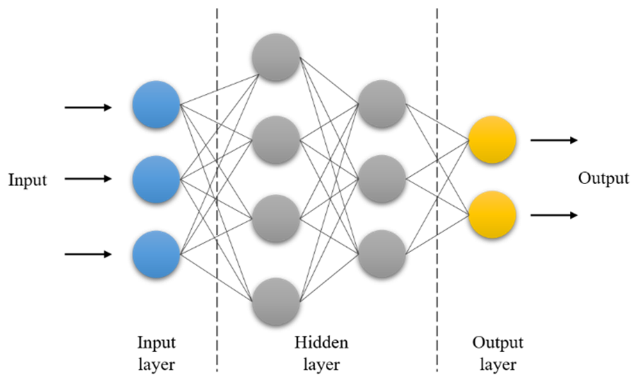

FIGURE 3. Multilayered feedforward NN.

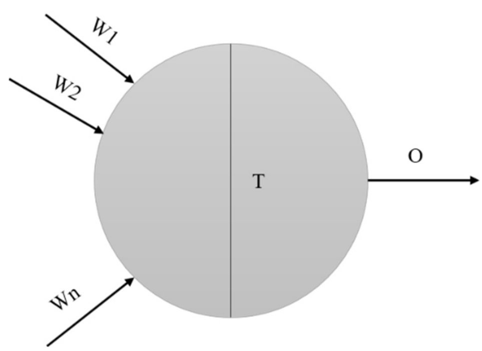

FIGURE 4. Neuron's structural model.

validated, as demonstrated in studies such as [37]. The fundamental components of PSO, as outlined in [38], encompass particles, population, global best, individual best, fitness, inertia weights, particle velocity, and time.

- ***Particles:*** Represent candidate solutions, denoted as $X_j(t) = [x_{j,1}(t), x_{j,2}(t), \ldots, x_{j,m}(t)]$, where j is the particle index, $x_{j,k}(t)$ refers to the position of the k^{th} dimension at time t, and m indicates the number of optimization variables.
- ***Population:*** It includes all n particles at time t: $P_t = [X_1(t), X_2(t), \ldots, X_n(t)]^T$.
- ***Global best:*** X_j^{**} is the position among all particles with the best fitness score.
- ***Individual best:*** X_j^{*} is the best position where a particle has encountered its best fitness score.
- ***Fitness:*** Represents the quality of a solution, measured by a fitness function assigning a fitness value to each particle.
- ***Inertia weights:*** Balances local and global exploration by controlling the impact of past velocities.
- ***Particle velocity:*** It can be expressed as $V_j(t) = [v_{j,1}(t), v_{j,2}(t), \ldots, v_{j,m}(t)]^T$, where $v_{j,k}(t)$ corresponds to the velocity of the j^{th} particle concerning the k^{th} dimension at time t.
- ***Time:*** A parameter t is used to count the elapsed time or epochs of the PSO, incremented in each generation.

During each iteration, each particle's velocity is updated based on its individual and global best positions and inertia weights. The fitness values guide the search for the optimal solution. The process is repeated over iterations until convergence. Figure 1 provides a visual representation of the PSO algorithm. Several optimization techniques depend on gradient information to optimize their processes, but the operational mechanism of particle swarm optimization differs substantially. Particle swarm optimization utilizes a probabilistic search technique, similar to a fuzzy search, in its optimization procedure. Although using several evaluation functions to assess particle fitness values is necessary, it provides clear benefits compared to conventional evolutionary algorithms.

The PSO algorithm operates without the constraints of centralized control, resulting in greater robustness since individual components do not influence the overall solution. Additionally, no direct information exchange occurs within the particle swarm, ensuring high scalability. To enhance overall solution efficiency, multi-processor distributed processing can be used to solve the particle swarm optimization algorithm. Due to its independence from specific problem continuity, particle swarm optimization has wide applications and boasts higher extensibility than traditional intelligent algorithms. Particle swarm optimization also requires

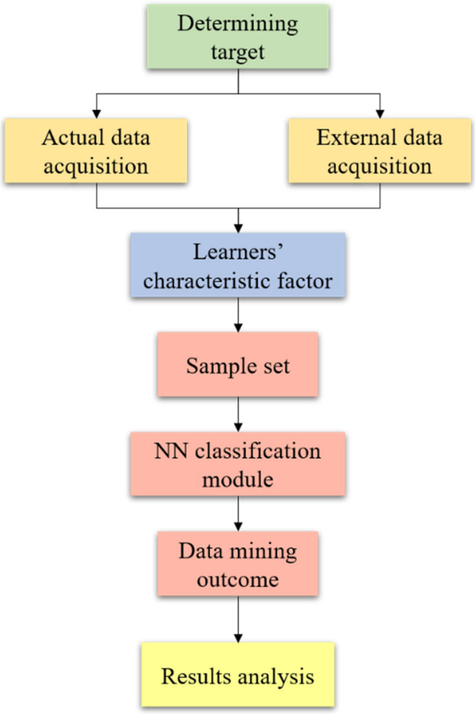

FIGURE 5. LCA model to analyze students' learning abilities.

minimal parameters during operations, allowing for straightforward configuration and adjustment.

PSO mainly involves determining particle positions and velocities, which is fairly straightforward. There are three main motion patterns for particles: convergence to a specific area, harmonic oscillation, and zigzag movement. Figure 2 illustrates particle states in different dynamic regions. Based on the assumption that $P_{id}(t)$ and $P_{gd}(t)$ are constants, we establish the empirical convergence of the PSO algorithm, represented by equation 1. Equations 2 and 3 specify the initial conditions, where $U(-1, 1)$ denotes a random number ranging from -1 to 1. First and second-generation particle positions are calculated using equations 4 and 5.

$$x_{id}(t+1) = (1 + w - \varphi_1 - \varphi_2).x_{id}(t) - wx_{id}(t-1) + \varphi_1 P_{id} + \varphi_2 P_{gd} \tag{1}$$

$$x_{id}(0) = U(-1, 1).r \tag{2}$$

$$v_{id}(0) = U(-1, 1)v_{max} \tag{3}$$

$$x_{id}(1) = (1 - \varphi_1 - \varphi_2).x_{id}(0) + wx_{id}(0) + \varphi_1 p_{id} + \varphi_2 p_{gd} \tag{4}$$

$$x_{id}(2) = (1 + w - \varphi_1 - \varphi_2).x_{id}(1) + wx_{id}(1) - wx_{id}(0) + \varphi_1 p_{id} + \varphi_2 p_{gd} \tag{5}$$

Artificial NNs typically consist of multiple nodes and neurons, with multilayered feedforward NNs being the most commonly used model [39], [40]. This model consists of three layers: input, output, and hidden. Data is collected from external sources, fed into the NN, and processed in the hidden layer, and the results are provided in the output layer. Figure 3 depicts the multilayered feedforward NN, while Figure 4 demonstrates the neuron's structural model.

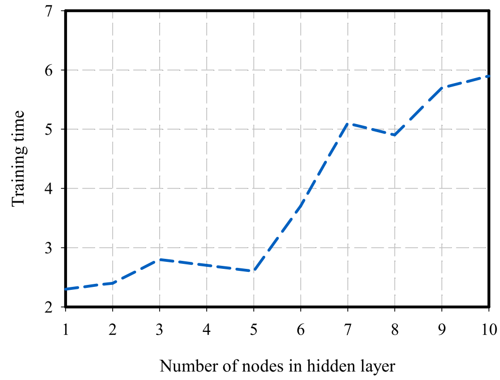

FIGURE 6. Training time for the network.

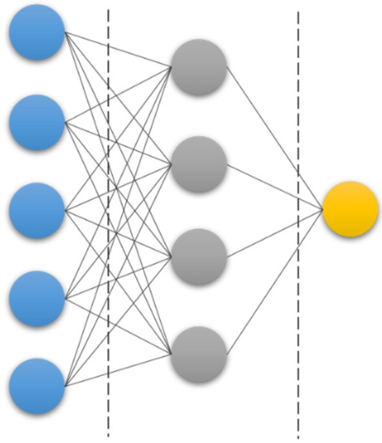

FIGURE 7. Network topology diagram.

For English teaching, acquiring objective data and analyzing it accurately is crucial. Figure 5 illustrates how a Learning Capability Analysis (LCA) model is used to analyze students' learning abilities during English teaching. In the LCA model, specific learning characteristics of students are analyzed, relevant information about students' learning states is obtained, and teaching tasks are tailored to individual students based on the analysis results, thereby improving the development of English teachers. During the data acquisition stage, a questionnaire survey is conducted. To eliminate interference from irrelevant data, the original data is preprocessed during the data extraction stage. The processed data is filled in to address any partial missing or omitted data before being entered into the NN.

The topology of the NN in the classification module is controlled by certain parameters, such as node count at input, output, and hidden layers [41]. Equation 6 calculates the hidden layer nodes. In this equation, N, M, and J stand for the number of nodes in the input, output, and hidden layers, respectively. In this study, J is set at 2. Using this equation, we establish the correlation between the number of hidden layer nodes and the training time for the network. Figure 6 depicts the correlation, demonstrating that the

Algorithm 1 Pseudocode for the Proposed Algorithm.

Initialize the PSO parameters:
- Set the population size, maximum number of iterations (epochs), and other control parameters
- Initialize the particles' positions and velocities randomly within the search space

Initialize the NN architecture:
- Define the number of inputs, hidden, and output neurons
- Randomly initialize the weights and biases of the NN

Initialize the best-known positions (Pbest) and global best position (Gbest) of particles

Repeat **until** the convergence criterion is met:
  For each particle in the population:
    Evaluate the fitness of the particle using the NN:
      - Forward pass: input the particle's position as input to the NN
      - Compute the output of the NN
      - Calculate the fitness (e.g., mean squared error) based on the output and target values
    Update the Pbest and Gbest positions based on the fitness value
    Update the particle's velocity and position using the PSO equations:
      - Update the velocity based on the cognitive and social components
      - Update the position based on the velocity
    Clip the particle's position within the search space boundaries
  End For
  Update the NN weights and biases based on the Gbest position:
    - Forward pass: input the Gbest position to the NN
    - Compute the output of the NN
    - Backpropagate the error and update the weights and biases using a suitable optimization algorithm (e.g., gradient descent)

End Repeat

Return the optimized NN model

network achieves the fastest training time when the hidden layer consists of 4 nodes. Therefore, a suitable network topology diagram is created, as shown in Figure 7.

$$J = \sqrt{M_1 \times N} \tag{6}$$

Algorithm 1 outlines the PSO algorithm's iterative process combined with the NN's training. The PSO algorithm optimizes the positions of particles in the search space, while the NN evaluates the fitness of each particle based on its position. The best positions found by the PSO are used to update the weights and biases of the NN, optimizing the overall system for English instruction enhancement.

IV. RESULTS AND DISCUSSION

To assess the efficacy of the proposed algorithm, a comparative analysis was conducted against several existing methodologies, including Conventional PSO [42], Segment PSO (Se-PSO) [43], Enhanced Segment PSO (ESe-PSO) [44], and hybrid genetic–PSO (GAPSO) [45]. A standard case study was employed, utilizing well-known benchmark functions such as the Rosenbrock function (Figure 8), Rastrigin function (Figure 9), Griewank function (Figure 10), and Ackley function (Figure 11). These functions are commonly used as benchmark problems in optimization algorithms due to their well-defined mathematical properties and varying levels of complexity. The experimental outcomes demonstrate that the enhanced PSO outperforms other algor333ithms, addressing premature convergence issues and enhancing the particle's ability to escape local extrema during the search process.

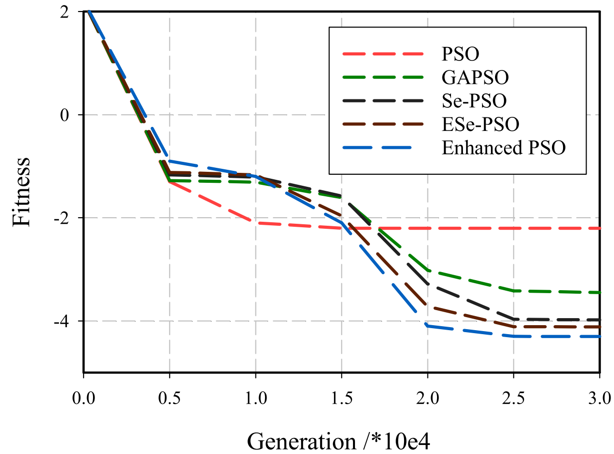

FIGURE 8. Rosenbrock function.

Figure 8 illustrates how the algorithm, particularly the extended PSO variant, navigates through the search space to converge to the global minimum. By analyzing the convergence behavior and trajectory of the particles, insights can be gained about the algorithm's ability to efficiently explore and use the search space. Figure 9 shows the Rastrigin function, a multimodal, nonconvex function with numerous local minima. This figure shows the algorithm's performance in bypassing local optima and converging to the global minimum. Through this analysis, the effectiveness of the extended PSO in tackling complex, multimodal optimization problems can be assessed.

Figure 10 shows the Griewank function, known for its high-dimensional and non-separable nature. This figure provides insight into how the algorithm adapts to the complex landscape of the function and navigates through multiple peaks to reach the global minimum. By evaluating the convergence speed and accuracy, the algorithm's robustness in tackling challenging optimization tasks can be assessed. Finally, figure 11 shows the Ackley function, characterized by many local minima and a wide, shallow valley around the global minimum. This figure demonstrates the algorithm's ability to efficiently explore the search space and identify the global minimum among numerous local optima. By analyzing the convergence behavior and the final solution quality,

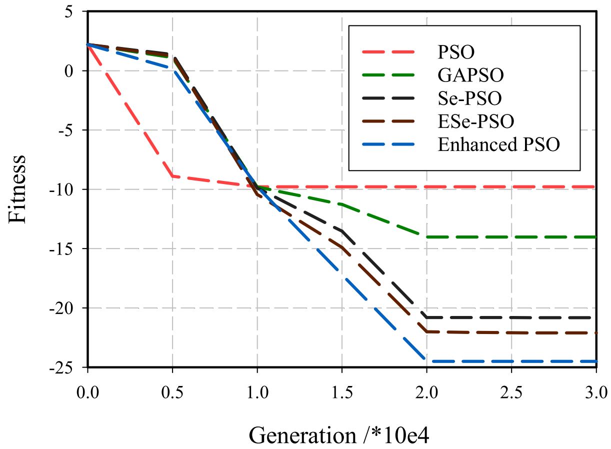

FIGURE 9. Rastrigin function.

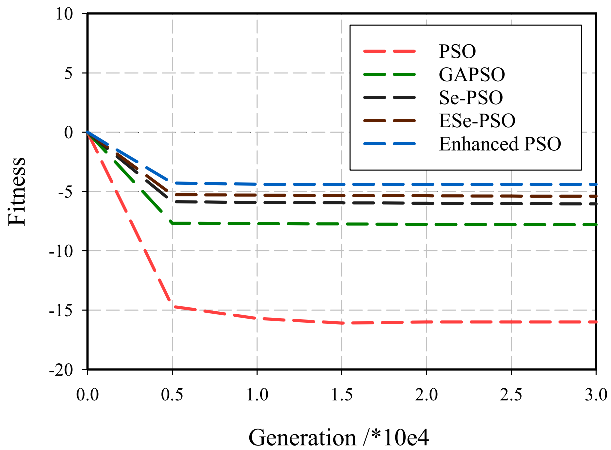

FIGURE 10. Griewank function.

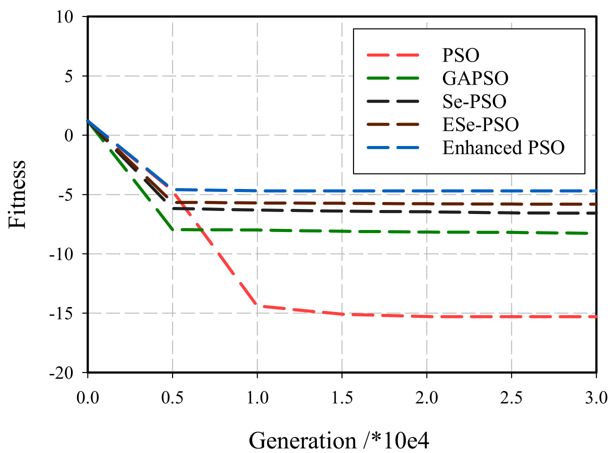

FIGURE 11. Ackley function.

the effectiveness of the improved PSO in resolving premature convergence problems can be assessed.

Subsequently, the enhanced PSO algorithm and the NN were employed to assess their impact on English teaching. The experiment was conducted on a Windows platform with a 500 GB hard disk and 8 GB RAM. The initial steps involved

TABLE 2. Simulation results: performance metrics for the proposed algorithm.

Patterns	Mean Squared Error (MSE)	Best particle (Pbest)	Epochs	Particle count
30	0.032	4	241	5
	0.045	6	429	10
	0.036	8	301	20

TABLE 3. Simulation results: error analysis for the proposed algorithm.

Training Sample Error (e_G)	Test Sample Error (e_T)	Mean squared error for test samples (MSE_G)	Mean squared error for training samples (MSE_T)	Particle count
13.91	6.41	0.039	0.215	5
27.92	13.12	0.331	0.331	10
29.14	9.81	0.284	0.042	20

collecting student English learning features, dividing them into two groups, and analyzing the LCAM model through an experiment. The NN was trained using Enhanced PSO Backpropagation (EPSO-BP), followed by model evaluation and testing.

During EPSO-BP training, parameters were set, including a precocious factor of 0.01, and values were randomly generated for other parameters. Particle numbers 5, 10, and 20 were employed, and the efficiency of these variations was analyzed. Table 2 presents the experimental results based on the student English proficiency sample set. The table includes patterns (number of training samples), particle count, Epoch (training cycles), Pbest number (number of particles with the best performance), and MSE (mean squared error). Results indicate that the proposed improved strategy consistently yields better solutions, demonstrating effective convergence.

Considering actual English teaching cases, seven samples were examined to assess the model's efficiency, employing 5, 10, and 15 particle swarm sizes. Investigation objectives included MSET (training sample MSE), MSEG (test sample MSE), eT (test sample error), and eG (training sample error), as shown in Table 3. The table illustrates that EPSO-BP achieves superior solutions for various particle group sizes. The error values are relatively small, highlighting the model's accuracy in analyzing English abilities. The trained neural network model effectively analyzes students' English proficiency, aiding teachers in estimating ability levels and providing valuable references for subsequent teaching steps.

V. CONCLUSION

Advances in technology have significantly influenced the landscape of English teaching. This study extensively delves into English instruction by combining the PSO algorithm and NN. A mathematical model was initially formulated, and subsequent exploration was conducted based on this model. To enhance the algorithm's suitability for English teaching, modifications were introduced to the traditional algorithm, and a comprehensive analysis of the algorithm was performed, culminating in the establishment of the LCA model. The experimental results affirm the correctness and effectiveness of the research methodology. The results of our study have significant practical implications for the field of English teaching. By harnessing the power of PSO-driven NN training, educators can adapt teaching methods to individual learning styles, increasing the effectiveness of English teaching. Future research could explore integrating real-time feedback mechanisms and adaptive learning platforms to personalize instruction. Furthermore, exploring the applicability of our approach in different educational settings and linguistic contexts could expand its impact on global language education initiatives.

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