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Research Article

An Antiforgetting Model for Higher Vocational English Learning Using BP Neural Network

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Currently, high-quality vocational education is an important foundation for the aspirations of China to create massive professionals and talented employees. Because of these, the advancement of modern vocational education is becoming increasingly important in the current era. Aside from these benefits, the use of artificial intelligence expertise in higher vocational English learning can effectively solve the unscientific problem of learning plan formulation in higher vocational English learning, increase the level of scientific learning, and strengthen students' autonomous learning ability. As a result, this research provides a BP neural network technique based on the Ebbinghaus forgetting curve that can effectively complete sample incremental training. It achieves performance comparable to the complete sample batch training approach while using many fewer samples to train. From experimental work, it is clear that the suggested work can effectively improve the training efficiency of the BP neural network to provide learners with a more suitable learning plan.

1. Introduction

These days, the importance of technical-vocational institutions as key scorers in network expertise has grown considerably, because of which the developer has made many enhancements for betterment. It is evident in the efforts of government, which vary from the acquisition and improvement of material to the standard of learning and instructors, as well as the program's modification [1]. As a result, overall educational organizations that train teachers must devise solutions to deal with the challenges of integrating English instruction at universities. Vocational education is a critical part of the national education system and capacity building. Higher vocational educational activities should welcome opportunities, promote education, encourage teaching method adaptation and innovation, enhance the quality of teaching, and develop more highly qualified potential [2].

In addition to the above, the process of English learning is an integrated learning process, including listening, speaking, reading, and writing, and all parts are interrelated. Because this feature of English learning, it also raises the need for an English learning system, specifically how to build a multifunctional English learning environment to help users learn English [3, 4]. At the same time, with the continuous development of the Internet and the continuous enrichment of English learning materials, how to help users find their own English learning mode has become very important, and it directly affects users' learning time cost and learning interest [5]. Ebbinghaus, a German psychologist, discovered that forgetting begins shortly after learning and that the process of forgetting is not uniform [6]. The forgetting pace was quite quick at first, and then, it progressively slowed. Ebbinghaus' forgetting curve is based on memory data collected from a vast number of tests. It is a common group law derived from the phenomena of individual memory that represents a memory rule at the balancing point.

In this regard, several scholars have added their contributions, among which [7] used the memory rules proposed by Ebbinghaus's forgetting curve to train his class on vocabulary memory. They compared and analyzed the data before and after training. Similarly, the work of [8] investigated a feasible English vocabulary memory method using the Ebbinghaus forgetting curve and proposed that the effect of interval repetition is better than cramming centralized memory. Making and structuring the review plan according to Ebbinghaus' forgetting curve, according to the scholar of [9], can overcome forgetting. The primary implication of the Ebbinghaus forgetting curve is that forgetting develops according to the law of "rapid before slow." According to the law of forgetting development, rememorizing "dense before sparse" can effectively avoid forgetting [10, 11].

As the working model of the BP neural network algorithm is similar to that of the human neural system to some extent, the author also follows this principle and designs a training sample loading mode for the BP neural network algorithm. It helps the BP neural network algorithm better assist English learning in higher vocational colleges and prevent learners from forgetting quickly. As a result, this study develops an antiforgetting model for higher vocational English learning based on the BP neural network algorithm to satisfy the demands for efficient memory in the building of the English learning system and increase the efficiency of English learning.

The below are among this paper's research contributions:

(1). Firstly, we recommend applying a BP neural network algorithm to a higher vocational English learning model that prevents forgetting.

(2). Secondly, we performed extensive testing on very famous and vocational organizations with varying number of students, comparing our technique to other methods for reading content in vocational English.

(3). We compare the errors of direct, full, and Ebbinghaus methods in samples of the old and new sample sets.

(4). Finally, our results suggest that the BP neural network algorithm outperforms the conventional training technique in terms of training effect. When the training impact is equivalent, the quantity of training computation required is significantly lesser than that of the whole sample batch training approach. At the same time, it may successfully safeguard the BP neural network's generalization capabilities. It is a strong and efficient incremental algorithm.

The organization of the paper is as follows: Section 2 provides an explanation of the materials we chose and the way we recommend for the antiforgetting model of higher vocational English learning. Our proposed antiforgetting methodology for English learning at higher vocational colleges is explained in Section 3. Section 4 provides a full summary of the training and outcomes of the proposed model, and Section 5 concludes our work.

2. Materials and Methods

2.1. The Present State of Higher Vocational English Learning and Issues. Higher vocational training puts a premium on learning as a feature of the form that, with the help of government policy, has been developing rapidly in recent years. Advanced vocational English learning is gaining the concentration of more significant academics and educationalists as a basis in the higher vocational training branch. The present state of higher vocational English learning and its issues can be illustrated in Figure 1.

2.1.1. From Students Aspect. Based on the evidence, the researcher summarizes the features and the power structure of vocational school students' present English learning, which are as follows:

(i) The fundamental level of English varies: students in higher vocational programs have considerable independence, and the choice of instructional materials varies, resulting in a significant disparity in basic English levels. Consequently, the pupil's fundamental English basis may be classified into several tiers. Many pupils in the class will be able to learn considerably, while others may struggle to absorb the material. Furthermore, throughout vocational school, higher vocational students place minimal emphasis on fundamental literacy class knowledge. Even some students despise the basic English education, which leads to their difficulties in learning English.

(ii) Inadequate learning motivation: the internal psychological impetus of English learning incentive is to encourage students' English learning practices, sustain English active learning, and maintain behavior toward an internal procedure of English educational objectives. According to research, higher vocational pupils' English learning objectives are inadequate [12]. According to the research, 36% of pupils learn English to pass tests and get a degree, 59% of pupils learn English to have a greater growth potential in their future profession and career, and just 2.4 percent of the students desire to learn English further because it is fascinating. More than 97.5 percent of students show no attempt to study but do so because of social pressures, and in attending lectures, inaccuracy in English class instruction is unavoidable. Learning desire is the most practical and effective aspect of learning inspiration, and it is the precursor of self-study learning and is the primary form of inspiration.

2.1.2. From Teachers Aspect

(i) Outdated concept and poor theoretical quality: because of the obvious intense teaching load, the studying environment at vocational schools is not robust. As a result, many vocational schools' English

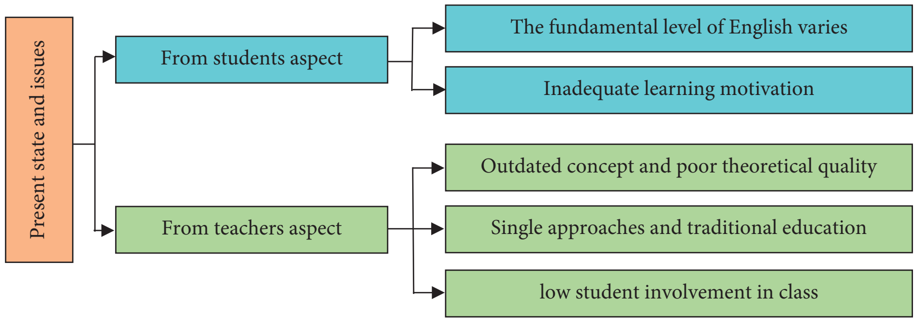

Figure 1: Present state of higher vocational English learning and its issues.

teachers lack detailed examination and updating in theory instruction. The theory quality of higher vocational English instructors has to be increased. The lack of theoretical guidance causes the instruction to be aimless. It is more difficult to modify higher vocational English instruction without proper planning and thinking.

(ii) Single approaches and traditional education: a majority of higher vocational English instructors still use the outdated "cramming learning" teaching techniques, where conditional learning is the primary way of instruction, notwithstanding some changes in higher vocational teachers' teaching strategies. Pupils virtually blindly accept the teacher's interpretation, and learning creativity, desire, and originality are curtailed. The eagerness to engage in classroom teaching events is low, which is not beneficial to the promotion of students' language communication skills.

(iii) Low student involvement in class: pupils' classroom involvement is low, both in and out of the classroom. Many greater vocational schools are now more interested in developing specialized and actual abilities, expanding the school leadership to a professional development path and starting to compact such fundamental English classes. As a result, higher vocational English teachers must keep pace. Numerous teachers believe that the teaching process takes time and is not as quick as explicit instruction. Therefore, conversations among teachers and learners in the English classroom are indeed rare. The majority take large classes teaching vocational school English classes with very low student participation [13].

2.2. BP Neural Network Algorithm. A neural network is made of linked input/output modules, each of which has a weight corresponding to one of its computer programs. It helps in the formation of prediction models from massive databases. This paradigm is based on the functioning of the neurological system and helps in picture interpretation, human cognition, computerized speech, and other tasks.

Backpropagation (BP) is the foundation of training and testing, which is made of 3 layers: input, hidden, and output. These layers are made of several equivalent neurons. Hence, every layer of the BP neural network is connected by neurons. The input layer receives the feature vector's input, the hidden layer receives the network's hidden neural layer, and the output layer receives the system algorithm's result [9, 10]. The BP neural network algorithm adopts the minimum mean square error learning method. In the learning stage, the error is propagated back to the input layer, and in the working stage, the input vector is propagated forward layer by layer to the output layer. Its structure is shown in Figure 2 [14]. When the hidden layer nodes can be set freely according to the needs, the three-layer forward BP neural network can realize any continuous function [15].

The flowchart of BP neural network algorithm for the antiforgetting model is shown in Figure 3.

As per the flowchart in Figure 3, let the number of neurons in the input layer be m, the number of neurons in the hidden layer be l, and the number of output neurons be n. The connection weight from the l neuron in the j layer to the $l+1$ neuron in the i layer is w^l_{ji}, P is the current learning sample, and o^l_{Pi} is the output of neurons in the P layer under the $l+1$ sample. The transformation function takes the sigmoid function, as shown in

$$f(x) = \frac{1}{1+e^{(-x)}}. \tag{1}$$

For the sample P, the output error E_P of the network, as shown in

$$E_P = \frac{1}{2}\sum_{i=0}^{n-1}\left(t_{Pj} - o^l_{Pi}\right)^2. \tag{2}$$

In the above equation, t_{Pj} is the ideal output of the P neuron when the i sample is input, and o^l_{Pi} is the actual output.

Determine the number of nodes in the input layer and output layer according to the empirical formula, and the number of nodes in the hidden layer can be given, as shown in

$$l = \sqrt{m+n} + a. \tag{3}$$

In the above equation, $a \in [1, 10]$ is constant.

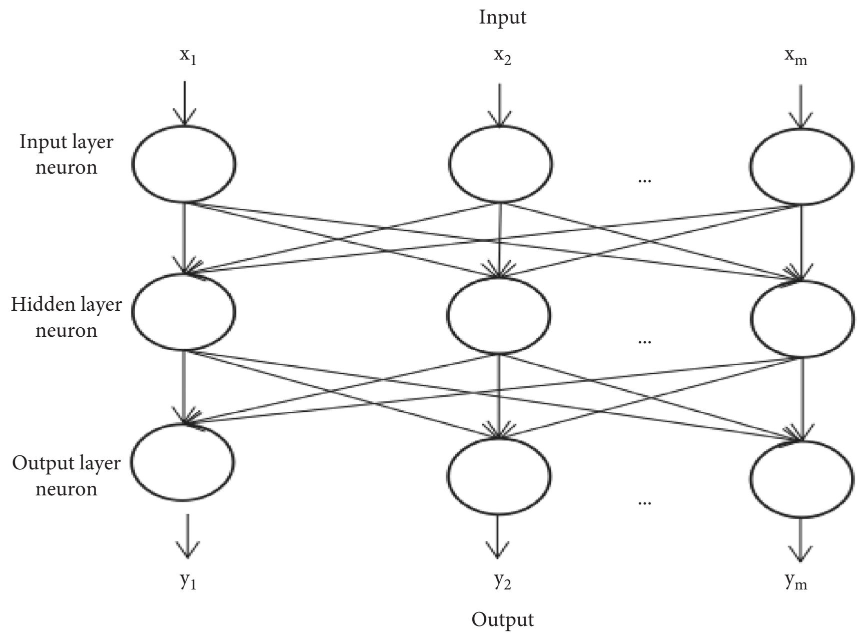

FIGURE 2: BP network structure diagram.

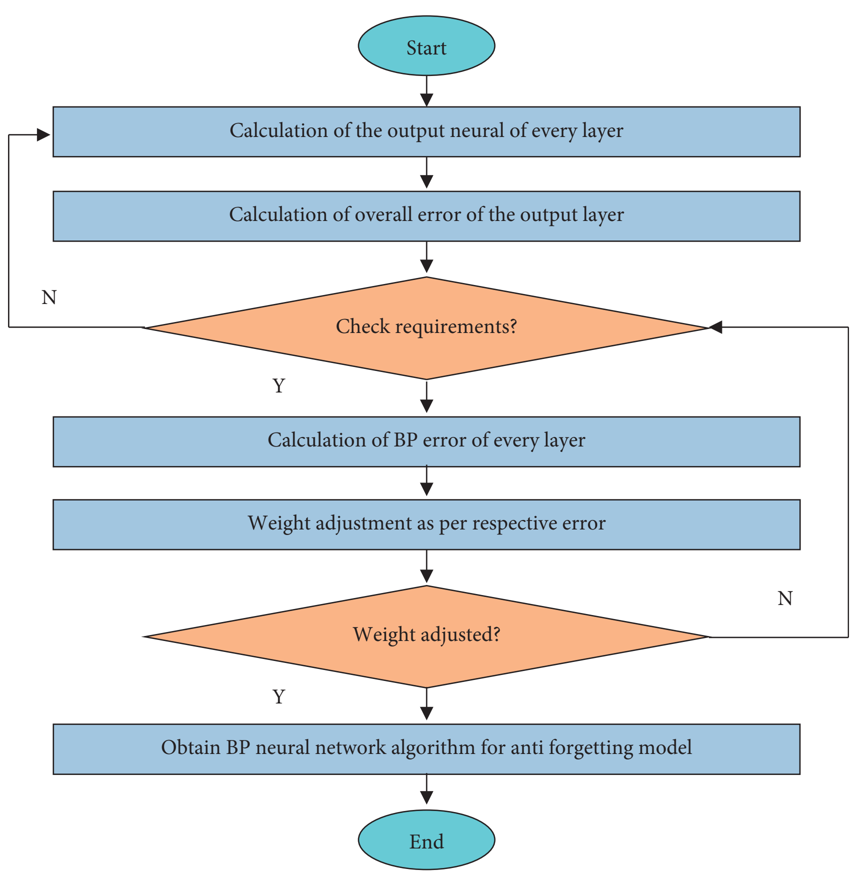

FIGURE 3: Flowchart of BP neural network algorithm for antiforgetting model.

3. Proposed Antiforgetting Model for English Learning in Higher Vocational Colleges

In this section, we provide a suggestion system based on the BP neural network algorithm to enhance users' reading activities and memory. In addition, the goal of this section is to find the best rules of recommendation for vocational English evaluation using the correlation rules recommender system and combine these with the Ebbinghaus memory curve depending on user feedback [16]. Figure 4 depicts the

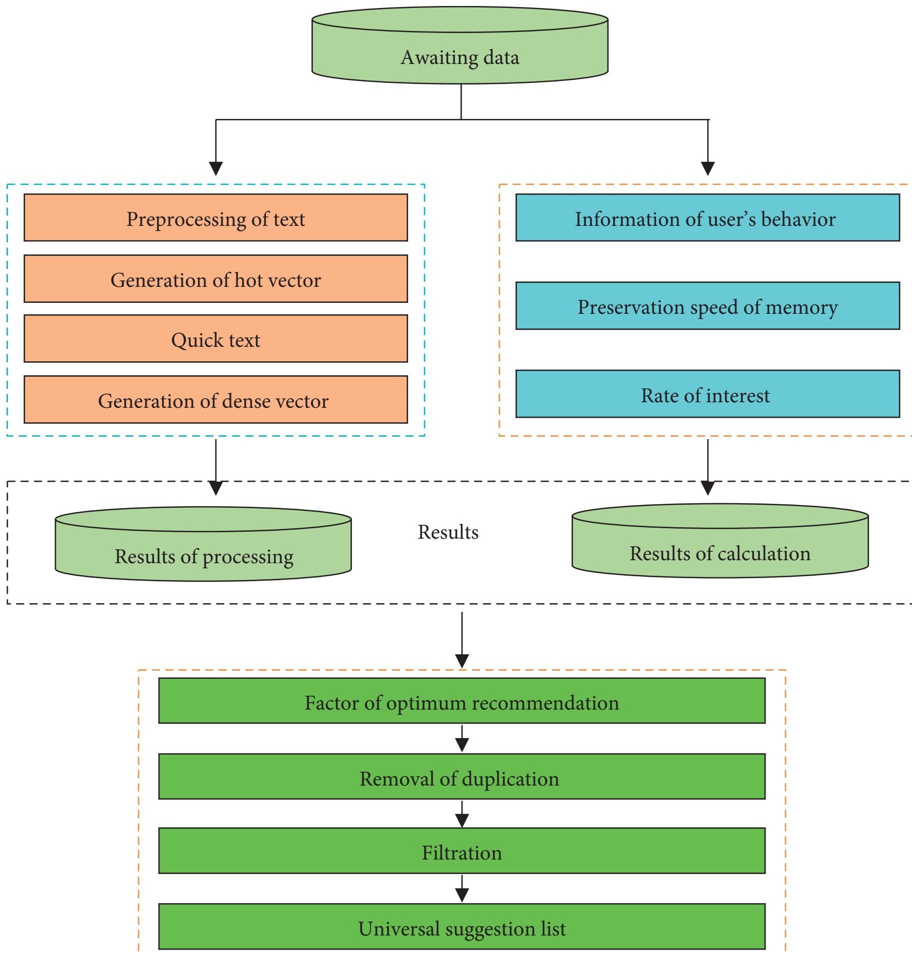

Figure 4: Logical framework of the English reading recommendation system for English in higher vocational institutions.

general logical framework of the English understanding suggestion system for English higher occupational institutions based on the BP neural network algorithm.

The Ebbinghaus curve of forgetfulness is a well-known memory paradigm. It demonstrates how learned knowledge fades from our minds over a period until we adopt steps to preserve it there. As the sharpest loss in memory occurs shortly after the acquisition, it is critical to review the knowledge we have acquired as soon as possible. Following that, frequent evaluations will aid in reinforcing it. However, we may allow significantly longer intervals between review sessions, which is a practice known as "spaced training."

At present, the technology of mathematical modeling is applied to Ebbinghaus's forgetting law. The more famous is the one-compartment model and two-compartment model [17].

3.1. One Compartment Model. The human brain is regarded as a compartment. After memorizing a certain amount of Dt materials, the amount of memory that remains after t is $x(t)$. It is supposed that the forgetting speed is constant k, as shown in

$$x(t) = De^{kt}\,(2 \cdot 1). \tag{4}$$

The curve obtained by formula (4) is consistent with the Ebbinghaus forgetting curve. Draw the measured data and use the least square method to determine a straight line to obtain the specific value of k, as shown in

$$t_{1/2} = \frac{0.693}{k}, \text{where } t_{1/2} = t. \tag{5}$$

Here, $t_{1/2}$ represents a constant, which explains the time that memory remains half of the innovative quantity. Both $t_{1/2}$ and k are used to reproduce the power of memory capability. The superior the $t_{1/2}$, the stronger the memory ability of this type of material t at this time, the lesser of the k value, and vice versa.

3.2. Two Compartment Model. Consider the brain to be split into 2 compartments: one for short-term memory and one for long-term memory, as illustrated in Figure 5.

At this time, for the memory amounts of t, compartment 1 and compartment 2 are supposed to be $x_1(t)$ and $x_2(t)$, respectively, as shown in

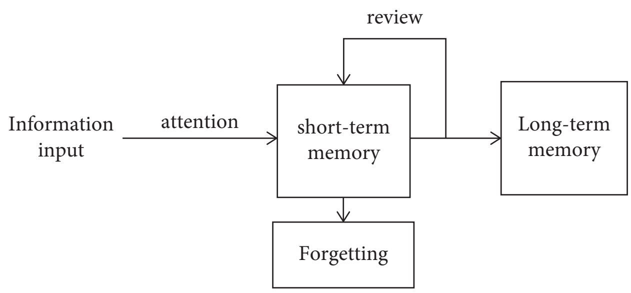

Figure 5: The connection between memory and forgetting.

$$\begin{cases} \dfrac{\mathrm{d}x_1(t)}{\mathrm{d}t} = K_{21}x_2(t) - (K_{12}+K)x_1(t), \\ \\ \dfrac{\mathrm{d}x_2(t)}{\mathrm{d}t} = K_{12}x_1(t) - K_{21}x_2(t). \end{cases} \tag{6}$$

Here, K is the forgetting speed constant, and K_{12} and K_{21} are the conversion speed constants between compartment 1 and compartment 2, respectively. Considering the initial conditions $t = 0$, $x_1(t) = 0$, and $x_2(t) = 0$, equation (7) is obtained.

$$\begin{cases} x_1(t) = \dfrac{D(d-K_{21})}{\alpha-\beta} e^{-at} + \dfrac{D(K_{21}-\beta)}{\alpha-\beta} e^{-\beta t}, \\ \\ x_1(t) = \dfrac{D(K_{21})}{\alpha-\beta}\left(e^{-\beta t} - e^{-at}\right). \end{cases} \tag{7}$$

Here, α and β in equation (7) are determined by

$$\begin{cases} \alpha + \beta = K_{12} + K_{21} + K, \\ \alpha \cdot \beta = K_{12} \cdot K. \end{cases} \tag{8}$$

Assume the following:

$$A = \frac{D(\alpha - K_{12})}{\alpha-\beta}, \quad B = \frac{D(K_{21}-\beta)}{\alpha-\beta}. \tag{9}$$

Equation (7) can be simplified into

$$x_1(t) = Ae^{-at} + Be^{-\beta t}. \tag{10}$$

According to the modeling of the law of memory forgetting according to literature [18], a mathematical model that is very reliable with the forgetting curve of Ebbinghaus can be obtained, such as

$$S(t) = \frac{1}{1+V_t}. \tag{11}$$

Hence, equation (12) can be obtained as follows:

$$t(s) = \frac{1/s - 1}{V}. \tag{12}$$

The previous equation only demonstrates that the quantity of memory is connected to the forgetting speed of memory, and everyone's forgetting speed is not the same. Hence, the forgetting speed V is a variable rather than a constant, which is in line with the characteristics of human memory. In this model, there is only one undetermined parameter.

4. Training and Results of the Antiforgetting Model of Higher Vocational English Learning Based on BP Neural Network Algorithm

This work primarily employs the Python programming platform for primary data processing, algorithm construction, and experimentation, with MATLAB tools used to compare and analyze the experimental findings. Python is an object-oriented interpretative programming language with strong frameworks, such as the deep learning package sklearn-learn, and accessible programmers to finish all types of applications. In addition, it has a robust visualization function and is appropriate for the comparative examination of experimental data.

4.1. Training of the Antiforgetting Model of Higher Vocational English Learning Based on BP Neural Network Algorithm. According to the forgetting development law suggested by the Ebbinghaus memory curve, the author puts forward the memory strategy of "first dense and then sparse" for new samples. In the training sequence, the first part uses new samples intensively for training and weight adjustment. After that, it gradually uses new samples loosely for training. When the new sample is not used for training, the sample set of the same size as the new sample set is randomly selected from the old sample set to train the BP neural network. According to this training strategy, the training distribution of a new sample is based on the non-Bonacci sequence. Fibonacci sequence [19], also known as the golden section sequence, refers to such a sequence as 1, 1, 2, 3, 5, 8, 13, 21, ... Mathematically, a Fibonacci sequence is defined by the recursive method, which is as follows: $F_0 = 0$, $F_1 = 1$, $F_n = F_n - 1 + F_n - 2$ $(n \geq 2, n \in N)$. The author selects seven items in the Fibonacci sequence, 1, 2, 3, 5, 8, 13, and 21, to form the distribution of a training unit. This unit has 21 training times, in which the new sample set is used for the 1st, 2nd, 3rd, 5th, 8th, 13th, and 21st time, while in other training rounds. For training, a collection of review sample sets of identical size as the new sample set are randomly chosen from the previous sample set using a uniform distribution method. It can be seen that the training based on Fibonacci sequence distribution is in line with the memory strategy of "dense before sparse" obtained from the Ebbinghaus memory curve. It is a training loading mode [20] following the Ebbinghaus memory law. The training unit can be repeatedly executed for multiple cycles until the present accuracy requirements or the maximum number of execution cycles is reached. Figure 6 explains the flowchart of the improved framework of the English understanding suggestion system for English higher professional institutions based on the BP neural network algorithm.

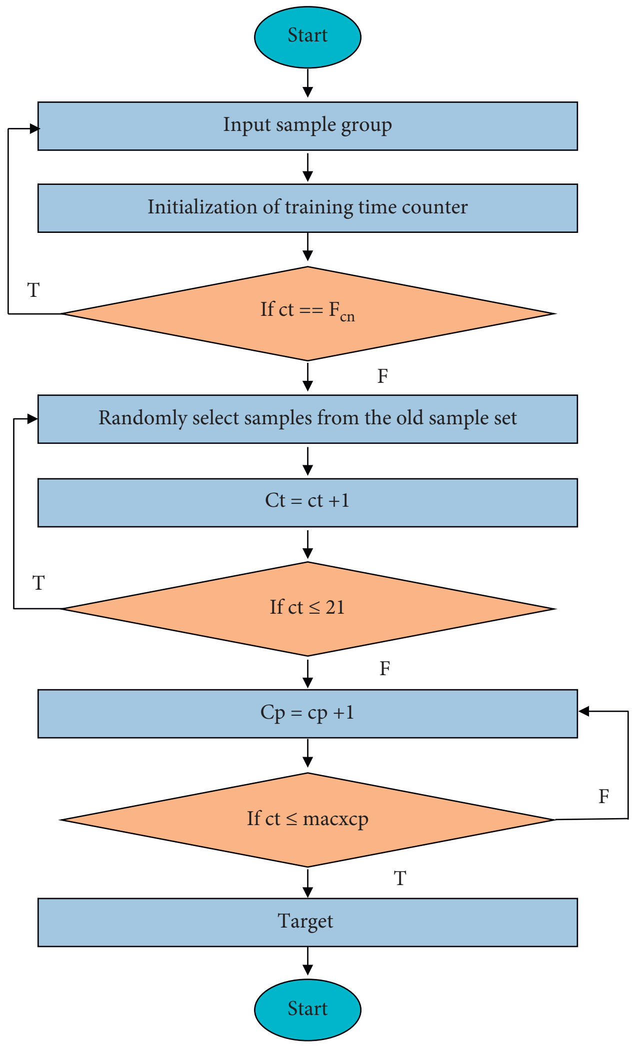

Figure 6: Improved framework of the English reading recommendation system for English higher vocational institutions based on the BP neural network algorithm.

Assuming that the n item of Fibonacci sequence is F_n, the algorithm above can be described as follows:

Step 1: assuming that the number of samples in the new sample group is k, initialize the training times counter $ct = 1$, sequence counter $cn = 2$, and cycle counter $cp = 1$. The maximum number of training cycles is maxcp and Fibonacci sequence.

Step 2: if $ct == F_{cn}$, $cn = cn + 1$, use the new sample group, and use the error back propagation algorithm to train the BP neural network. Else, randomly select samples from the old sample set with uniform distribution to form a sample group, and use the error backpropagation algorithm to train the BP neural network.

Step 3: $ct = ct + 1$.

Step 4: if $ct \leq 21$, return to step 2 to continue training.

Step 5: $cp = cp + 1$.

Step 6: if $ct \leq$ macxcp and the training errors of the new sample do not reach the target error, return to the first step and repeat the above training process.

Step 7: if the $ct >$ macxcp or new sample training error has reached the target error, the training is over.

The above is an algorithm based on the Ebbinghaus forgetting curve. This method is suitable for incremental training or learning the existing BP neural network when new samples are added. When there are many new samples, the new samples can be divided into sample groups with the number of samples, and then each sample group can be incrementally trained for the current BP neural network using the above method. After a group of training is completed, this group of samples will be added to the old sample set, and the next group of new samples will continue to be used for incremental training until all new samples are added to the old sample set.

4.2. Training Results of the Antiforgetting Model of Higher Vocational English Learning Based on BP Neural Network Algorithm. After the BP neural network has been incrementally trained, it is used to predict the output of six samples from the old sample set. These 6 samples from the new sample set and the 10 test samples are used to compute the root mean square error between the results of the HFSS simulation and the original sample set. In addition, assess the old sample's prediction ability, the new sample's prediction ability, and the untrained sample's generalization ability. Table 1 shows the calculation of comparison data onto 6 samples from the old sample set.

The comparative data into 6 samples of the calculated new sample set are shown in Table 2.

The HFSS output and the prediction output of BP neural network obtained by incremental training using three methods are shown in Table 3.

Figure 7 shows the comparison among the errors of direct, full, and Ebbinghaus methods. According to this figure, the prediction error of the direct training method of old samples is 0.572712, which is the largest of the three methods. There is the phenomenon of learning new samples and forgetting old samples. The minimum error of the old sample of the full sample batch training method is 0.261549. The error of the Ebbinghaus method is 0.348263, which is better than the direct training method and close to the full sample batch training method.

Figure 8 shows the comparison among data into 6 samples of the calculated new sample set. According to this figure, the direct training method has a good fitting quantity for new samples because of the direct training for new samples, and the error is 0.215562. The error of the Ebbinghaus method is 0.277839. It is slightly better than 0.297454 of the full sample batch training method. In addition, 10 test samples not included in the old sample set and the new sample set are randomly selected.

Figure 9 shows the comparison among the errors of direct, full, and Ebbinghaus methods in the samples of the new sample set. According to this figure, for the test samples that do not appear in the training samples, the maximum

Table 1: Samples in the old sample set.

r (mm)	Y_p (mm)	S (HFSS)	S (Direct)	S (Full)	S (Ebbinghaus)
0.1	−0.300	−12.11	−11.9287	−11.2935	−12.8727
0.3	−0.900	−19.24	−18.8283	−19.2834	−19.8273
0.6	0.600	−11.46	−12.8273	−11.2835	−10.8267
0.7	−1.000	−25.44	−24.2823	−25.2818	−25.9284
0.8	0.600	−10.08	−10.2891	−10.0293	−9.8172
0.9	−0.500	−15.57	−15.3452	−15.3922	−15.2924
	E_{RME}		0.572712	0.261549	0.348263

Table 2: Samples in the new sample set.

r (mm)	Y_p (mm)	S (HFSS)	S (Direct)	S (Full)	S (Ebbinghaus)
0.1	−0.100	−11.82	−11.2345	−11.5334	−11.6273
0.2	0.600	−11.23	−11.2342	−11.3723	−11.8731
0.3	0.200	−15.32	−14.2452	−15.2983	−15.3917
0.5	0.000	−17.42	−17.4557	−16.8728	−16.3913
0.6	0.500	−12.34	−11.8273	−12.1291	−12.4093
0.7	0.100	−14.01	−14.0289	−14.8273	−14.8267
	E_{RME}		0.215562	0.297454	0.277839

Table 3: Samples in the new sample set.

r (mm)	Y_p (mm)	S (HFSS)	S (Direct)	S (Full)	S (Ebbinghaus)
0.5	0.000	−17.46	−34.1080	−34.7611	−34.9270
0.6	0.500	−12.15	−11.5744	−11.6857	−11.6927
0.7	0.100	−14.05	−12.7040	−12.5693	−12.6536
0.641	−0.727	−32.87	−24.9640	−25.3339	−25.3751
0.239	−0.577	−16.88	−23.6859	−23.5275	−23.5862
0.123	−0.296	−12.92	−14.9693	−14.5818	−14.5944
0.462	−0.619	−24.17	−12.1443	−13.3641	−13.3848
0.908	0.392	−10.37	−10.7205	−11.2639	−11.2687
0.894	−0.416	−15.07	−18.4429	−18.2303	−18.2292
0.232	−0.939	−16.40	−12.0549	−12.1588	−12.1007
	E_{RME}		0.772632	0.573262	0.587371

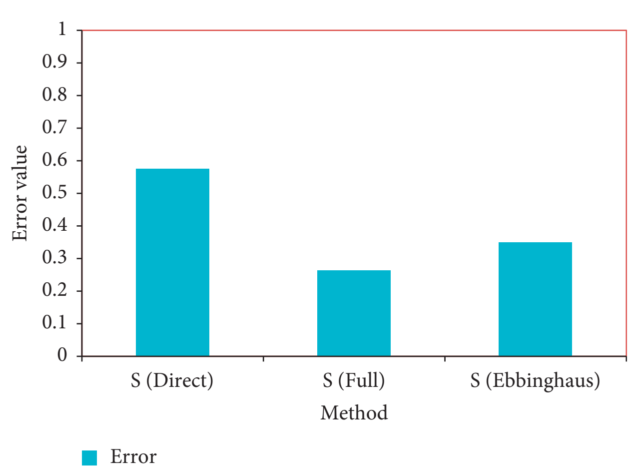

Figure 7: Comparison among the errors of direct, full, and Ebbinghaus methods.

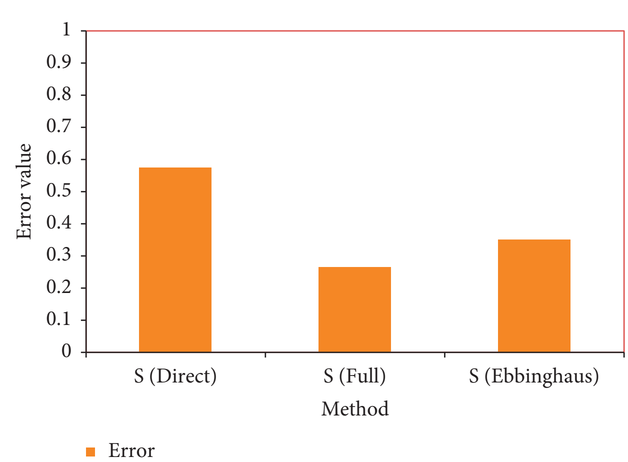

Figure 8: Comparison among data into 6 samples of the calculated new sample set.

error of the direct training method is 0.772632. It shows that the direct training method reduces the generalization ability of BP neural network algorithms. The minimum error of the full sample batch training method is 0.573262. The error of the Ebbinghaus method is 0.587371, which is better than that of the direct training method and close to that of the full sample batch training method.

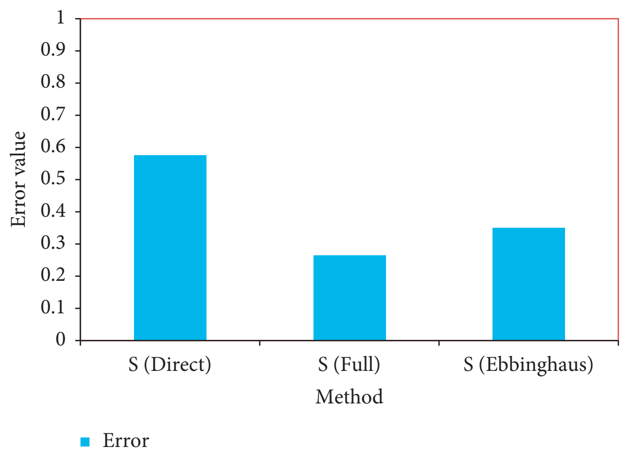

Figure 9: Comparison among the errors of direct, full, and Ebbinghaus method in samples of the new sample set.

From Tables 1–3 and Figures 7–9, we conclude that the prediction accuracy of the Ebbinghaus method is much better than the direct training method but very close to the full sample batch training method, indicating that it protects the generalization ability of the BP neural network. In the above training process, the direct training method processes the sample data 180 times, the full sample batch training method 3570 times, and the Ebbinghaus method 126 times, which is the least of the three training methods. It can be seen that the calculation cost of the Ebbinghaus method is far lower than that of the full sample batch training method. In addition, the training effect is close to that of the full sample batch training method and far better than that of the direct training method. Ebbinghaus method can ensure the learning of new samples and the maintenance of the training results of old samples with only limited training operation. It protects the generalization ability of the network and keeps the performance of the BP neural network stable when adding new sample information. There will be no significant fluctuations. Experiments show that the algorithm based on the Ebbinghaus memory curve is an effective and efficient incremental algorithm.

5. Conclusions

In conclusion, the Ebbinghaus forgetting curve shows that forgetting occurs immediately after memory, and the process is fast at first and then slows, with negative acceleration. After learning, knowledge needs to be studied repeatedly, so that knowledge can stay in the mind for a longer time. Using the Ebbinghaus forgetting curve as a theoretical guide, an antiforgetting model of higher vocational English learning based on the BP neural network algorithm must be developed. The Ebbinghaus forgetting curve will eliminate the issue of "easy forgetting" and increase learning effectiveness by automatically reminding students to study and revisit the material they have learned at the proper moment. In particular, when the learned sample set is in the state of dynamic update, the BP neural network algorithm has high efficiency after learning and using the incremental training method. Experiments reveal that the BP neural network algorithm outperforms the direct training technique in terms of the training effect. When the training impact is equivalent, the quantity of training computation required is significantly less than that of the whole sample batch training approach. At the same time, it may successfully safeguard the BP neural network's generalization capabilities. It is a powerful and effective incremental algorithm.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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