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Research Article

Analysis of English Translation Model Based on Artificial Intelligence Attention Mechanism

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The particularity and quantity of English translation terms have a great impact on the quality and effect of machine translation and can not meet the requirements of English translation of terms. At the same time, technical exchange and communication in different fields need the expression of professional terms. In addition, although the neural machine translation model has good translation performance, it is not ideal for target languages with small translation needs and limited corpus resources. In order to solve the problems existing in the English translation model, this paper constructs the transformer model by replacing the cyclic neural network variables and introducing the attention mechanism. The term information is integrated into two pretraining models to improve the learning ability of model language sentence relationship. Maintain the integrity of terminology information by fully completing the training. The experimental results show that, compared with the other three term translation models, the translation model in this paper has the advantage of term information. At the same time, the deep neural network English term translation model can obtain more fine-grained word relevance. In different corpora, the Bleu score of the model is good, showing obvious translation performance advantages. This study provides a good professional reference value for the translation of English terms.

1. Introduction

Natural language processing technology has been gradually developed and valued in the process of continuous communication among countries all over the world. Machine translation has gradually replaced the simple task of natural language translation. However, the formation of language is greatly influenced by social culture and has its own unique structure and language characteristics. Therefore, machine translation can not achieve the refinement of words and smooth meaning as manual translation. Modern high and new technology provides the driving force for the development of artificial intelligence technology. Its application in the field of natural language processing technology provides a new direction for the development and research of machine translation. In the era of information explosion, machine translation corpus contains a large amount of data information, rich content, and many professional fields. It not only has strong technicality and professionalism, but also contains the specific background of the times [1]. The massive text corpus will inevitably have duplicate content, which will affect the quality of machine translation. The information processing ability of the traditional machine translation model can not meet people's translation requirements. After the introduction of artificial intelligence technology into machine translation, under the framework of the original translation principles, it will use the translated corpus to compare and translate the reoccurred content in a short time, greatly improve the translation efficiency, and ensure the consistency of the translation content, and so the quality of the translation results is better, which is enough to complete the general translation task [2].

With the development of high and new technology, the refinement of professional fields, and the continuous renewal of knowledge system, the core vocabulary of different professional fields has changed, and a batch of new professional terms have emerged. Terms express specific meanings in specific fields. Therefore, in machine translation, the translation of professional terms requires higher accuracy, professionalism, and scope than general translation requirements, which increases the difficulty of machine translation [3]. The knowledge base expert system in artificial intelligence combined with big data technology provides technical support for term translation in professional fields. The constructed translation model and database provide a direct and automatic translation method for term English translation according to the corresponding relationship between source language and target language. The application of neural network improves the effect of machine translation in language learning and expression and improves the quality of translation. However, direct automatic translation is difficult to ensure the accuracy of translation for a large number of unlisted words [4]. In addition, in order to improve the translation effect of specific professional fields, the machine translation model based on neural network needs to be trained through a large number of bilingual materials to obtain the required word vector. Many professional fields with limited translation resources are difficult to fully train the model. Therefore, some scholars propose to introduce the word vector model for translation model corpus training [5]. On this basis, some scholars put forward the improvement of the parameter initialization problem. The parameters at either end of the model are randomly initialized, and the other end is completed through the pretrained fast text. The experimental results show that this method significantly enhances the translation quality of the model [6]. Other scholars used Elmo neural network in the pretraining of monolingual corpus of Ukrainian English translation and achieved better translation results [7]. In addition, some scholars believe that term English translation can integrate term information through the decoding of constraint decoding in the neural machine translation model, so as to realize the specified translation and improve the quality of term English translation [8].

The innovative contribution of the research lies in simplifying the internal structure of the machine translation model through the improvement of the deep loop neural network and introducing the attention mechanism to construct the transformer model. Through the comparative experiments of the four translation models, it can be seen that the size of the non-Analects database of the deep neural network English term translation model and the fusion of term information show good translation performance. It reduces the difficulty of learning the corresponding relationship and information between the source language and the target language words in the translation modeland achieves the purpose of improving the accuracy and professionalism of term English translation. The fluency of translation results, term matching, and expression standardization are closer to the requirements and requirements of term translation norms.

2. Research Status and Development of English Machine Translation Combined with Artificial Intelligence Technology

The research of artificial intelligence technology starts with giving human thinking to machines and assisting human behavior research. Language has always occupied an important position in human behavior and communication. Therefore, artificial intelligence technology has been deeply applied and studied in the task of natural language machine translation and has achieved good research results [9]. Model training is required in the early stage of the application of artificial intelligence technology. The machine algorithm model can improve the algorithm performance, learn more relevant knowledge, accumulate relevant expert knowledge on the basis of understanding the control target object and control law, and build an integrated system of expert knowledge and experience. The machine algorithm model can view the distribution of data and compare the relationship between data, cultivate intuition of data, summarize data, etc. The exploratory data analysis method is simply to understand the data, analyze the data, and figure out the distribution of the data. It mainly focuses on the real distribution of data and emphasizes the visualization of data. So the analyst can see the hidden rules in the data at a glance, so as to get inspiration and to help the analyst find a model suitable for the data [10]. The system can not only help MT solve various complex problems in translation, but also provide powerful decision support for MT and realize control optimization [11]. The combination of neural network and machine translation greatly improves the autonomous learning ability and information processing ability of translation model and shortens the distance between machine translation and human language use thinking. Neural machine translation, first published in 2013, takes encoder decoder as the translation framework and performs source language related information acquisition, semantic vector conversion, and decoding through convolutional neural network and cyclic neural network to complete target language translation [12, 13]. The operation of this model marks the formal transformation of deep neural network from machine translation optimization auxiliary model to a model that can complete translation tasks independently. After that, many scholars conducted in-depth research on the basis of this model. Some scholars pointed out the problems existing in the cyclic neural network and proposed to introduce its variants to simplify the structure. The experimental results show that the gap between the two translation effects is small [14]. According to the characteristics of language translation, some scholars have added attention mechanism to the neural machine translation model to solve the problem of fixed word vector length [15]. For the research of neural machine translation framework, some scholars have designed the coding structure and bidirectional decoding of bidirectional cyclic neural network, and others have proposed a dynamic bidirectional decoding model with random direction of word decoding [16].

With the strengthening of exchanges in different cultures and fields, translation in many languages and professional fields, such as small translation demand and small use scale, has gradually become one of the hotspots of machine translation research. Some scholars have completed the initial parameterization of masked language translation model through three different pretraining models, which has improved the effect and quality of Mongolian Chinese translation [17]. Other scholars have completed the translation output of the preset language through grid beam search and lexical constraints [18]. In addition, some scholars believe that there is a certain gap between the preset translation results and the meaning of the original word itself, which can not reflect the integrity of the source language, and the fluency of the text and meaning of the target language results are limited. Therefore, they try to complete the model training by replacing the source language phrases and strengthen the accuracy and rationality of the use of professional terms [19]. Machine translation technology is bound to develop in a more specialized and intelligent direction in the future. The development and combination of intelligent decision support system, data processing technology, information mining, and other technologies will continue to improve the performance of machine translation, optimize model structure and translation technology schemes, improve translation efficiency, provide diversified translation schemes and results according to different translation needs and requirements, and optimize the economic benefits of machine translation models [20].

3. English Term Translation Model Based on Artificial Intelligence Technology

The machine translation model introduces artificial intelligence technology to diversify the posttranslation strategies, adjust the translation parameters according to the information such as cultural and language characteristics and determine the translation standards for different needs [21]. Different languages have their own language patterns [22]. Machine translation needs accurate simulation on the basis of language structure and flexible processing of language information. The application of neural network in machine translation can improve the autonomous learning ability and adaptive performance of translation model and improve the efficiency of language signal processing, detection, and operation through dynamic learning. With the updating of neural network learning strategies, the performance and quality of machine translation have been improved. Therefore, this paper will integrate professional term information into neural machine translation to study the English translation effect of terms.

3.1. Construction of English Machine Translation Model Based on Neural Network. The translation of natural language should be carried out as a whole on the premise of sentence understanding. Only paying attention to the meaning of each word or disconnecting the relevance between words cannot achieve the ideal translation effect. Therefore, the neural network in machine translation needs to be connected with the previous information when processing information, especially when there is a large gap between the output prediction content and relevant information. Neural network still needs to complete the translation task according to the memory information, and the variant of cyclic neural network, long-term and short-term memory cyclic neural network, can meet this demand. The cyclic link formed by the hidden layer of simple cyclic neural network without nonlinear activation function is shown in the following formula:

$$h_t = W^T h_{t-1}. \tag{1}$$

When the time is t, the hidden layer is expressed as

$$h_t = \left(W^t\right)^T h_0. \tag{2}$$

The weight matrix is decomposed and the orthogonal matrix result is substituted into formula (2), and the time is hidden layer representation can be obtained, as shown in

$$W = Q\Lambda Q^T, \tag{3}$$

$$h_t = Q^T \Lambda^T Q h_0. \tag{4}$$

The diagonal elements contained in Λ in the formula are the eigenvalues of the weight matrix. It can be seen that the multiplication of the weight matrix will have a great impact on the hidden layer of the simple cyclic neural network layer, resulting in the gradient problem. The long-term and short-term memory is introduced into the cyclic neural network, and three control gate structures are added in the hidden layer, as shown in Figure 1.

The three control gates in the hidden layer mainly filter and update the information according to the requirements of the gate layer state unit. Through formula (5), the forgetting gate can filter out the information to be forgotten:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right). \tag{5}$$

In the formula, the weight matrix of the gate is expressed as W_f, and its bias term is expressed as b_f. The dimensions of x_t, h_{t-1} and hidden layer state are d_x, d_h, d_c, respectively, and the dimension of weight matrix can be obtained as $d_c \times (d_x + d_h)$.

The first mock exam is the input gate that stores new information, which is divided into two parts, such as

$$\widetilde{C}_t = \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right), \tag{6}$$

where C_t represents the hidden layer state and the alternative $\widetilde{C}_t$ is obtained after the first part is updated.

The second part is shown in

$$m_t = \sigma\left(W_m \cdot [h_{t-1}, x_t] + b_m\right). \tag{7}$$

The information contained in $\widetilde{C}_t$ will determine the amount of cell state information added through the sigmoid layer of the second part.

The update of the unit status after passing through the above two control doors is shown in

$$C_t = f_t \odot C_{t-1} + m_t \odot \widetilde{C}_t. \tag{8}$$

The output gate filters out the output information according to the relevance of the information before and after the update. The final output is shown in

$$\sigma_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right), \tag{9}$$

$$h_t = \sigma_t \odot \tanh\left(C_t\right). \tag{10}$$

In computer vision, the essence of attention mechanism is to find the correlation between them based on the original data and then highlight some of its important features. This is also a natural feature of the human eye for a long time. For example, in the decoder layer of the transformer, we use masked attention. This operation can be understood as that the model sees the remaining answers in advance to prevent the decoder from "cheating" when decoding the output of the encoder layer. Therefore, it is necessary to force the model to carry out attention according to the results on the left of the input sequence. Transformer model introduces the self-attention mechanism into the cyclic neural network to urge the translation encoder to pay attention to its words when encoding each word. Its calculation formula is shown in

$$\text{attention}(Q, K, V) = \text{soft}\max\left(\frac{QK^T}{\sqrt{d_k}} V\right). \tag{11}$$

The word vector input in the self-attention mechanism will have query vector, key vector, and value vector. The corresponding matrix is expressed as Q, K, V, and d_k representing the dimension of key vector, respectively.

3.2. A Machine Translation Model of English Terms Based on Term Information. In the English neural machine translation model based on transformer model, the domain term information that needs to be translated is fused. Firstly, the bilingual corpus in the process of data preprocessing is segmented through the definition of term dictionary. At present, the performance of neural machine translation depends on high-quality large-scale parallel corpora. Due to the limitation of computing resources, training time, and model framework, model training can only use parallel sentence pairs with moderate length. Too long sentence pairs will be discarded, resulting in a waste of resources. Therefore, the research on how to segment long bilingual sentences into effective sentence pairs has important theoretical significance and practical value. Traditional bilingual sentence pair segmentation methods include rule-based, statistics based, rule-based, and statistics combined methods. This paper studies the segmentation method of long sentence pairs in bilingual parallel corpus based on deep learning, so as to improve the utilization of corpus and the translation accuracy and quality of translation system. At the same time, the word vector obtained from a large number of monolingual corpus after training has both text and term information. The parameters of the embedding layer of the translation model are initialized according to the two word vectors, and the unlisted words of terms in the field in the translation are found and replaced through the external term dictionary. Figure 2 shows the translation framework of English neural machine translation model based on transformer model integrating term information.

As can be seen from the frame diagram, there are two pretraining models of word vectors in the model, in which glove model obtains the required complete set of word vectors from the statistical information and context information of the paragraphs to be translated through pretraining. Word2vec is a group of related models used to generate word vectors. These models are shallow and double-layer neural networks used for training to reconstruct linguistic word texts. The network is represented by words, and it is necessary to guess the input words in adjacent positions. Under the assumption of word bag model in word2vec, the order of words is not important. The pretraining word vector of word2vec is completed through the continuous word bag model; that is, the training word is placed near the predicted center word, which can reduce the difficulty of learning the corresponding word relationship between the two languages. The calculation formula of likelihood function is

$$\prod_{t=1}^{T} P\left(w^{(t)} \mid w^{(t-i)}, \ldots, w^{(t-1)}, w^{(t+1)}, \ldots, w^{(t+i)}\right), \tag{12}$$

where T represents the length of the text sequence, $w^{(t)}$ represents the time step of the word t, and i represents the size of the background window.

Assuming that the key word whose index is c in the term dictionary is represented by w_c and its background word is represented by GG, the calculation formula of occurrence probability is shown in

$$P\left(w_c \middle| w_o\right) = \frac{\exp\left\{u_c^T vo\right\}}{\sum_{m\in V} \exp\left\{u_m^T vo\right\}}, \tag{13}$$

where vo represents the average of w_o vector, u_m, u_c represents the vector of the central word with the index word m, c, respectively, and V represents the vocabulary composed of all words.

3.3. Experimental Analysis of English Term Translation Model Based on Deep Neural Network. The professional terminology field of model translation experiment is electrical field. Before model translation test experiment, corpus and professional terminology database need to be established. The establishment of corpus is mainly based on the characteristics of the experimental object corpus, large-scale retrieval of scientific and technological papers on related topics, obtaining text materials containing bilingual and monolingual corpus, and then cleaning the corpus. According to the source of the corpus, it can be divided into three corpora. After cleaning, more than 30000 pairs of sentence pairs remain in each corpus, of which the second and third corpora are large corpora. The corresponding electrical terminology library obtains the term pairs in the electrical field through relevant standard documents, dictionaries, and relevant authoritative websites. In addition, through the extraction model and related website translation, the bilingual term word pairs of the professional term library are expanded, and finally

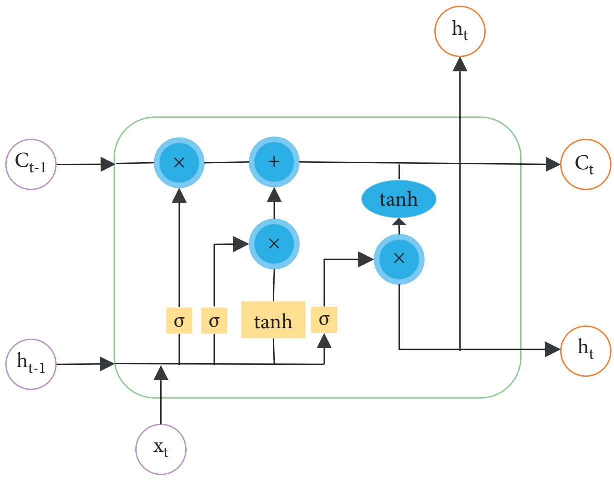

Figure 1: Example of LSTM neural network structure diagram.

about 41000 electrical professional term word pairs are obtained.

The deep neural network English term translation model with term information is tested and compared with the transformer model without term information and two models with other different term word segmentation and translation. The coder and decoder layers of the four models in the experiment are the same, which are six layers, and the dimension of the hidden layer is 512. The translation quality of the four models is measured by Bleu value, and its calculation formulas are shown in

$$BLEU = BP \times \exp\left(\sum_{j=1}^{J} w_j \times \log p_j\right), \tag{14}$$

$$BP = \begin{cases} 1, & l_c > l_r, \\ \exp\left(1 - \dfrac{l_r}{l_c}\right), & l_c \le l_r. \end{cases} \tag{15}$$

In the formula, the length of the translated text is expressed in l_c, and the minimum length of the reference translated text sentence is expressed in l_r. Generally, $j = 4$, w_j are the weights, and p_j represents the accuracy of the corresponding coincidence of the sentences contained in the corpus.

In addition, the translation quality of the four models will be evaluated manually. Ten relevant personnel will score the sentences translated by the four models and take the corresponding average value as the final evaluation score.

The four machine translation models are trained in three corpora for multiple rounds until the performance of the model is the best and the training ends when the model shows convergence at the same time. Figures 3–5 show the Bleu value curve of four English term translation models in three different corpora. It can be seen from the data in the comprehensive figure that the training times increase, and the scores of the four models in each corpus fluctuate in a small range, showing an increasing trend as a whole. The

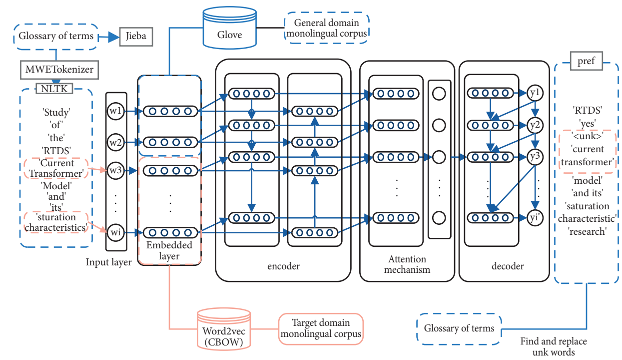

Figure 2: Translation framework of English neural machine translation model based on transformer model with term information.

transformer model introduces the term segmentation translation model, and the score in any language database is the lowest among all the model scores. The occurrence frequency of electrical professional terms in the text is high and there are long-term words, resulting in the term segmentation staying at the coarse-grained level, reducing the coverage of thesaurus, and the translation quality and score are not high. The translation model of this paper performs best in all corpora. Except for the score of the first corpus, the scores of the model with term replacement are higher than those of the transformer model. First, the corpus is small, the training data set has some limitations, the training of translation model is insufficient, and the quality is relatively low. Due to the small scope of corpus, it is easier to obtain correct translation results by directly replacing target terms in source prediction training, but the score of term replacement model is only higher than that of term segmentation model. The two word vector training methods in this paper are relatively less difficult to obtain the mapping relationship between the source language and the target language in a small corpus, and the Bleu score of the best translation is 29.79.

Second, after the data scale of electrical terms in the corpus has been expanded several times, the quality of the four English term machine translation models has been greatly improved, especially that the translation scores of this model and term replacement model are higher than 70 points. The training is sufficient, the model performance is improved, and the translation quality is increased, but the gap between the translation quality scores of the two models tends to expand with the increase of epoch. Term replacement in a large range of corpora has lost its advantage in a small corpus. The more the word mapping relationships learned in this model, the stronger its translation expression and the better the term translation effect. In addition, the number of words selected in the translation process of this model is higher than that of term replacement; that is, the granularity level is finer, which makes it easier to obtain the semantic relationship between words and enhance the overall translation performance.

The third corpus is a mixed corpus; that is, its scale is large, but the proportion of corpus about electrical terms is

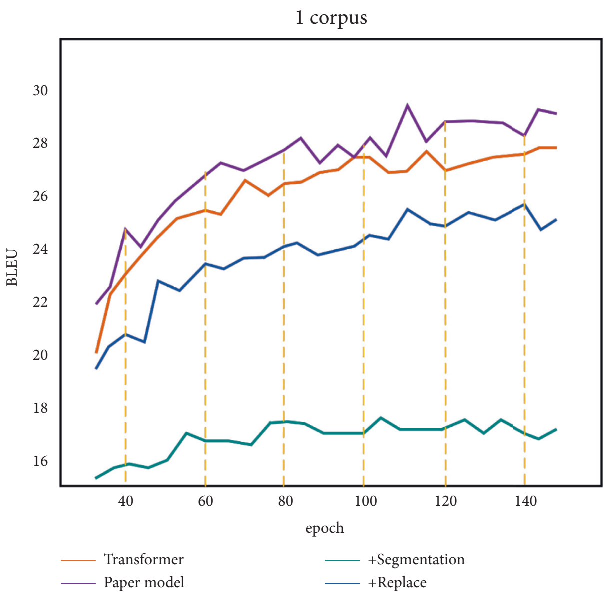

FIGURE 3: Bleu value curve of four English term translation models in the first corpus.

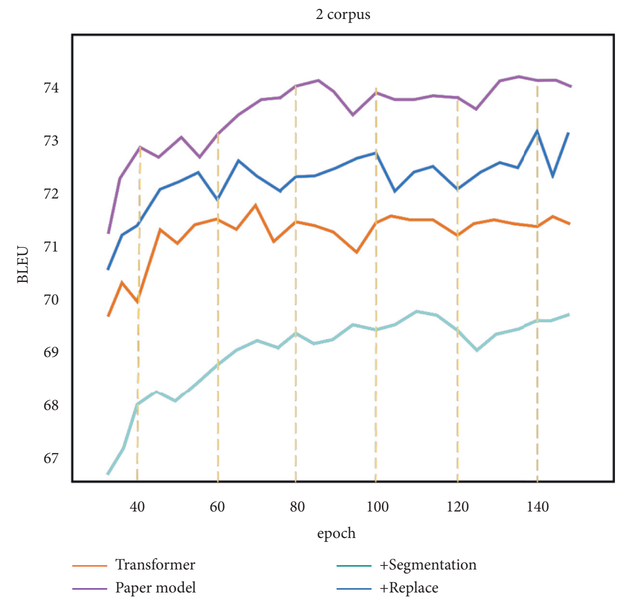

FIGURE 4: Bleu value curve of four English term translation models in the second corpus.

lower than that of the second corpus, and the structural difference between sentences is more obvious. The Bleu scores of the four translation models are reduced slightly, and the score difference between the models in the early stage of training is reduced. The gap between term replacement model and transformer model is significantly reduced compared with the first two corpora, while the gap between this model and term replacement model will continue to expand with the improvement of training adequacy.

Figure 6 shows the comparison results of the best Bleu value and manual score of the four English term translation models. The measurement of English translation quality of electrical terms by relevant professionals focuses on the accuracy, fluency, matching, tense change, expression standardization, and acceptance of translated sentences. The figure shows that the size of the corpus has a certain impact on the translation quality evaluation of the translation model. The model can obtain more word association information in a large corpus, show higher fluency and standardization in translation expression, and be closer to the actual translation requirements of professional terms in terms of format. Combined with Bleu evaluation score, the performance of this translation model and term replacement model is outstanding, and the score gap between the two manual evaluations is small. The score of translation quality sorting of this model is slightly better, indicating that its translation quality is more widely accepted and the matching degree of professional terms is higher.

In general, two languages with large cultural differences will choose an independent thesaurus, which is different from the actual model training. For the translation model, the joint thesaurus method will provide more word semantic association information that can narrow the language difference. Figure 7 shows the comparison results of Bleu evaluation average values of four English term machine

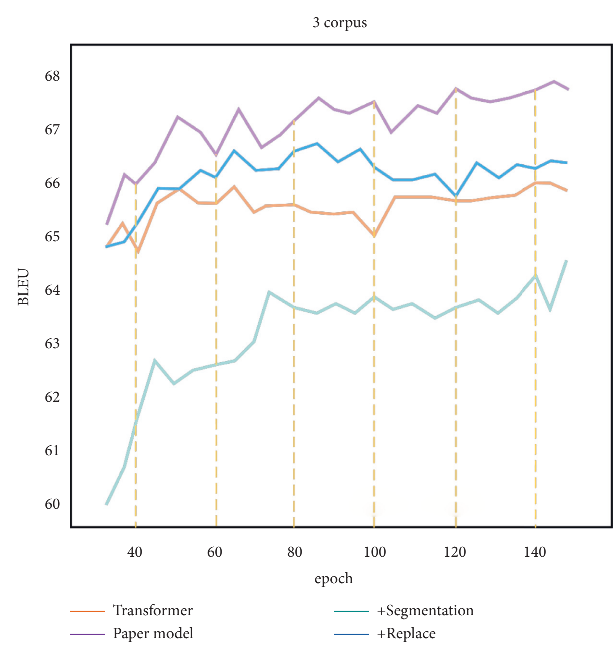

FIGURE 5: Bleu value curve of four English term translation models in the third corpus.

translation models in independent thesaurus and joint thesaurus. The results show that the transformer model has little difference in the performance of the two word lists and maintains the performance stability. The evaluation scores of the other English term translation models through the joint thesaurus are better than the independent thesaurus. The translation performance of this translation model in the joint thesaurus has been significantly improved.

To sum up, the deep neural network English term translation model integrating term information is easier to

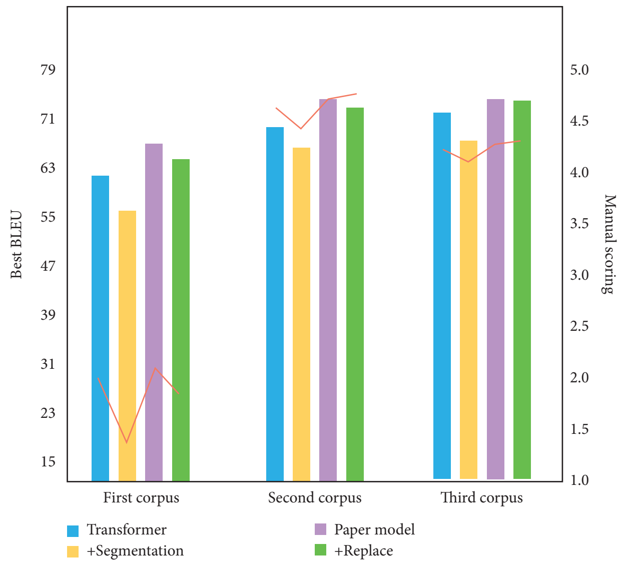

Figure 6: Comparison of the best Bleu value and manual score of four English term translation models.

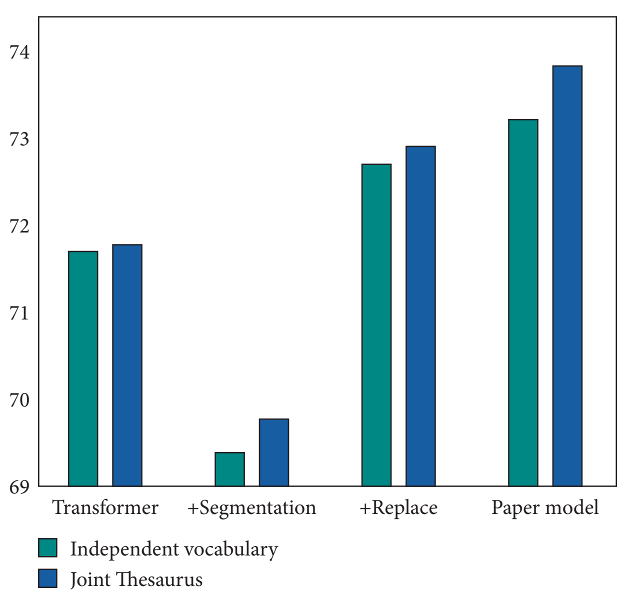

Figure 7: Comparison of Bleu evaluation average values of four English term machine translation models in independent thesaurus and joint thesaurus.

obtain the relevance information between words at the fine-grained level, showing good translation performance and better translation results in different corpora. In a large corpus, adequate training can improve the translation performance of the model and expand the translation advantages. The manual scoring shows that the model has higher translation accuracy of electrical terms and higher term matching while maintaining the fluency of translation results, and the expression standardization is closer to the requirements of the actual standard expression of terms.

4. Conclusion

Terms play an important role in professional communication and patent documents and will affect the translation effect of machine translation to a great extent. At the same time, the development of technology and the renewal of knowledge system will add more professional terms and improve the difficulty of English translation of machine terms. In this paper, the internal structure of machine translation model is simplified through the variant of deep circulating neural network, and the attention mechanism is introduced to construct transformer model. On this basis, the electrical term information is integrated into the two word vector pretraining modes to improve the ability of the model to map the words between the source language and the target language. Through the comparative experiment of four translation models, it can be seen that the size of the non-Analects database of the deep neural network English term translation model fused with term information shows good translation performance. The two pretraining modes of copper drum are easier to obtain the word connection information with finer granularity, improve the adequacy of model training, and improve the integrity and accuracy of electrical terms. In large-scale corpus, the model shows that the translation advantage will be continuously improved with the increase of training times. In addition, among the manual evaluation scores, the model has the highest score, which indicates that the fluency, term matching, and expression standardization of its translation results are closer to the requirements and requirements of term translation norms.

However, in this study, the scale of the experimental corpus is relatively limited, and a larger corpus is needed to verify the translation effect of the model terms. We can also try to optimize and adjust model parameters to improve the overall translation effect. Therefore, further analysis is needed in future research.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding this work.

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