

Application Analysis of Improving English Teaching Quality Based on PSO Algorithm

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ABSTRACT: *With the acceleration of globalization, English, as the universal language for international communication, has become increasingly important in education. This article studies the application analysis of particle swarm optimization algorithm (PSO) based on English teaching quality improvement. The aim is to use the PSO algorithm to optimize the English teaching process and improve teaching quality. This article first introduces the basic principle of the PSO algorithm and English teaching quality evaluation indicators and then elaborates on how to apply the PSO algorithm to improve English teaching quality, including teaching plans, classroom teaching, extracurricular tutoring, and teaching evaluation. Finally, the effectiveness and feasibility of the English teaching quality improvement method based on the PSO algorithm were verified through experiments.*

Keywords: Particle Swarm Optimization, BP Algorithm, English Teaching, Research

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1. Introduction

Particle swarm optimization, also known as foraging algorithm (POS), is derived from the intelligent study of the laws of nature proposed by Kennedy and Eberhart in the mid-90s last century, inspired by the [1] of birds. The most effective strategy for birds to search for food is to search for [2], the nearest bird in the current situation. In the following research, scholars gradually established the mathematical model of the particle swarm optimization algorithm. The particle swarm algorithm model's structure is simple, with high search precision and convergence of short cycles. It is a kind of intelligent evolutionary algorithm, from the point of random solutions, the optimal solutions for finding the global calculation by iteration, and the fitness to evaluate the optimal solution value [3]. The particle swarm algorithm is better than a genetic algorithm, simulated annealing algorithm and other intelligent algorithms for computing simple rules. It does not require complex operations such as crossover and mutation; only by following the current search of the optimal value will be able to find the global solution [4]. Artificial neural network (ANN) simulates the brain learning and storing large amounts of information. It is an essential direction of artificial intelligence research and has achieved extensive results in many industries and fields. A neural network, as an abstract mathematical model, uses many neural nodes to reflect the structure and function of the human brain. This

complex neural network can simulate human learning, memory, reasoning, computing and other behaviours. BP neural network is an essential model of the artificial neural network, but the standard BP neural network with error square system and as the objective function, so that the convergence rate is affected, there may be a local minimum value, the numerical relationship between the number of large gap data prediction model is not accurate enough [4]. Therefore, this paper proposes a particle swarm optimization algorithm to improve the BP neural network.

2. State of the Art

As a parallel algorithm, particle swarm optimization (PSO) represents new intelligent optimization algorithms. In the algorithm, each particle is equivalent to a bird in the flock; it is equal to the specific problem of a potential solution by using the fitness function, which is the objective function to calculate the fitness of each particle, index selection and evaluation of its [5]. To search for the optimal solutions in the population, each particle velocity vector by itself in continuous learning, in the process of changing the particle velocity vector, the particle in the feasible solution for the optimal solution space [6]. There are three basic concepts involved here. One is a particle. As the most basic component of the algorithm, it embodies the essence of the optimization problem and represents the feasible solution to each problem. The particle corresponds to a point in the multidimensional space, and the movement of the point is the process of searching for the optimal value [7]. The second is population. The number of birds in the population is the number of particles. Population size represents the size of feasible solutions. The particles in the population can share and learn from each other in group effect and finally find the optimal solution [8]. The third is the fitness function. That is to say, the objective function of the algorithm is presented in the particle, the objective function can be substituted, and the particle's fitness value, which can evaluate the performance of the particle in iteration termination, best fitness of the best particle is the global solution of [9].

BP neural network is the most attractive and widely used research model in artificial neural networks. The BP neural network adopts an error backpropagation algorithm model and uses a [10] with a tutor training method. BP neural network can provide a simple way for nonlinear modeling of complex systems to achieve arbitrary precision close to arbitrary nonlinear mapping through independent learning changes in the internal network connection value to adapt to the change of the system, which has good fault tolerance and robustness, multiple input and output structure model, and system state make better use of multiple variables. The introduction of the particle swarm algorithm to optimize the BP neural network is mainly to solve the control problem of the inertia weight and learning factor algorithm, which can effectively improve the global search results.

3. Methodology

3.1. Particle Swarm optimization Algorithm

The basic principle of particle swarm optimization is similar to birds looking for food. Suppose that there are n particles in a population in a D -dimensional search space. Here, the D dimensional vector of the particle is expressed as i , which can show the I particles in the range of search space location in the D dimension, which was also a solution to the algorithm problem. In the use of the fitness function corresponding to each particle is calculated, the fitness value is the evaluation of the particle as a standard value of candidate solutions. When the value of the objective function is the minimum, it shows that the fitness value is the best, and the closer to the minimum, the better the performance is

$$\begin{aligned} V_{id}^{k+1} &= wV_{id}^k + c_1r_1(P_{id}^k - X_{id}^k) + c_2r_2(P_{id}^k - X_{id}^k) \\ X_{id}^{k+1} &= X_{id}^k + V_{id}^{k+1} \end{aligned} \quad (1)$$

The velocity of the i particle is set as $V_i = (V_{i1}, V_{i2}, \dots, V_{iD})^T$, the individual extremum is set as $P_i = (P_{i1}, P_{i2}, \dots, P_{iD})^T$, and the population extremum of the population is set as $P_c = (P_{c1}, P_{c2}, \dots, P_{cD})^T$. In each iteration, each particle updates its position and speed by using the extreme values of individuals and groups and is represented by formula (1). Among them, W is inertia weight $d = 1, 2, \dots, D$; $i = 1, 2, \dots, n$. K is the current iteration number, V_{id} is the speed of particles, and c_1, c_2 are genisly called self-learning factor and global learning factor, on empirical value $c_1 = c_2 = 1.49445$. c_1 is the ability of particles to learn from themselves. c_2 representing particles to learn from populations. r_1 and r_2 are the random numbers between $[0, 1]$. The procedure of the standard particle swarm optimization is shown in figure 1.

From the flow and basic formula of the particle swarm optimization algorithm, it can be seen that the main results of the algorithm are three parts. One is the current iteration speed of particles, and the other is the cognitive ability of individual

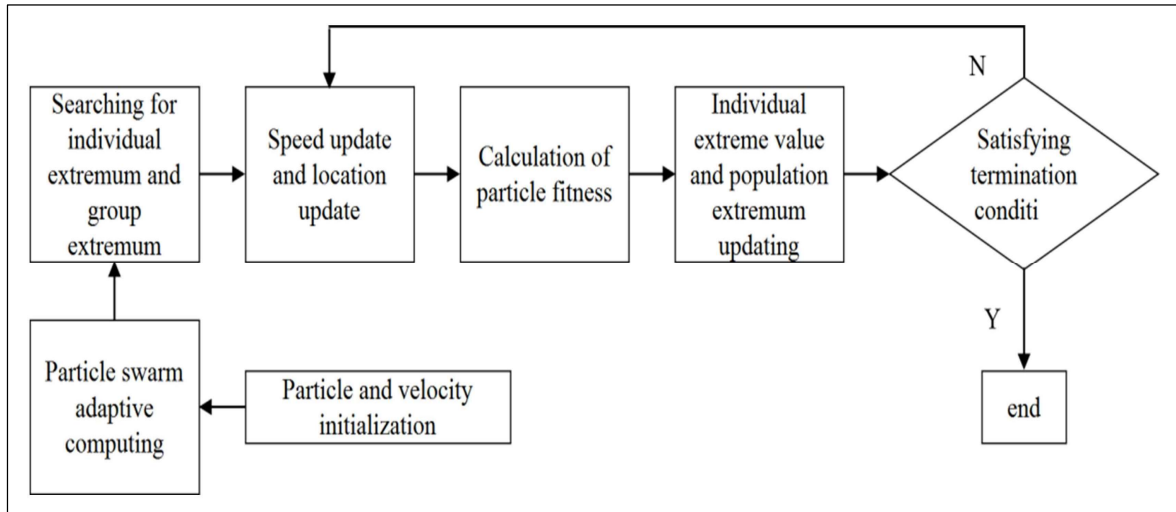


Figure 1. Flow chart of particle swarm optimization algorithm

particles, which reflects the learning state of the particle itself. It is the key to obtaining better searchability and preventing particle search from moving into local search. The third is the sharing of social information between particles. Under the combined action of the three parts, the particles adjust their states constantly, thus searching for the global optimal solution. When the learning factor $c_1 = c_2 = 0$, it shows that the particle's unique learning ability and social learning capacity are not available, the particles will only continue to fly at constant speed so that the optimal solution cannot be found. At the same time, when $c_1 = 0$, the particle has no individual cognitive learning ability, which is the particle swarm algorithm model only social cognitive ability, at this time, the whole search process of particles into the local optimum. When $c_2 = 0$, the particle's social learning cognitive ability is not so, the particle swarm algorithm models only individual learning cognitive ability, and finding the optimal solution is also very difficult. In the state of $c_1 = c_2 = 0$, the model will search the current optimal position and the most global position to control the particle speed; at this time, the particle search cycle and time will increase significantly, resulting in reduced efficiency. Figure 2 is a diagram of the particle velocity update, which represents the possible velocity state of the particles.

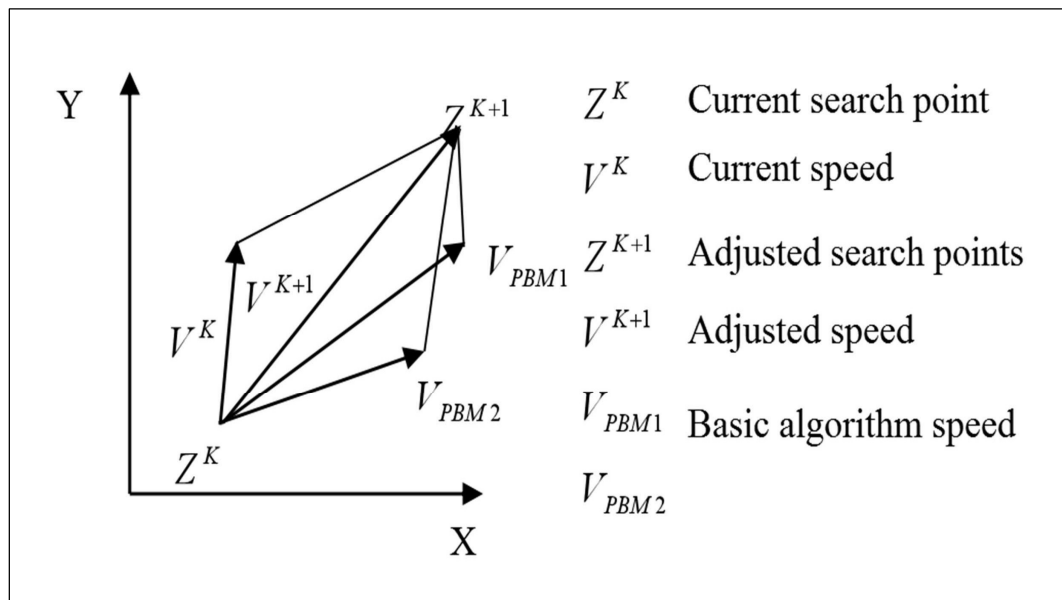


Figure 2. Sketch map of particle velocity update

In order to avoid the inefficiency of blind search in particle swarm optimization, it is necessary to limit the particle velocity to the V_{min} and V_{max} interval. V_{max} represents the maximum velocity, that is, the maximum value of the coordinates of the particles that can occur in each iteration. If V_{max} is too large, the particle will miss the optimal solution, resulting in the divergence of the iterative process. If V_{max} is too small, it will directly reduce the search speed of the population or make the population search become the search for the local optimal value, and then it cannot find the global optimal value. Assuming that X represents the position vector of a particle, $w V_{max} = X_{max} - X_{min}$, the maximum velocity of the particle is the best-performing state at that time. Figure 2 is a diagram of the particle velocity update indicating the possible velocity state of the particles. To improve the learning ability of learning factors, the inertia weight should be calculated. The inertia weight is linear, and the weight value is mainly determined by experience value. In the process of the inertia weight from the large to the small, the global search ability of the particles in the initial state is guaranteed, and the local search ability is also retained. Figure 3 is the influence diagram of the inertia weight on the number of iterations.

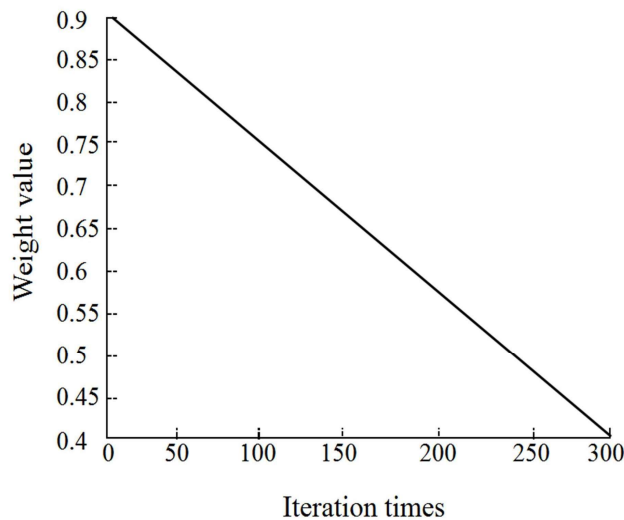


Figure 3. The change of weight and iteration number

3.2. Particle Swarm Optimization Algorithm to Optimize BP Neural Network

The basic algorithm of the BP neural network is to teach teacher learning; the basic learning algorithm of its main calculation steps are the initialization of the weights w and θ , and determining the input layer to the hidden layer neuron connection weights W_{ij} and to the hidden layer to the output layer weights W_{jk} , hidden layer threshold is set as θ_j , and to output layer neurons θ_k in a given threshold (0, 1) between the smaller value. The input vector of the input value is determined as $X_i = (X_1, X_2, L, X_m)$, and the input vector $\hat{Y}_i = (\hat{Y}_1, \hat{Y}_2, L, \hat{Y}_n)$ that corresponding, and then input the value of x_i to the neuron node of the input layer according to the $x_j^i = f\left(\sum_{i=0}^n W_{ij} x_i - \theta_j\right)$ ($j = 1, 2, L, u$) to the forward calculation or according to $y_k = f\left(\sum_{k=0}^n V_{jk} x_j - \theta_k\right)$ ($k = 1, 2, L, u$) to go through the reverse calculation. The error between output neuron output value and expected output value is calculated. If the error result is in line with expectation, the training is finished, if the gap is too large, it will enter the reverse calculation link of model calculation again. After repeated correction function calculation, get the weight to meet the requirements, the model calculation is finished, and output the signal. Figure 4 is a BP network model structure diagram.

The advantage of the BP neural network is obvious, but the deficiency is obvious. It is mainly in the practical application that the convergence period is long, the speed is slow, it is easy to enter local search, the optimal value becomes the local minimum, and the generalization ability is not strong. Therefore, particle swarm optimization (PSO) is introduced to optimize the BP neural network to improve these defects. The principle of an improved particle swarm optimization algorithm for BP based on a neural network is to find a suitable set of BP network weights using a particle swarm algorithm, that is, let the corresponding weights and thresholds of individual particle swarm particle location and BP network the BP neural net

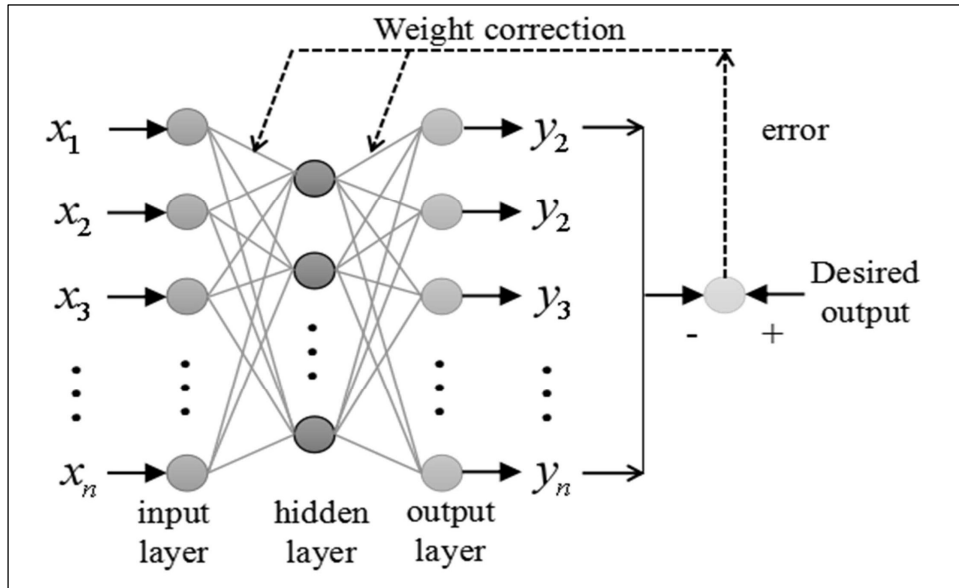


Figure 4. Structure of BP neural network

work weight and threshold value to decide calculation of dimension particle algorithm, BP network error as particle swarm algorithm to the initial value, if the smaller the error performance of the better quality of said particles, through the standard to test particle swarm update. The particle swarm algorithm effectively improves the evolution of its combination of BP networks. To get a minor error, the optimization algorithm meets the needs of the design or the number of iterations is completed, the initial weights of the BP network algorithm and output result, that is, the optimal position of the particle. Figure 5 is a flow chart of the particle swarm optimization BP algorithm.

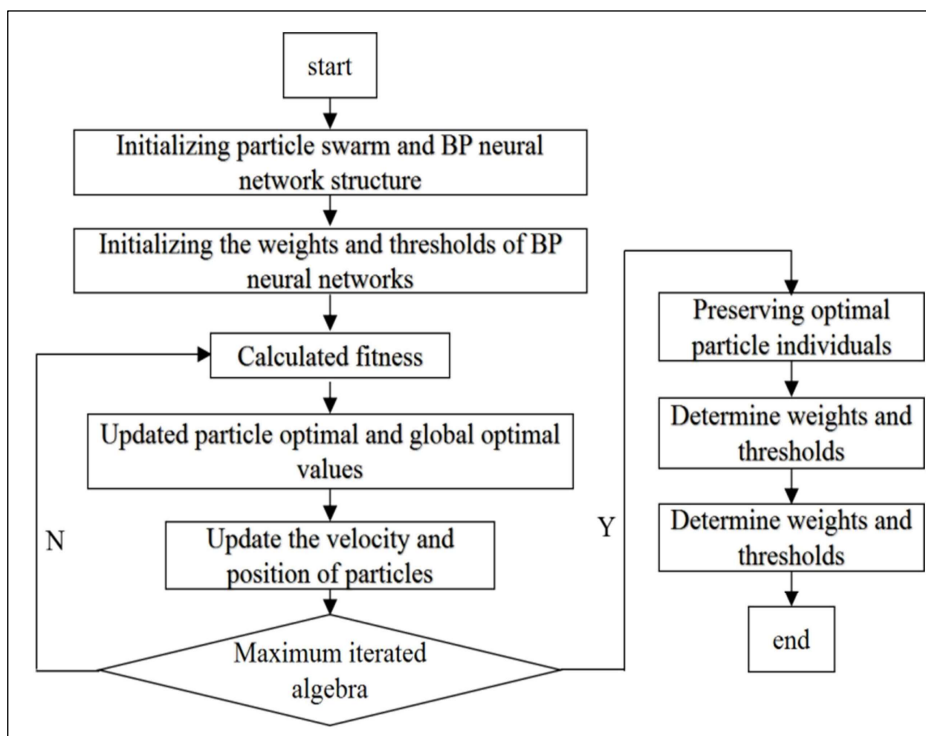


Figure 5. Flow Chart of Particle Swarm optimization BP algorithm

The main idea of particle swarm optimization is to consider whether the particle will be affected, not enter the optimal region, and premature, and premature convergence state. To improve the convergence ability of the basic particle swarm optimization algorithm. Based on the particle velocity formula, this paper introduces the inertia weight W to obtain the optimization algorithm formula of particle velocity, such as formula (2) to express.

$$X_{i,j}(t+1) = V_{i,j}(t+1) + X_{i,j}(t) \tag{2}$$

To find the global optimal solution, the appropriate inertia weight is needed, and the learning factor is set. If c_1 is large c_2 is small, particles will easily get into the local search by self-learning, if c_1 is smaller c_2 , particles will lead to a reduction in the convergence of the algorithm, and the algorithm is not accurate enough. So, the linear decrement function is introduced to reduce the learning factor with the increase of iteration. In order to achieve the regulation of particle motion, assuming $c_1 = c_2 = c$, that here $c_1 = [c_{min}, c_{max}]$, and c_{min} is the minimum learning factor value, c_{max} is the maximum learning factor value. The optimization formula of the learning factor is shown in formula (3).

$$V_{i,j}(t+1) = \omega V_{i,j}(t) + c_1 \cdot r_{1,i,j}(t) \cdot (P_{i,j}(t) - X_{i,j}(t)) + c_2 \cdot r_{2,i,j}(t) \cdot (G_{i,j}(t) - X_{i,j}(t)) \tag{3}$$

Among them, T represents the current iteration number, and P denotes the positive coefficient of the hypothesis. At $t = 1$, in time, $c = c_{max}$, when $t \rightarrow \infty$, $c = c_{min}$. Under this formula, the range of the learning factor is specified $c \in (c_{max}, c_{min})$. To improve the particle search speed at the later stage and find the accurate global optimal solution, the local search is accurate. It is to estimate the sum of all applicable values in each iteration to solve the mean value and to judge the difference between the current adaptation values in each iteration. If the difference is less than zero, the average value is retained as the optimal value. The current fitness is taken as the optimal value if the difference is greater than zero. As shown in formula (4).

$$c = (c_{max} - c_{min}) / t^p + c_{min} \tag{4}$$

4. Result Analysis and Discussion

This paper uses the particle swarm optimization (PSO) algorithm to improve the English teaching effect of the BP algorithm in the Department of English of M University. First is the student's English learning ability data collection and sample selection. The sample data of 50 students from the English department were selected as training data, and the data of 10

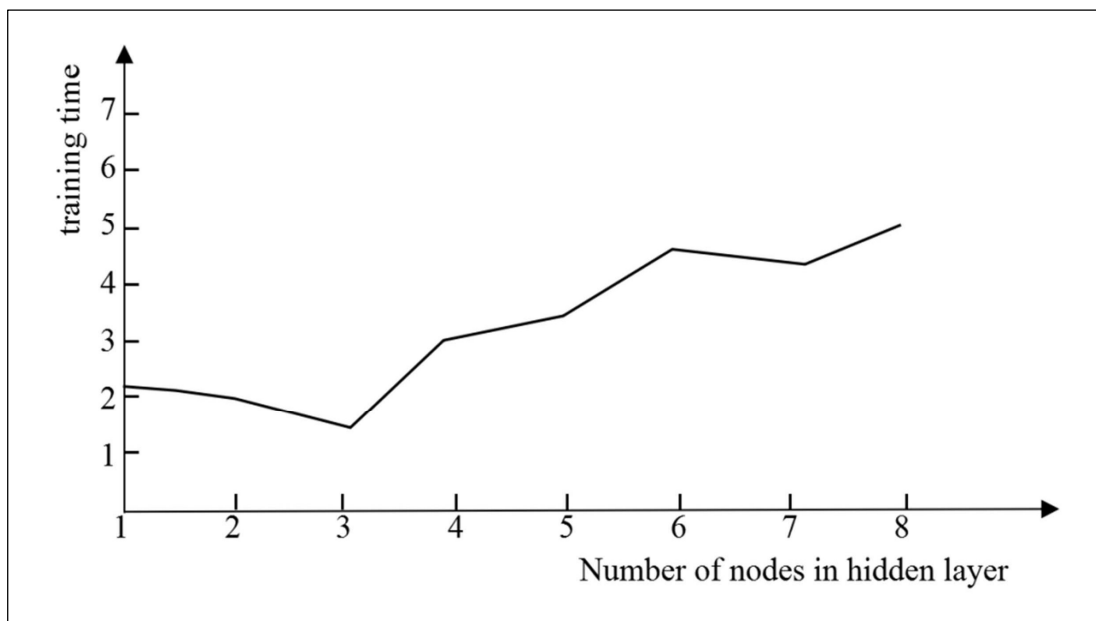


Figure 6. The change of training time when the number of hidden layer nodes increases

students were selected as the test data, which were compared and analyzed by the model. Firstly, the number of nodes in the input layer of the BP neural network is set to 5, and the output energy node number is set to 1. The number of nodes in the hidden and hidden layers significantly impacts the whole network's performance. In different network applications, the number of hidden nodes required by the hidden layer should be carefully considered according to the actual situation. In this paper, the experimental method is used to determine. The basic principle is that the number of nodes in the hidden layer can be reduced as much as possible when the input and output connections can be correctly responded to effectively control the network structure. When the number of input nodes is greater than the number of nodes in a small network, the number of nodes in the best-hidden layer is used, in which J is the number of hidden layer nodes, $M1$ is the number of hidden layer nodes, and N is the number of nodes in the input layer. After calculation, the number of nodes in the hidden layer is 2. To avoid the difference caused by random factors in the algorithm, the training time of each network is five times. Thus, the training time of the network is increased when the number of nodes in the hidden layer increases. As shown in figure 6.

In this paper, the simulation test uses the *DevC++* software on the Windows operating system platform to achieve, and the implementation of data mining classification processing is applied to the memory of a 256M computer. In the sample set of learning characteristics of students learning English, the experiment of the LCAM model is mainly carried out. The IPSOBP algorithm is used to train the neural network. After the data are pre-processed, the weights and thresholds of the initialization of the network are set. The particles' initial weights, acceleration systems and inertia factors are randomly generated, and the constant premature factor is 0.01. The particle number 5, 10 and 20 is selected to do experiments, respectively, and the particle swarm algorithm proposed in this paper is used to improve the running efficiency of the BP algorithm under different particle number. The results are shown in table 1.

Algorithm	Patterns	ParticleCoun	Epoch	Pbest_Number	MSE
IPSOBP	30	5	245	3	0.03115
		10	436	6	0.04789
		20	299	5	0.03879

Table 1. Experimental Results of Algorithm Simulation

Patterns are the number of samples, *ParticleCoun* is the number of particles, Epoch represents the number of iterations at the end of the training, *Pbest_Number* is the encoding of the global optimal particle, which corresponds to the weights of the neural network, and MSE is the mean square error value. The table shows that the initialization parameters of the IPSOBP algorithm are randomly selected, so the periodic value and MSE value are different when the training result is correct in each execution. When the number of particle swarms is different, the BP neural network training cycle is not good enough, which shows that the algorithm has better convergence ability. But from the Epoch and MSE values, we can see that the effect of training convergence and the number of particle swarms does not directly impact.

Algorithm	Particle	MSEt	MSEg	ϵ_t	ϵ_g
IPSOBP	5	0.0234	0.0453	6.8	14.5
	10	0.0315	0.3078	13.4	28.7
	20	0.0458	0.2897	11	29.6

Table 2. Experimental Results of Algorithm Simulation

Table 2 is the experimental result of 10 test samples. The data also show that the algorithm's expected and error values are small, providing good guidance and reference for improving English teaching.

5. Conclusion

The particle swarm algorithm, through the study of birds searching for food in the process to select the optimal group under the target value, the model of a simple algorithm, the characteristics of a single rule, has been widely used in many fields of artificial intelligence, multi-objective optimization, data mining, constraint optimization etc. Therefore, this paper studies the effect of English teaching improved BP algorithm based on particle swarm algorithm to improve the teaching methods and the quality of the target with the optimized algorithm after analyzing the operation process and modelling the advantages of the BP neural network algorithm, aiming at the defects of the neural network model, introducing the particle swarm algorithm to improve the structure. From the point of improving the accuracy of the particle swarm algorithm, the particle swarm algorithm learning factor formula of inertia weight formula was improved, optimized with adaptive degree of formula, to promote better play the role of hybrid algorithm. Then, the improved particle swarm optimization (PSO) algorithm BP is applied to M College English teaching. The application effect of particle swarm optimization to BP algorithm is obtained. The application results show that the particle swarm optimization algorithm based on BP algorithm parameters optimization is successful. Of course, the test results also show that the particle swarm optimization algorithm and the improved space, thus further improving the search precision of the optimal value is the research direction in the future.

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