Research Article

An Improved Quality Evaluation Method for Foreign Trade English Using GA-RBF Neural Network

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The teaching evaluation of foreign trade English has been in a quite difficult position because some universities have foreign trade courses, but there is no corresponding foreign trade practice base, so the evaluation of this course is currently relatively simple. This research provides an improved BP neural network evaluation method to address the issues of single teaching evaluation and poor accuracy rate of English as foreign trade in English courses. First, an improved genetic algorithm is utilized to obtain the weight factor of the neural network, which is the data input of the neural network. Second, the middle layer of the network is optimized, so that the output efficiency can be further improved. Finally, the improved and optimized neural network is simulated. The experimental simulation shows that the method proposed in this paper has an energy-efficient and objective evaluation of the quality of foreign trade English teaching with certain accuracy.

1. Introduction

Neural networks are multidisciplinary, including a wide range of disciplines, for example, computer science, statistics, neural networks, and intelligence research. It is founded on the computer network's smart computing, which mimics a biological brain network and is capable of coping with nonlinear issues and large computations. The neural network has a much more than 75-year history, and thousands of neural network models have been presented, each with its excellence in dealing with diverse situations. A 3 layers feed-onward system with a hidden layer is a radial-basis-function (RBF) neural system. It can approach any functional form with arbitrary accuracy and has several good features, such as organization adaptive assessment, which is nondependent of the beginning value of outcome. Its supremacy is based on the use procedures of linear learning to finish the job previously completed by nonlinear learning procedures. At the same time, it preserves the nonlinear algorithms' extraordinary accuracy. It has properties such as best approximation, globally optimal, and so on.

The fundamental distinction between RBF neural networks and conventional forward neural networks, for example, back-propagation networks [1] is that BRF networks feature extra hidden layer neurons and layer-to-layer connections from the printed layer to the output. There is only one set of weights. The beginning function for the stacked layer is the radial base function, which is commonly the Gaussian function [2]. In the training process, both supervised and unsupervised learning have been employed. Every neuron in the RBF neural network's hidden layer correlates to a vector of the similar size as a single data point, which serves as the neuron's center. K-means clustering is commonly used to find the centers. This appears to be unsupervised learning. Nonlinear mapping functions have little effect on neural system quality in the RBF system. The choice of the middle vectors of the kernel function is critical. The performance of an RBF system is defined by the middle of the hidden layer, which defines whether or not the neural network was successfully trained and can be used in exercise. A genetic algorithm, on the other hand, is created by natural choice and principles of evolutionary. It is a search method with extremely parallel, randomized, and adaptable features. A genetic algorithm use group search technologies to examine the population for the answer to a group inquiry. The incorporation of the GA and neural system procedure had

attained achievement and was widely used by performing a sequence of genetic processes such as choice, crossover, and mutation, to create a fresh population generation and progressively change till obtaining the ideal condition with the estimated ideal result [3].

How to evaluate a course is presently a major issue in all institutions, therefore we must develop an assessment technique to assess a school's teaching capacity, while teaching evaluation can reflect objectivity and justice. However, evaluating education is a difficult and continuous process. Because teaching evaluation is two-way and not one-way, one is student input and the other is teacher reflection. The school may target the instructors themselves through two-way feedback to make necessary business improvements and training. English teaching is an important aspect of university education; however, the process of evaluating English teaching quality is hard and developing an objective and scientific teaching quality evaluation model is a hot research topic [4, 5]. For the problem of university teaching quality evaluation, researchers have proposed various evaluation methods, such as gray correlation analysis [6], expert system, improved algorithm, hierarchical analysis [7], fuzzy comprehensive evaluation method [8], etc. However, all of these techniques have the limitation that they are only applicable to linear models, whereas teaching assessment is nonlinear, dynamic, unpredictable, and prone to subjective unpredictability. As a result, mathematical models cannot be built, and hence correct evaluation models cannot be established, resulting in inaccurate instructional assessment. As a consequence, the literature [9] built a distance learning evaluation model of quality founded on vector institutions, and this evaluation mechanism may be extended to nonlinear models, resulting in superior evaluation outcomes. Because neural networks are adaptable to nonlinear models and the model has quicker convergence rate and evaluation accuracy through experimental simulations [10], the work of [11] employed a standard neural network to evaluate training. Using GAs to improve the RBF neural system is generally single improving the weights of connection or design of network, therefore in this study, we explored the teaching quality assessment model of international trade English to acquire the optimum impact of RBF. We presented and developed an RBF neural network based on an enhanced genetic method. Our technique was primarily used to evaluate nonlinear dynamics education. The simulation results demonstrated the algorithm's efficacy and superiority. The key contributions of this research work are listed as below:

(1) First, an improved genetic algorithm is used to obtain the weight factor of the neural network, which is the data input of the neural network.

(2) Second, the middle layer of the network is optimized, so that the output efficiency can be further improved.

(3) Finally, the improved and optimized neural network is simulated.

The rest of this research paper is planned as: Section 2 is based on related work, Section 3 consists of our proposed genetic algorithm optimization radial basis function (RBF) neural network for foreign trade English quality evaluation, Section 4 is based on analysis and testing foreign trade English teaching quality evaluation model, and finally, Section 5 concludes our work and discuss our future plan.

2. Related Work

With the advancement of globalization in a variety of industries, business English is becoming more commonly utilized. With the widespread usage of business English, the demands for interpretation in corporate operations have become increasingly stringent. Business English, being a worldwide communication language, comprises a wealth of expert knowledge of terminology furthermore to a common language. As a result, there are significant distinctions between business English translation and ordinary translation of English [12]. Because of the extraordinary skilled standards of business English, the demands for expertise and effectiveness in the procedure of translating are correspondingly advanced. We need to examine to be fit for successful communication in the corporate world as a type of English translation. We frequently experience communication difficulties in the procedure of translation of business English owing to variances in the usage of national languages, dissimilar everyday expressions, various convolutional cultural lexicons, and so on. To improve linguistic communication, we must address the issue of conflict induced by differences in culture [13]. As per the BP classical machine learning model, effective educational training material may translate and minimize needless time throughout the model construction process [14]. First, we must manually record the breadth of differences in culture during the model-building process to better evaluate the disparities and address the interpretation challenge in light of the present context. Second, we must demonstrate business professionalism and successfully differentiate between business and public English translation [15]. The optimized simple language is employed for expansion in the formulation of translation phrases, and the reduced language may be used for successful communication [16]. We must guarantee the correctness and timeliness of the entire translation while employing reduced language to represent the overall idea. Finally, in procedure of business English conversion, the rules of secondary and primary phrases must guarantee the softness of conversion phrases and the link between main and secondary phrases.

Radial basis function (RBF) neural networks are introduced to incorporate the benefits of learning for the intense workload and complicated statistics of college English teaching jobs. Furthermore, the authors suggest an enhanced fuzzy RBF neural network model based on back-propagation learning by combining association, identification, adaptation, and fuzzy information processing [17]. In [18], the authors outlined the evaluation phase of English for general academic purposes (EGAP) blended course, aimed mostly at second-year undergraduate Japanese students from Osaka University's Faculties of Law, Letters, Economics, and Human Sciences. The National Prescribing Curriculum

(NPC) was the highest rated open access resource using an innovative technique and assessment metric to locate, classify, and rate English language CP e-Learning resources [19]. The AHP technique and gray theory were then used to create an evaluation model for the teaching quality of English writing [20]. The work of [21] aims to scrutinize and specify the semantics of English terms «appraisal», «assessment», and «evaluation» and to identify their Ukrainian equivalents capable of adequately conveying the meaning of the above English words in Ukrainian educational discourse. The investigation outcomes show that the model created has decent performance [22]. The authors of [23] analyze the key difficulties and complexity of making an ideal learning quality assessment scheme. To solve these issues, we developed an enhanced optimized GA RBF neural network for evaluating international trade English quality, which was further optimized using the GA adaptive degree variation and entropy approach.

3. Genetic Algorithm Optimization Radial Basis Function (RBF) Neural Network

3.1. RBF Neural Network. A radial basis function (RBF) network is a type of feed-forward neural network that uses the radial basis function as its activation function to solve nonlinear model problems. Because it is a global optimal network, it is widely used in various nonlinear models such as pattern recognition, signal processing, and so on [24]. RBF may straight record input variables to the hidden space lacking linking via weight by using the function of radial basis as that of the base of the hidden element to form the hidden layer. The hidden layer converts low-dimensional inputs into a high-dimensional territory, allowing a linearly intractable issue in small dimensional space to be linearly divisible in extraordinary dimensional space. The output may of network be derived by summing the hidden cell output linearly. RBF networks typically have 3 layers: input, hidden, and output. Figure 1 depicts the construction of the radial basis function neural network.

In this case, the maximum number of input levels is n and they are made up of signal source nodes that merely send data without transforming it. The vector, on the other hand, is transferred from the lower dimensional n to the higher dimensional space m using the radial basis function, such that linear difference in the small dimension is turned into linear distinction in the high dimension. Similarly, the amount of production levels is l, and the network output is derived by the linearly weighted sum of hidden unit signals. However, in the neural network used in this paper, there are a total of 3 layers of the network, the input layer, the hidden layer, and the output layer, the hidden layer is also known as the weight layer, where the first and second layers are static and the output is dynamic, so the output is dependent on both the first and second layers. There are weighting factors between the first and second layers, and these weighting factors are in turn weighted with the activation function, this is the key factor of the NN planned in this paper, so its expression is by equation (1).
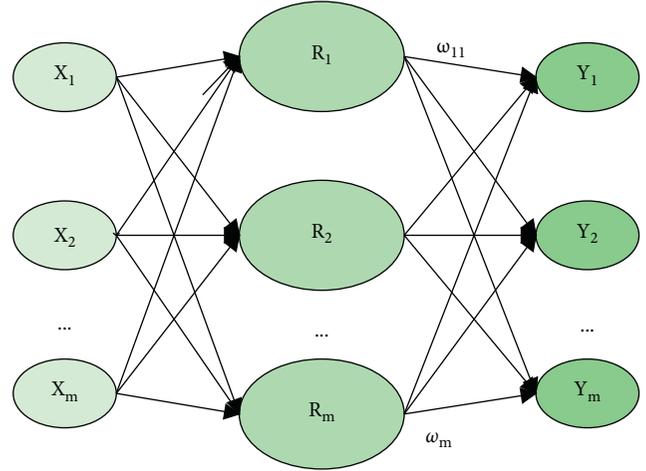

Figure 1: Construction of radial basis function neural network.

$$R\left(x_p - c_i\right) = \exp\left(-\frac{\left\|x_p - c_i\right\|^2}{2\sigma^2}\right), \tag{1}$$

where $\|x_p - c_i\|$ is the parametric number of $(x_p - c_i)$ and x_p is the second layer and the first layer. Here x_p denotes the data input of sample to the input layer and c_i and σ present the middle of network and radial basis function's width, separately. After determining the parameters of radial basis function and network weights, the output of the RBF neural system can be calculated by Equation (2).

$$y_j = \sum_{i=1}^{h} \omega_{ij} \exp\left(-\frac{\left\|x_p - c_i\right\|^2}{2\sigma^2}\right), \quad j = 1, 2, \ldots n, \tag{2}$$

where ω_{ij} is the second and third layer in the network proposed in this paper.

According to the mathematical solution process of the neural network proposed in this paper, optimization is the focus of this paper. Because the neural network is suitable for nonlinear models, approximating the solution is an important process to be faced by the whole network. In this neural network, we use nonstop iterations, i.e., updating the input states so that the whole network converges quickly and to reach the desired goal.

We begin by establishing plausible teaching evaluation factors, however, these elements are artificial, and then we gather crucial indications of teaching evaluation in the form of questionnaires. We utilize an updated evolutionary algorithm for optimization to assure the global optimum after screening appropriate and representative assessment indicators and quantifying these indicators. The network's output will be more accurate as a result.

3.2. Genetic Algorithm. A genetic algorithm (GA) is a search method with massively parallel, randomized, and adaptable characteristics that are generated by natural selection and natural principles. It employs group search technologies to search the population for answers to group inquiries. With

the incorporation of the GA and NN algorithm had proved highly successful and was widely used [3] by performing a series of genetic processes such as choice, crossover, mutation, etc., to create a fresh population of generation and progressively change till obtaining the ideal condition with the estimated optimum result.

In addition, it begins with a population of the presented possible solution set. On other hand, the population is made up of a particular number of coded gene people, which are entities with distinct chromosomes. The solved encoding technique and the architecture of the genetic operators are the two most difficult challenges to solve while building a genetic algorithm. When confronted with various optimization strategies, we must employ various advanced capabilities and genetic operators of various processes. The fundamental element in deciding whether the implementation of the genetic algorithm may work is to resolve the degree of comprehension of the difficulties. Figure 2 depicts the genetic algorithm procedure. This figure preserves a candidate solution for each iteration and ranks them based on the quality of the solutions. Following that, selects some of the solutions based on various indications and computes those using genetic operators to create a new iteration of candidate solutions. As a result, this procedure will be repeated until it reaches a certain convergence score.

3.3. Improved Genetic Algorithm.
In the neural network presented in this study, we use the assessment criteria received from the questionnaire and the key indicators obtained after screening as the neural network's data input. We primarily employ the enhanced genetic algorithm to establish the starting values of these parameters. The revised evolutionary algorithm can screen the parameters in parallel, resulting in a quicker screening speed, and it can also realize the adaptive network in high-dimensional space to accomplish multidimensionality search. Figure 3 explains the steps of improved genetic algorithm.

3.3.1. Chromosome Encoding.
Every chromosome in this form of encoding is a sequence of integers representing numbers in a series. Every chromosome is simply a permutation or configuration of several genes. The population is the present collection of combinations, while the search space is the entire number of potential permutations. Because the neural network is a continuous search process, we utilize floating-point values for encoding, which increase data accuracy; however, the downside is that if the floating point is too high. It will use CPU and computer memory resources to boost the neural network's convergence speed. As a result, while utilizing the genetic algorithm for initial value selection, we will choose the ideal value to achieve not just a faster convergence speed but it also improves accuracy because when we partition the network, we may use fewer weights to encode fewer chromosomes in the genetic algorithm.

3.3.2. Adaptation Function.
Any heritable characteristic that aids an individual, such as animals or plants, in surviving
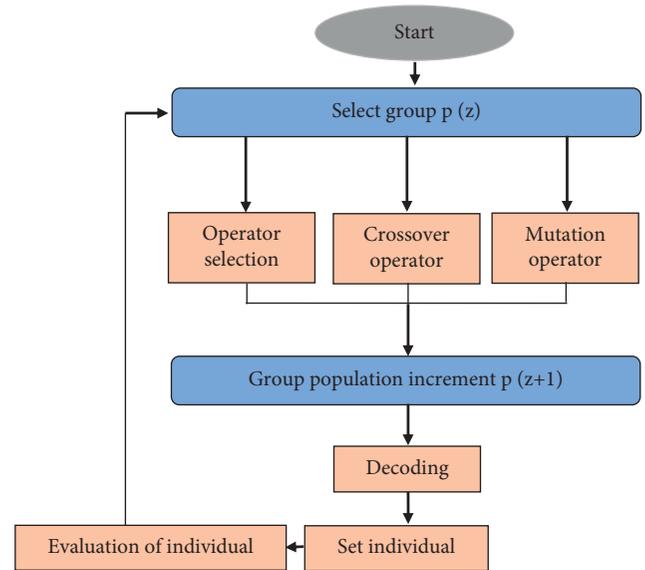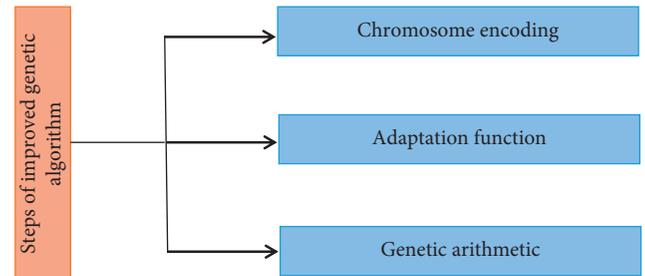

FIGURE 2: Process of genetic algorithm.

FIGURE 3: Steps of improved genetic algorithm.

and reproducing in its environment is referred to as an adaptation. When using the improvement and optimization of neural networks, we want the system output error to get smaller and smaller until it tends to zero, which indicates that the chromosomes are getting better and better. So we can use the following formula to calculate the desired output and the mean squared error of the system and match the better function.

$$E = \frac{1}{\sum_{k=1}^{N} \left(T_k - Y_k \right)^2}. \tag{3}$$

where N denotes the number of all evaluation parameters in the genetic algorithm, Y denotes the system output, and T denotes the desired output, and all errors are $E = Y - T$.

3.3.3. Genetic Arithmetic.
In this research, we employ a modified genetic algorithm, which means that we first use a matching function to do the adaptive matching for each parameter, and then rank the parameters based on their weights or relevance. If the fitness is higher, it indicates that the parameter is more essential, and hence has a higher likelihood of being chosen as an input. This assures not only that the best data is chosen at the moment of entry but also that the convergence space is maintained. For example, for

parameter bi, if the fitness function value is E_{bi}, then the probability of this parameter being selected as per Equation (4).

$$P(b_i) = \frac{E_{b_i}}{E},\tag{4}$$

where E presented error.

From equation (4), it is clear that the probability of a chromosome being selected is determined by its fitness. However, in order to increase the diversity of the population and avoid being trapped in a local optimum, it is also necessary to select some of the chromosomes with low fitness to be inherited into the next-generation population.

In a GA, to raise the variety of organisms, we need to cross mutate chromosomes, which is the core of the GA. However, in the genetic algorithm, the original chromosome will almost probably contain some individual adaptability; therefore we should improve the individual adaptability and make it more adaptable in subsequent cross mutations. This algorithm cannot improve the genetic algorithm's optimum capabilities. As a result, equation (5) may be used to compute the crossover probability in this work.

$$P_c' = \begin{cases} P_{c\,\max}, & E_{\max} < E_{\text{mean}} \\ P_{c\,\max} - \dfrac{P_{c\,\max} - P_{c\,\min}}{\text{iter}_{\max}} \times \text{iter}, & E_{\max} \geq E_{\text{mean}} \end{cases}\tag{5}$$

Mutation refers to the process of biological evolution in which some genetic positions of chromosomes are disturbed and mutated to produce new chromosomal individuals. In the evolutionary process of GA, the mutation is also a significant part to update individual's chromosome and increases the genetic merit-seeking capability. In a genetic algorithm, there is another most important operation, that is, controlling gene mutation, because in cross mutation, if the gene in the chromosome mutates, the chromosome will no longer play any role. And this chromosome is not conducive to the implementation of the whole genetic algorithm. In traditional genetic algorithms, we usually set the mutation probability of a chromosome to a fixed value. Although this can reduce gene mutation, this artificial method is not conducive to the adaptive ability of chromosomes. Therefore, this paper proposes an adaptive random probability to set the primary chromosome, so that the chromosome has stronger adaptability. Therefore, the adaptive algorithm set in this paper can be calculated utilizing equation (6).

$$P_m' = \begin{cases} P_{m\,\max}, & E_{\max} < E_{\text{mean}} \\ P_{m\,\max} - \dfrac{P_{m\,\max} - P_{m\,\min}}{\text{iter}_{\max}} \times \text{iter}, & E_{\max} \geq E_{\text{mean}} \end{cases},\tag{6}$$

where E denotes the value of chromosome fitness functions to be mutated in the root population and iter and $\text{iter}_{\max}$ denote the number of current and maximum iterations, respectively. Equation (6) shows that when the value of
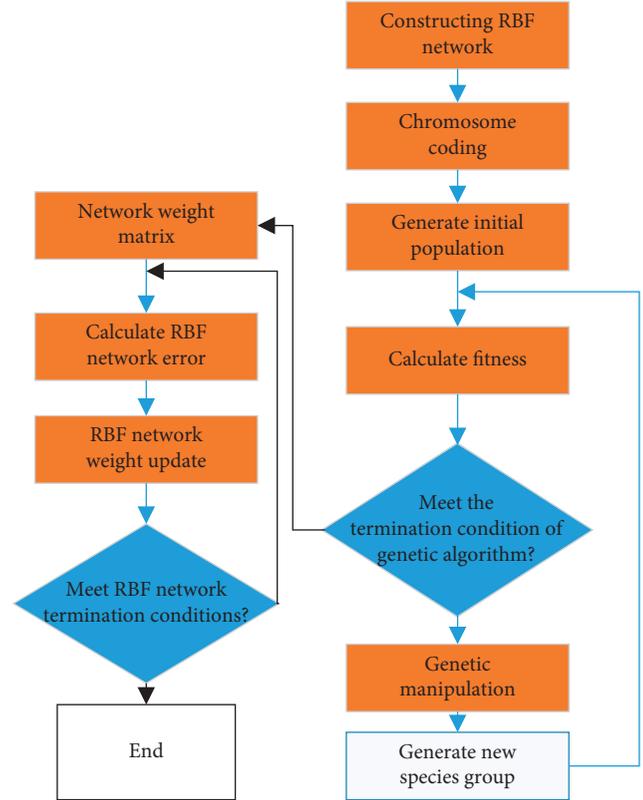

FIGURE 4: Genetic algorithm optimized RBF neural network.

fitness function of chromosome is lower than the mean value at the early stage of evolution, the probability of mutation is set lower and the good chromosome individuals can be retained. As the genetic evolution continues, when the chromosome fitness function value is more than the mean value, the variation probability can be adjusted upward to increase the local merit-seeking ability of the genetic algorithm.

3.4. Optimization Model. In comparison to the BP network, RBF may self-adaptively alter the hidden layer during the training phase based on the individual challenges. The capability, classification, and dispersion of the training images may all be utilized to define the assignment of neurons in the hidden layer. The center points and width of the hidden layer's neurons, as well as the hidden layer, may be recognized continuously, and it learns quickly. Once the BP network's architecture has been determined, the design does not alter throughout training. The number of hidden layers and neurons is hard to calculate. The network's convergence speed is poor, and training has some association with the awaiting sample, method selection, and network design. As a result, the RBF network outperforms the BP network in terms of results. The improved genetic algorithm used in this paper can improve the input of the neural network, that is, the initial value. According to the research content of this paper, the improved genetic algorithm is added to the neural network, and the algorithm flow chart is shown in Figure 4. From this figure, we can see that our algorithm needs to add

the initial value of the improved genetic algorithm when building the neural network, which is more conducive to the output of the neural network.

4. Analysis and Testing Foreign Trade English Teaching Quality Evaluation Model

4.1. Analysis of Key Evaluation Indicators. At present, according to the preliminary questionnaire survey, we got a lot of key technical indicators, but we have to analyze these indicators one by one and filter out the indicators we need, if some indicators are not very relevant or weak, then the first round we will first eliminate, which can ensure the accuracy and efficiency of the algorithm and can reduce the complexity of the neural network, so that the computing speed will also. Therefore, in this section, to improve the operation speed of the whole neural network and delete the redundancy of some indicators, we mainly discuss the relevance of these indicators and then streamline the evaluation indicators, to improve the teaching quality and evaluation standards. The main process is as follows:

$$X = (X_1, X_2, \ldots, X_P), \tag{7}$$

where p is the total number of different teaching indicators. We must first acquire additional data and then screen it. As a result, we must quantify and standardize the filtered data. Equation (8) shows the standardized version.

$$\overline{x}_{ij} = \frac{x_{ij} - \overline{x}_j}{s_j}, \tag{8}$$

where

$$\left\{ \overline{x}_j = \frac{1}{n} \sum_{i=1}^{n} x_{ij} s_j = \frac{1}{n-1} \sum_{i=1}^{n} \left(x_{ij} - \overline{x}_j\right)^2 \tag{9}$$

After the teaching quality evaluation indexes were standardized, the correlation coefficient matrix of the evaluation indexes was calculated as per equation (10).

$$R = (r_{ij}) p \times p, \tag{10}$$

Where, r_{ij} denotes the correlation coefficient between the ith is the sample of the evaluation of teaching quality and the jth index, calculated by equation (11).

$$r_{ij} = \frac{1}{n-1} \sum_{k=1}^{n} \overline{x}_{ki} \overline{x}_{kj}. \tag{11}$$

Construct the Eigen equation ($\lambda u = \text{Ru}$), Equation (12) calculates the eigenvalues and eigenvectors of the Eigen equation.

$$\begin{aligned} \lambda &= (\lambda_1, \lambda_2, \ldots, \lambda_p), \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0 \\ u &= (u_1, u_2, \ldots, u_p). \end{aligned} \tag{12}$$

Calculating the contribution of the main components of ELT quality evaluation indicators 12 to the cumulative variance:

$$\zeta = \sum_{i=1}^{P} \alpha_i, \tag{13}$$

where α_i denotes the most important critical index in the whole foreign trade English teaching evaluation system, to choose the most critical index from the many evaluation index parameters, then we mainly illustrate the contribution rate. If the contribution rate of the selected indicator is more than 90% in the whole index, we say that this indicator is the main parameter, i.e. the key indicator, so this is our criterion for selecting the parameter. The subsequent indicator parameters are evaluated in terms of the contribution rate. From 90% contribution rate to 40% contribution rate, this can ensure the performance while effectively reducing the dimensionality, thus improving the evaluation efficiency.

4.2. Foreign Trade English Teaching Quality Evaluation Model. After we have selected all the parameters, we can use them as the basis of the whole teaching evaluation, objective and fair evaluation is the guarantee of teaching evaluation, although there are many ways of all teaching evaluation systems at present, the construction model of this paper is shown in Figure 5.

4.3. Model Testing and Analysis. The acquired data are utilized in this research to test the efficiency of the revised method suggested in this study. According to the model indexes in Section 4.2, we gathered a total of 500 sets of data before doing classification training, with 450 sets being training data and 50 sets being testing data. Table 1 shows the teaching quality evaluation indexes that were assessed utilizing the suggested principal element examination of foreign trade English evaluation indexes, and the indexes that contributed the most to the teaching quality assessment were chosen.

4.3.1. Selection of Evaluation Indicators by Principal Component Analysis. The results of the major component analysis are depicted in Figure 6. In this figure, we can see that the eight major parameter indicators we chose are the greatest contributors to the overall evaluation of teaching quality, accounting for 95 percent of the total. The remaining indicators contribute 5%, indicating that the first eight key indicators may adequately capture all of the evaluation information. This can also be used for other quality assessments and as a reference for future teaching quality evaluations.

4.3.2. Analysis of the Results. The neural network with an improved genetic algorithm used in this paper evaluated the teaching quality of foreign trade English. Figure 7 explains the model mean square error curve. In this figure, we can see that the variance curve of the model shows a decreasing trend, and the variance tends to 0 from the original 1.5, after 60 iterations, although it does not reach 0 completely. However, it also tends to 0 infinitely, which is a very good
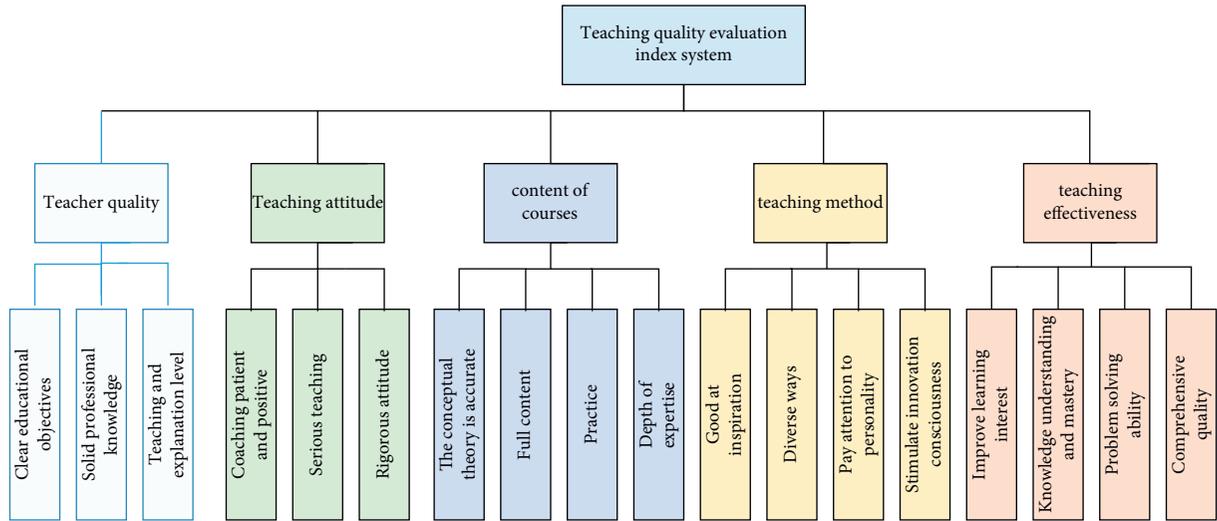
Figure 5: Teaching quality evaluation index.

Table 1: Selected test input data.

Serial number	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
1	0.65	0.83	0.86	0.87	0.68	0.74	0.59	0.69
2	0.87	0.83	0.84	0.86	0.80	0.85	0.78	0.69
3	0.79	0.75	0.84	0.83	0.83	0.81	0.83	0.71
4	0.82	0.84	0.76	0.79	0.84	0.83	0.87	0.76

Figure 7: Model mean square error curve.

Figure 6: Results of principal component analysis on evaluation indexes.

phenomenon. From the number of iterations, this algorithm starts to converge after 30 iterations, which shows the effectiveness of this algorithm.

The model evaluation accuracy curve is depicted in Figure 8. This figure also shows that the accuracy of the current approach increases after 40 iterations, indicating that the technique suggested in this research may enhance the model's prediction number. In addition, we can see that the accuracy of the network algorithm proposed in this paper is higher than 82% compared to the neural network algorithm without optimization, which also fully illustrates that the accuracy of the algorithm proposed in this paper is
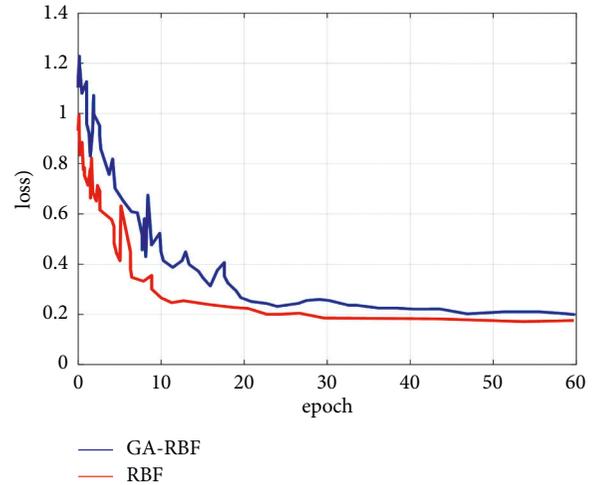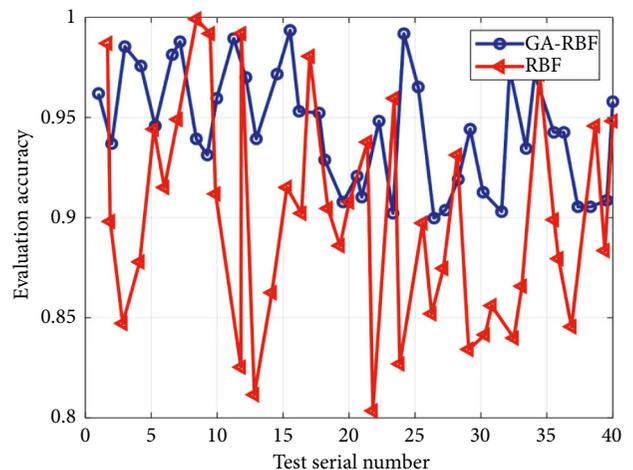

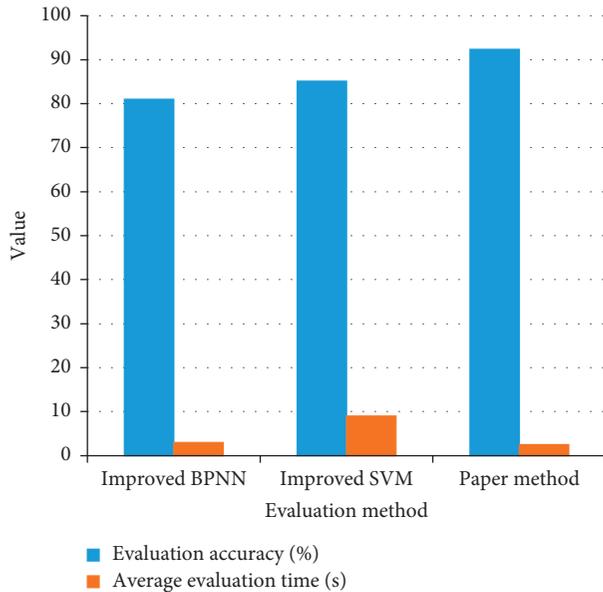Figure 8: Model evaluation accuracy curve.

FIGURE 9: Comparison of evaluation performance results.

much higher than that of the ordinary neural network. After statistics, we have achieved 95% accuracy of our data in all test groups and experimental groups, which also indicates the high accuracy of the algorithm in this paper.

The comparison of evaluation performance results can be shown in Figure 9. Here we have compared three evaluation methods such as improved BPNN, improved SVM, and the proposed method. The accuracy of the method suggested in this work is significantly greater than previous algorithms, and the consumption time will be lowered, as shown in this figure.

5. Conclusions and Future Plan

The quality of physical education programs is an important component of college and university education. This research develops a nonlinear, dynamic international trade English teaching quality rating model based on an upgraded genetic algorithm neural network, with data collected from a large number of surveys. Following that, the collected data are analyzed and filtered, and the key index approach is used to screen the key indexes by neural network iteration. The modified genetic algorithm is used to optimize the input key parameters. Finally, establishing the quality evaluation of international trade English instruction through simulation demonstrates the excellence of this paper's approach. Furthermore, the approach presented in this research gives a new way for other assessment methods. We intend to improve its convergence speed and accuracy in the future.

Data Availability

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

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