Prediction of Translation Ability of Complex English Sentences Based on Artificial Neural Network

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Abstract—The current translation training programs at colleges and universities are not fully adequate for students majoring in English, and some students do not perform well in their execution of translation tasks. Translation ability is a frontier topic in the field of translation. A number of studies have provided some new ideas for research on the main goals of translation education and the evaluation of students' translation abilities, but few has used artificial intelligence to predict students' translation abilities. This paper analyzes the prediction of the translation ability with respect to complex English sentences. First, based on the principles of accuracy, operability and scientificity, an evaluation indicator system was built to fully reflect the basic characteristics of students' ability to translate complex English sentences, which is in line with the training needs of translation talents at colleges and universities. Then, based on the characteristics of the logical structures of complex English sentences, a grey Bernoulli prediction model was constructed for the translation ability of complex English sentences. The particle swarm optimization algorithm was selected as the parameter optimization algorithm for the prediction model of translation ability with respect to complex English sentences, with the optimization targets being the Bernoulli parameters and the order of the fractional-order accumulation generation. The experimental results verified the effectiveness of the proposed model.

Keywords—neural network, English translation, complex sentences, translation ability prediction

1 Introduction

Translation is currently the main tool for international communication between different countries [1–8]. In recent years, with the development of the language and translation service market, the demand for translation of academic papers and works with professional, practical and academic values has grown rapidly [9–14]. However, academic papers and works contain compound sentences with complex clauses and conjunctive forms, making the translation quite challenging [15–18]. Unfortunately, the current translation training programs at colleges and universities are not fully adequate for students majoring in English, and some students do not perform well in translation tasks, resulting in varying translation abilities of students with respect to academic papers [19–25]. Considering the deficiencies exposed in the current translation education, scholars need to summarize the logic structural characteristics of the sentences in academic translation, and study the translation rules and skills.

Today, college students are growing in the information age. How to effectively use advanced information technology to improve college English teaching and how to transform Internet terminals into powerful English teaching tools have become important subjects in college English education. Wang and Liu [26], on the basis of exploring the advantages of intelligent learning environment in college English teaching, expounded the specific classroom design under the background of intelligent classroom in combination with teaching practices, and provided a new direction and idea for improving the effect of college English teaching. Translation ability is considered one of the most difficult language abilities to measure. A typical way to measure translation ability is to ask translators to translate sentences and have professional evaluators rate the translations. This places a heavy burden on both translators and evaluators. Ehara et al. [27] proposed a practical translation ability evaluation method, whose core idea is to evaluate the translators' translation abilities according to their vocabulary knowledge. The specific way is to ask translators whether they know the given words. With this vocabulary information, a probabilistic model was built to estimate translators' vocabulary and translation abilities simultaneously. With the development of the translation profession in China, a reform is truly needed for the traditional translation teaching method, which has to rely on the studies on translation ability, the Internet and modern educational technologies. In order to effectively train students' overall literacy translation ability, Zhang [28] proposed an Internet-based translation ability model by analyzing the characteristics of literacy translation ability and the possible applications of various Internet platforms in translation education. Hong [29] studied the relationship between English proficiency and translation ability of English major students, as well as the relationship between English and translation teaching. It used the principal component analysis to quantify and analyze the relationships between translation ability and English listening, reading, error correction and writing skills, and then obtained the quantitative relationship between translation ability and its influencing factors, which provides decision-making basis for the improvement of English translation skills and teaching.

Theoretically speaking, translation ability is a frontier topic in the field of translation. A number of studies have provided new ideas for the research on the main goals of translation education and the evaluation of students' translation abilities. However, artificial intelligence is rarely used in the prediction of students' translation abilities. This paper opens up a new perspective for the application of artificial neural network in the prediction of translation abilities with respect to complex English sentences. This paper is mainly organized as follows: 1) based on the principles of accuracy, operability and scientificity, an evaluation indicator system was built to fully reflect the basic characteristics of students' ability to translate complex English sentences, which is in line with the training needs of translation talents at colleges and universities; 2) based on the characteristics of the logical structures of complex English sentences, a grey Bernoulli prediction model was constructed for the translation ability of complex

English sentences; 3) the particle swarm optimization algorithm was selected as the parameter optimization algorithm for the prediction model of translation ability with respect to complex English sentences, with the optimization targets being the Bernoulli parameters and the order of the fractional-order accumulation generation. The experimental results proved the effectiveness of the proposed model.

2 Construction of the prediction model

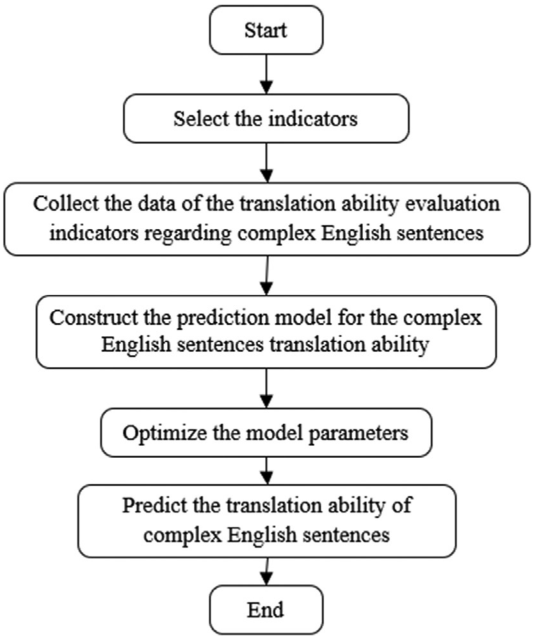

Fig. 1. Prediction process of the translation ability regarding complex English sentences

In this study, the complex English sentences to be translated were structurally broken down, as there are differences in the main and subordinate clauses of the sentences. Different English grammars also have different definitions of main clauses and subordinate clauses in complex English sentences. Usually, a complex English sentence consists of a main clause with several subordinate clauses. It is easier to identify all subordinate clauses and the main clause of a complex English sentence based on the structure. Also, in most written sentences containing complex clauses in academic papers and works, there are usually some differences between the main clauses and the subordinate ones and even between words and phrases in terms of importance. Usually a single main clause or main word is used with several subordinate clauses or auxiliary words used for description or as supplements and comments. One complex English sentence may also be structurally broken down differently due to different understandings, so to translate those sentences well, students need to be able to analyze complex English sentences. This ability is usually measured from the identification of three different clauses, including noun, adjective and adverbial clauses.

The evaluation of the translation abilities of students with respect to complex English sentences is important to measuring their academic translation abilities, but it is also a difficult task, as only through multi-level and multi-angle comprehensive evaluation of students' abilities to translate complex English sentences, can the measurement results be accurate and credible. In this paper, based on the principles of accuracy, operability and scientificity, an evaluation indicator system was built to fully reflect the basic characteristics of students' abilities to translate complex English sentences, which is in line with the training needs of translation talents at colleges and universities. The specific evaluation indicators include close logical cohesion, clear relationship between sentence components, processing of passive voice in line with the reading habits of Chinese readers, reasonable choice of word order for parallel components, reasonable segmentation and adjustment of multi-layered nested sentences, clear and concise translation of modifier components, no lack of semantic correlation between sentences with various logical relationships, reasonable reordering of postpositional head words, and careful choices of correlatives.

In order to predict the translation ability of complex English sentences, a grey Bernoulli prediction model was built in this paper based on the characteristics of the logical structures of complex English sentences. This model can solve the problems of traditional prediction models, such as poor adaptability to nonlinear data sequences and low prediction accuracy. In addition, it also has the advantages of simple prediction process and no excessive dependence on data dimensions. The following part elaborates the main processes in the model, such as the accumulation generation of the original evaluation indicator data sequence, the construction, solution and differencing of the Bernoulli differential equation, and the solution of coefficient vectors:

Suppose the original evaluation indicator data sequence is expressed as follows:

$$a^{(0)} = [a^{(0)}(1), a^{(0)}(2), a^{(0)}(3), \cdots, a^{(0)}(m)] \tag{1}$$

Eq. (2) shows the expression of the first-order accumulated generated sequence:

$$a^{(1)}(l) = \sum_{i=1}^{l} a^{(0)}(i) \tag{2}$$

$l = 1,2,3, \ldots, m$, and then:

$$a^{(1)} = [a^{(1)}(1), a^{(1)}(2), a^{(1)}(3), \cdots, a^{(1)}(m)] \tag{3}$$

The above sequence is highly similar to the exponential sequence that can be solved by a first-order differential equation. Assuming that the development coefficient is represented by φ, and that the grey action is represented by δ, Eq.(4) gives the expression of the constructed grey differential equation:

$$\frac{da^{(1)}}{dp} + \phi a^{(1)} = \delta [a^{(1)}]' \tag{4}$$

Φ and δ represent the trend of the evaluation indicator data sequences and the correlation between the sequences, respectively; the Bernoulli parameter s satisfies $s \in S$, $s \neq k$, and is used to adjust the structure of the differential equation.

Eq.(2) gives the expression of the difference equation:

$$\frac{\Delta a^{(1)}}{\Delta p} = \frac{a^{(1)}(l+1) - a^{(1)}(l)}{l+1-l} = a^{(1)}(l+1) - a^{(1)}(l) = a^{(1)}(l) \tag{5}$$

The neighbor mean of $a^{(1)}$ can be calculated by the following formula:

$$c^{(0)}(l) = \beta a^{(1)}(l) + (1-\beta) a^{(1)}(l-1) \tag{6}$$

Let $\beta = 0.5$, and then there is:

$$a^{(0)}(l) + \phi c^{(1)}(l) = \delta [c^{(1)}(l)]^{s} \tag{7}$$

The model is usually simplified. Eq.(8) and (9) are the expressions of matrices Y and B:

$$Y = \begin{bmatrix} -c^{(1)}(2) & [c^{(1)}(2)]^{s} \\ -c^{(1)}(3) & [c^{(1)}(3)]^{s} \\ \vdots & \vdots \\ -c^{(1)}(m) & [c^{(1)}(m)]^{s} \end{bmatrix} \tag{8}$$

$$B = \begin{bmatrix} a^{(0)}(2) \\ a^{(0)}(3) \\ \vdots \\ a^{(0)}(m) \end{bmatrix} \tag{9}$$

The model parameter matrix obtained by the least squares method is expressed by Eq.(10):

$$[\phi, \delta]^{T} = [Y^{T}, Y]^{-1} Y^{T} B \tag{10}$$

Combining Eq.(4) with the above equation, there is the expression of the time response function as follows:

$$a^{(1)}(l) = \left[\left[[a^{(1)}(1)]^{(1-s)} - \frac{\delta}{\phi} \right] o^{-x(1-s)(l-1)} + \frac{\delta}{\phi} \right]^{-\frac{1}{1-s}} \tag{11}$$

The final prediction result of the complex English sentences translation ability is obtained by the accumulated reduction of the prediction result:

$$\hat{a}^{(0)}(l) = \begin{cases} \hat{a}^{(0)}(1), (l=1) \\ \hat{a}^{(1)}(l) - \hat{a}^{(1)}(l-1), (l = 2, 3, ..., m) \end{cases} \tag{12}$$

In order to reduce the volatility of the original evaluation indicator data sequence and improve the priority of new information in the process of improving students' abilities to translate complex English sentences, this paper changed the original evaluation indicator data processing method to fractional-order accumulation generation. The corresponding original evaluation indicator data sequence is presented as follows:

$$a^{(0)}=[a^{(0)}(1),a^{(0)}(2),a^{(0)}(3),...,a^{(0)}(m)] \tag{13}$$

Assuming that $a^{(s)}$ is the s-order accumulated sequence of $a^{(0)}$, the obtained fractional-order accumulated generated sequence can be expressed as:

$$a^{(s)}(l)=\sum_{i=1}^{l}D_{l-i+s-1}^{l-i}a^{(0)}(i) \tag{14}$$

The accumulated generated sequence obtained by the s-order accumulation generation is highly similar to the exponential sequence. The following formula shows the constructed grey differential equation:

$$\frac{da^{(s)}}{dp}+\phi a^{(s)}=\delta \tag{15}$$

The neighbor mean of $a^{(s)}$ can be calculated by the following formula:

$$c^{(s)}(l)=\beta a^{(s)}(l)+(1-\beta)a^{(s)}(l-1) \tag{16}$$

The model is usually simplified. Eq.(17) and (18) show the expressions of the matrices Y and B:

$$Y=\begin{bmatrix}-c^{(s)}(2) & 1\\ -c^{(s)}(3) & 1\\ \vdots & \vdots\\ -c^{(s)}(m) & 1\end{bmatrix} \tag{17}$$

$$B=\begin{bmatrix}a^{(s)}(2)-a^{(s)}(1)\\ a^{(s)}(3)-a^{(s)}(2)\\ \vdots\\ a^{(s)}(m)-a^{(s)}(m-1)\end{bmatrix} \tag{18}$$

The parameter matrix of the corresponding model can be expressed as:

$$[\phi,\delta]^{T}=[Y^{T}Y]^{-1}Y^{T}B \tag{19}$$

The corresponding time response function is expressed as:

$$a^{(s)}(p)=\left[a^{(0)}(1)-\frac{\delta}{\phi}\right]o^{-xl}+\frac{\delta}{\phi} \tag{20}$$

The final prediction result is:

$$\hat{a}^{(0)}=\begin{Bmatrix}x^{(0)}(1),\hat{a}^{(r)(1-r)}(2)\\ -\hat{a}^{(s)(1-s)}(1),...,\hat{a}^{(s)(1-s)}(m)-\hat{a}^{(s)(1-s)}(m-1),...\end{Bmatrix} \tag{21}$$

3 Optimization algorithm and calculation process

In this paper, the particle swarm optimization algorithm was selected as the parameter optimization algorithm for the prediction model of the complex English sentences translation ability. The optimization targets are the Bernoulli parameters and the order of the fractional-order accumulation generation.

Suppose that the dimension of the particle swarm target search area is m, and that the particle swarm size is n. Let the position vector expression of the i-th particle be denoted as $A_i = (a_{i1}, a_{i2}, \ldots, a_{in})$, where $i = 1,2, \ldots, n$, and let the velocity vector of the i-th particle be denoted as $U_i = (u_{i1}, u_{i2}, \ldots, u_{in})$, the optimal position of the i-th particle be represented by $T_i = (t_{i1}, t_{i2}, \ldots, t_{in})$, and the optimal position of the particle swarm be represented by $T_v = (t_{u1}, t_{u2}, \ldots, t_{un})$. The following shows the update formula of the position and velocity information of an individual particle:

$$u_{ij}^{l+1} = qu_{ij}^{l} + d_1 s_1 (t_{ij}^{l} - a_{ij}^{l}) + d_2 s_2 (t_{hj}^{l} - a_{ij}^{l}) \tag{22}$$

$$a_{ij}^{l+1} = a_{ij}^{l} + u_{ij}^{l+1} \tag{23}$$

The calculation process of optimizing the grey Bernoulli prediction model using the particle swarm optimization algorithm mainly consists of the following steps:

Step 1: collect the data of the evaluation indicators of complex English sentences translation ability. In this study, the data were collected from the evaluation results of English major students in the target college regarding their translation abilities of complex English sentences. If there is any abnormal or missing data, replacement or supplemental data will be generated by the interpolation method.

Step 2: determine and optimize the grey Bernoulli parameters of the constructed grey Bernoulli prediction model based on the particle swarm optimization algorithm, and the optimization objective is to minimize the average absolute percentage error of the training sample set.

Step 3: perform fractional-order accumulation of the processed original evaluation indicator data sequence, in which, the order of the fractional-order accumulation is obtained through the optimization of the particle swarm optimization algorithm. The optimization objective is also to minimize the average absolute percentage error of the training sample set, so as to get the newly obtained fractional-order accumulation sequence.

Step 4: determine the parameter matrices of the prediction model after optimization of the two parameters based on the least squares method.

Step 5: combine the parameter matrix with the grey Bernoulli differential equation to obtain a time response function, based on which the students' abilities to translate complex English sentences can be predicted;

Step 6: finally, compare the prediction results of the students' complex English sentences translation abilities with their actual abilities, and then evaluate the prediction performance of the model based on the prediction errors.

4 Experimental results and analysis

Table 1. Correlation coefficients of the 8 evaluation indicator variables

Correlation Coefficient	1	2	3	4	5	6	7	8
1	1	0.9582	0.9142	0.9154	0.9471	0.9324	0.9847	0.9125
2		1	0.9325	0.9837	0.9117	0.9244	0.9162	0.9847
3			1	0.9615	0.9381	0.9182	0.9384	0.9162
4				1	0.9967	0.9793	0.9842	0.9384
5					1.	0.8984	0.9143	0.9842
6						1	0.8544	0.9143
7							1	0.8544
8								1

First, the correlation coefficients of the 8 evaluation indicator variables, namely close logical cohesion, clear relationship between sentence components, processing of passive voice in line with the reading habits of Chinese readers, reasonable choice of word order for parallel components, reasonable segmentation and adjustment of multi-layered nested sentences, clear and concise translation of modifier components, no lack of semantic correlation between sentences with various logical relationships, reasonable reordering of postpositional head words, and careful choices of correlatives, were calculated. Table 1 shows the correlation coefficients of the 8 evaluation indicator variables. It can be seen that the multi-collinearity among the 8 evaluation indicator variables is significant.

Table 2. Summary of the prediction results of the complex English sentences translation abilities

No.	1	2	3	4	5	6
Interpolation and fitting model	1852.41	2362.18	3928.62	4817.62	6592.38	8841.36
Time series prediction model	1482.69	2518.43	3582.47	4621.35	6528.91	8746.95
Markov prediction model	748.15	1615.35	2265.19	3348.51	5462.29	6841.35
Grey Bernoulli prediction model before optimization of the data processing mode	915.27	1625.15	2615.94	4518.27	6315.49	8154.37
Grey Bernoulli prediction model before optimization by the particle swarm optimization algorithm	1362.84	1627.06	2369.51	4518.72	6925.38	7741.58
Proposed model	1740.25	1635.49	2341.84	4625.35	5514.92	7485.35

(Continued)

Table 2. Summary of the prediction results of the complex English sentences translation abilities *(Continued)*

No.	7	8	9	10	11	12
Interpolation and fitting model	15249.72	13629.48	23261.74	29105.63	37152.49	55623.15
Time series prediction model	16295.81	15263.48	19257.31	25162.93	33162.84	38415.95
Markov prediction model	9485.17	12516.38	19623.51	16158.36	19152.84	28451.62
Grey Bernoulli prediction model before optimization of the data processing mode	11259.62	13512.41	16529.48	141253.25	15263.73	22153.62
Grey Bernoulli prediction model before optimization by the particle swarm optimization algorithm	11635.94	13528.46	19529.42	15241.05	16527.11	21504.83
Proposed model	11623.59	15142.81	11325.49	14835.52	16527.94	23652.45

Table 2 presents a summary of the prediction results of the complex English sentences translation abilities. The predicted values of the proposed model were compared with those of the other five reference models, namely: interpolation and fitting model, time series prediction model, Markov prediction model, grey Bernoulli prediction model before optimization of the data processing mode, and grey Bernoulli prediction model before optimization by the particle swarm optimization algorithm. Figure 2 shows the comparison results of the absolute values of errors.

It can be seen from Table 2 and Figure 2 that from the perspective of the absolute value of error, compared with the grey Bernoulli prediction model before optimization of the data processing mode and grey Bernoulli prediction model before optimization by the particle swarm optimization algorithm, the proposed model has a relatively smaller error, but that if the model is not optimized in the data processing mode or by the particle swarm optimization algorithm, it is easy to encounter a large prediction error on a single sample, which shows that the proposed model after optimization of the data processing mode and by the particle swarm optimization algorithm has stable performance in predicting the translation ability of complex English sentences.

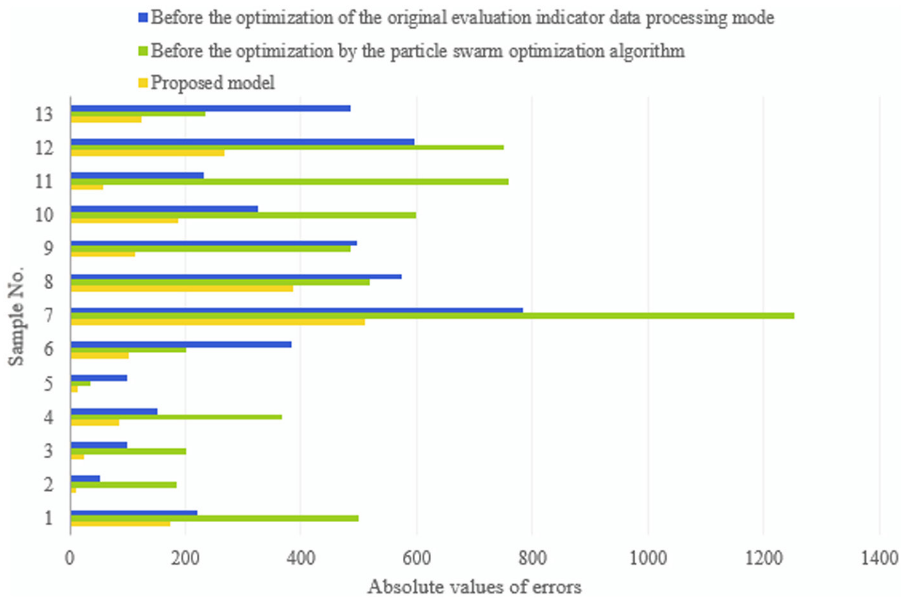

Fig. 2. Comparison results of the absolute values of errors

In order to analyze the effectiveness of the two optimization steps, i.e. optimization of the data processing mode and optimization by the particle swarm optimization algorithm, this paper further evaluates the optimization degree of the model based on the calculation results shown in Figure 2. The evaluation results are presented as follows.

Table 3. Evaluation results of model optimization degree

Model for Comparison	Compared With	P_{MAPE}	P_{SMSE}
Proposed model	Grey Bernoulli prediction model before optimization of the data processing mode	22.51%	29.58%
Proposed model	Grey Bernoulli prediction model before optimization by the particle swarm optimization algorithm	41.36%	45.18%
Grey Bernoulli prediction model before optimization by the particle swarm optimization algorithm	Grey Bernoulli prediction model before optimization of the data processing mode	28.41%	13.26%
Grey Bernoulli prediction model before optimization by the particle swarm optimization algorithm	Grey Bernoulli prediction model before optimization by the particle swarm optimization algorithm	91.62%	95.47%
Grey Bernoulli prediction model before optimization by the particle swarm optimization algorithm	Interpolation and fitting model	46.57%	45.13%
Grey Bernoulli prediction model before optimization of the data processing mode	Interpolation and fitting model	96.37%	95.41%

It can be seen from Table 3 that, compared with other reference models, the proposed model has greater performance in the prediction accuracy of complex English sentences translation abilities due to the combined optimization of the model. The use of fractional-order accumulation generation operator to optimize the data processing mode effectively reduces the volatility of the original evaluation indicator data sequence, thereby improving the prediction accuracy of the model. After optimization by the particle swarm optimization algorithm, the grey Bernoulli parameters and the order of the fractional-order accumulation generation have better data adaptability, thus leading to higher prediction accuracy of complex English sentences translation abilities.

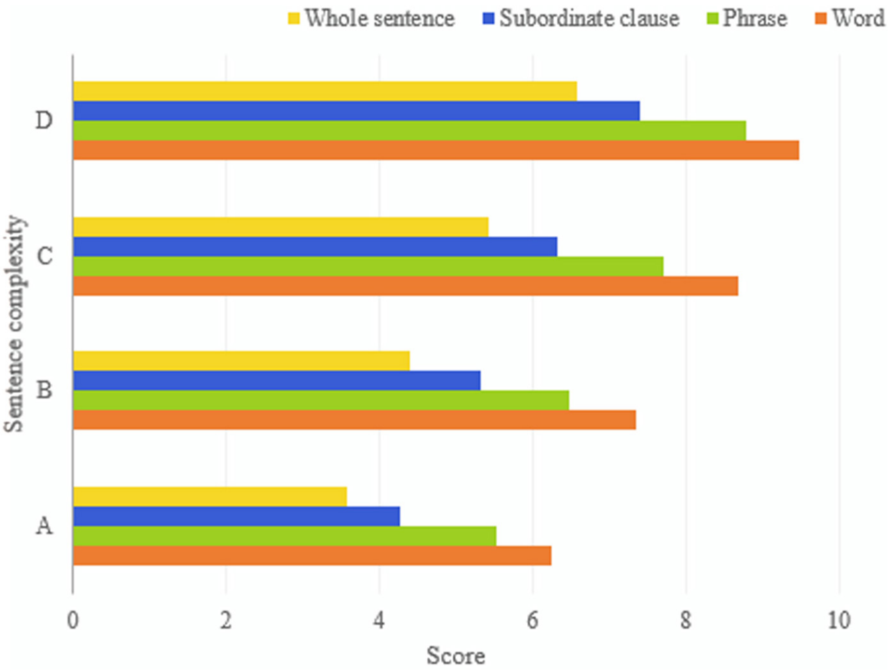

Fig. 3. Prediction of translation performance with respect to different sentence complexities

Table 4. Comparison of translation performance of the high sentence complexity group and the low complexity one

		F	Sig.	t	df	Sig (2-tailed)	Mean Difference	Std. Err
1	Homogeneous	7.625	0.25	0.52	23	0.62	0.5248	1.32628
	Non-homogeneous			0.67	21.625	0.49	0.6253	9.8577
2	Homogeneous	0.58	0.14	–0.62	22	0.69	–0.1528	1.5284
	Non-homogeneous			–0.25	18.524	0.63	–0.1524	1.5948
3	Homogeneous	0.52	0.49	–0.35	22	0.75	–0.6247	1.1326
	Non-homogeneous			–0.41	25.162	0.69	–0.1241	1.6235
4	Homogeneous	0.27	052	0.35	25	0.41	0.3622	1.6259
	Non-homogeneous			0.52	25.4141	052	0.3582	1.4284
5	Homogeneous	0.857	0.52	0.67	23	0.59	0.5286	9.5261
	Non-homogeneous			0.36	21.418	0.48	0.5381	1.6259
6	Homogeneous	0.59	0.24	0.63	23	0.495	0.1547	1.3269
	Non-homogeneous			0.19	25.481	0.58	0.2514	1.0268
7	Homogeneous	1.6259	0.68	–1.48	25	0.64	–1.3425	8.4157
	Non-homogeneous			–1.25	21.485	0.64	–1.3265	8.4153
8	Homogeneous	1.6259	0.68	–1.48	25	0.64	–1.3425	8.4157
	Non-homogeneous			–1.25	21.485	0.64	–1.3265	8.4153

Next, the translation abilities with respect to complex English sentences with different complexities were predicted. Figure 3 shows the specific prediction results. It can be seen that, when the sentence complexity changed from a higher Level A to a lower Level D, the students' performance of translating complex English sentences decreased accordingly. While the complexity of the sentence remained unchanged, the translation performance gradually decreased in the sequence of words, phrases, subordinate clauses and whole sentences. The above prediction results are consistent with the actual situation, which further verifies the effectiveness of the proposed model.

To reveal the difference in the translation abilities of high and low sentence complexity groups, an independent t-test was carried out. Table 4 shows the comparison of the translation performance of the high and low sentence complexity groups. It can be seen that there is little difference in the translation abilities of the experimental group with high sentence complexity and the one with low sentence complexity. Although the two groups of students participated in the translation tasks of different difficulties, their overall translation abilities were not significantly different, so it can be concluded that there is a certain correlation between the translation ability of complex English sentences and the complexity of sentences.

5 Conclusions

This paper analyzed the prediction of students' translation abilities with respect to complex English sentences based on artificial neural network. First, based on the principles of accuracy, operability and scientificity, an evaluation indicator system was built to fully reflect the basic characteristics of students' ability to translate complex English sentences, which is in line with the training needs of translation talents at colleges and universities. Then, based on the characteristics of the logical structures of complex English sentences, a grey Bernoulli prediction model was constructed for the translation ability of complex English sentences. The particle swarm optimization algorithm was selected as the parameter optimization algorithm for the prediction model of translation ability with respect to complex English sentences, with the optimization targets being the Bernoulli parameters and the order of the fractional-order accumulation generation. Through an experiment, the correlation coefficients of 8 evaluation indicator variables were summarized, and it was verified that the multi-collinearity among the 8 evaluation indicator variables was significant. Then, the prediction results of the complex English sentences translation ability were given, and the proposed model was compared with other ones in terms of the absolute value of error. It shows that the model proposed in this paper has better performance in the prediction stability of the complex English sentences translation ability through optimization of the data processing mode and by the particle swarm optimization algorithm. The evaluation results of the model optimization degree further proves the effectiveness of the two-step optimization (optimization of the data processing mode and by the particle swarm optimization algorithm) adopted in the proposed model. The prediction of the translation ability with respect to sentences with different complexities was also analyzed, and the translation performance was also compared between the high sentence complexity group and the low complexity one, which verifies that the translation ability of complex English sentences has a certain correlation with the sentence complexity.

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