Fault Diagnosis with BERT Bi-LSTM-assisted Knowledge Graph Aided by Attention Mechanism for Hydro-Power Plants

Bilei Guo[1], Yining Wang[1], Weifeng Pan[1], Yanlin Sun[1], and Yuwen Qian[2(✉)]

[1] State Grid Electric Power Research Institute, Nanjing 210003, China
{guobilei,wangyining,panweifeng,sunyanlin}@sgepri.sgcc.com.cn
[2] School of Electronic and Optical Engineering, Nanjing University of Science and Technology, Nanjing 210094, China
admon@njust.edu.cn

Abstract. To minimize the risk of Hydro-Power Plant failure, it's crucial to detect and precisely repair the damaged components. In this paper, we propose a knowledge graph-based fault diagnosis method for Hydro-Power Plants. Then, the improved BiLSTM-CRF algorithm is developed to recognize entities for fault diagnosis, and the BERT relationship extraction algorithm is designed to construct a fault diagnosis knowledge graph for the Hydro-Power Plant. The real experimental test results validate the proposed methodology.

Keywords: Hydro-power Plant · Fault Diagnose · BERT · Knowledge Graph · Bi-LSTM

1 Introduction

Hydro-power plants are becoming increasingly complex, leading to a higher frequency of automation system failures, which results in a significant fluctuation in plant reliability [5]. Furthermore, the equipment in the hydro-power plants is subject to a more complex and severe working environment due to natural and other factors [6]. Therefore, it is crucial to conduct effective fault diagnosis for hydro-power plants to prevent such events from occurring [7].

Through the continuous improvement of the data acquisition technology of Hydro-Power Plant equipment, which has realized the collection of process automation data, unit parameters, and electrical parameters [13]. Based on these data resources, two technical methods, namely, the machine learning model and the mathematical model, have been adopted for the diagnosis of working conditions. Still, both methods have certain limitations [4]. The traditional mechanism model has two representative methods: the current method and the holding diagnosis method. After a fault occurs, both of them need to be analyzed by experts according to the characteristics of the recorded data [2,8].

J. Liu et al. (Eds.): TridentCom 2023, LNICST 523, pp. 85–95, 2024.
https://doi.org/10.1007/978-3-031-51399-2_5

The post-processing method leads to a poor real-time system, which requires rich experience in Hydro-power plant conditions to make accurate judgments on the detection results [9]. The mathematical model adopts big data and deep learning technology for real-time analysis and establishes a fault diagnosis model by analyzing the historical working condition sample data and extracting parameter features [10]. However, It's challenging to gather enough fault data, which affects diagnostic accuracy [12].

In recent years, relevant literature has been applied to knowledge mapping in fault diagnosis. For example, the authors of [11] construct an engine-oriented knowledge graph, through the engine production failure and after-sales maintenance reports to build the domain knowledge graph. Furthermore, the knowledge graph is used for visualization retrieval and assisted decision-making. The authors of [3] proposed a methodology for constructing and reasoning a knowledge graph for engineering machinery faults. The approach involves using preset rules to automatically extract ternary groups from construction machinery maintenance documents. Moreover, an auxiliary decision-making model is obtained through alternate iteration training to assist in troubleshooting engineering machinery, providing a new perspective on problem-solving. Through exchanges with hydropower technicians, we found that there are still many uncertainties and a lack of systematic research on the application of knowledge mapping in the hydropower plant [1]. For example, Hydro-Power is skeptical about the prospect of applying a knowledge graph and is not sure how to use it in the processes of fault diagnosis, system recovery, gathering, and transportation in hydro-power plants. In addition, there is a lack of knowledge-based fault diagnosis process for Hydro-Power.

In this article, a fault diagnosis approach is proposed by using the BERT BiLSTM-assisted knowledge graph with an attention mechanism for hydropower plants. The main contributions of this paper are listed as follows.

- A fault diagnosis method is proposed based on a BERT BiLSTM-assisted knowledge graph with an attention mechanism, as seen in Sect. 2.
- The BERT method is adopted to integrate parameters into the BiLSTM-CRF model, which improves the model generalization and solves the out-of-vocabulary problem, as seen in Sect. 3.
- a word attention mechanism layer is added to the BERT model to improve the relationship classification accuracy, which solves the problem that the previous knowledge graph is only used for retrieval and characterization and realizes the quantitative reasoning of the knowledge graph, as seen in Sect. 4.
- Simulation results demonstrate that the entities and relationship between these entities can be effectively extracted, and the faults in hydropower plants can be found by using the proposed BERT BiLSTM-CRF aided knowledge network with attention mechanism, as seen in Sect. 5.

2 Construction of Knowledge Graph

The diagnostic knowledge graph construction and application process includes specifying the domain ontology type of Hydro-Power Plant equipment troubleshooting, domain entity identification, relationship extraction, and Neo4j graph database construction based on Neo4j [8]. The specific construction process is as follows.

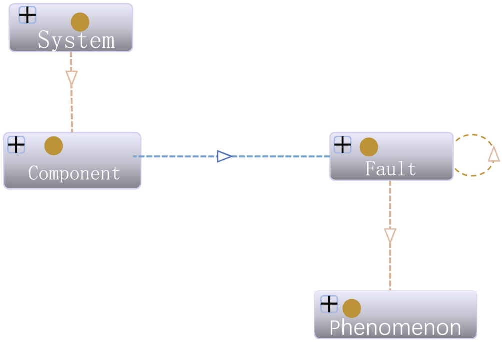

Fig. 1. The ontology LSTM with Attention Model

First, we define the ontology type through expert judgment and application requirements and determine the types of entities and relationships in the graph. Second, we label the dataset of Hydro-Power Plant fault diagnosis using the wizard annotation assistant software. Use Wizard annotation assistant software to annotate the dataset of the fault diagnosis part of the corpus, and train the fault domain entity recognition model. Use the training model to recognize the entities of the fault diagnosis corpus, and construct the entity set. Third, label the above dataset with relationships to train the fault domain relationship extraction model. Use the trained relationship extraction model to extract the relationships in the fault diagnosis corpus, and build a set of relationship pairs. The entity and relation of the knowledge network are listed in Table 1.

Table 1. Entity and Relation of the Knowledge Network

Domain	Objectproperty	Range
System	Consists_of	Component
Component	Occure	Fault
Fault	Cause	Phenominent
Fault	Cause	Fault

After completing the entity identification and relationship extraction, combine the entities and relationship pairs into a ternary. Then, import the ternary into the knowledge graph construction tool Neo4j to construct a knowledge graph for Hydro-Power Plant fault diagnosis.

3 Ontologies Construction

When constructing a domain-specific knowledge map, ontologies should be constructed based on experts' knowledge to provide specifications for entity recognition and relationship extraction. we focus on the field of Hydro-Power Plants, i.e., we construct a knowledge map of Hydro-Power Plants troubleshooting. Therefore, we construct an ontology based on the expert's empirical knowledge of Hydro-Power plant troubleshooting. In this paper, the Protege tool is used to design the ontology, and the visualization of the ontology is shown in Fig. 1.

3.1 BERT-BiLSTM-CRF Network

In this Subsection, we build the BERT-BiLSTM-CRF model by integrating BERT parameters according to the widely used BiLSTM network. The proposed model can dynamically adjust the information of words, and improve the recognition accuracy of synonymous polymorphic words. Figure 2 shows the BERT-BiLSTM-CRF model.

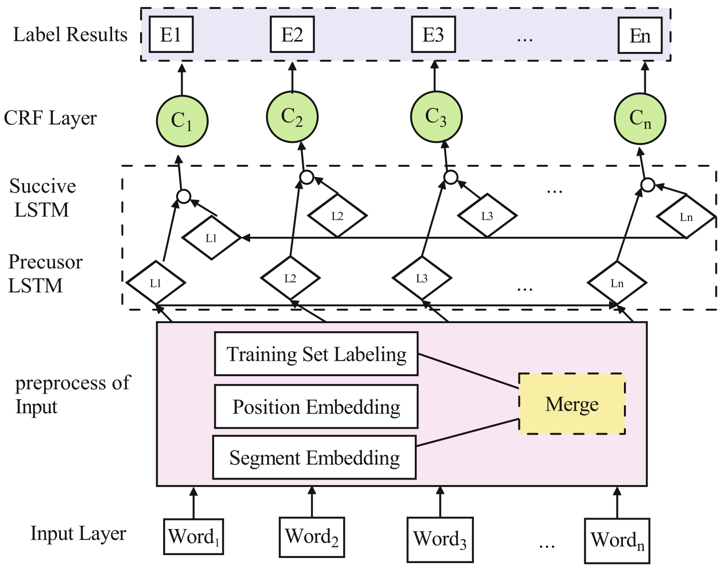

Fig. 2. The Bi-LSTM scheme with CRF

BERT Pre-training. The sentence is pre-trained by BERT to form the feature vector of each word, and the constructed vector sequence is input to the BiLSTM model for feature extraction. In addition, the semantic features are passed through the CRF layer to obtain the most probable label identifier, the BiLSTM layer.

BiLSTM. BiLSTM sets up forward and backward LSTM networks and the output layer results are determined by both the forward and backward LSTM networks. Among the LSTM networks, each LSTM computational module contains an input gate, a forgetting gate, and an output gate. The specific computational process is given by the following equations as

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \tag{1}$$

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \tag{2}$$

$$o_t = \sigma(w_0[h_{t-1}, x_t] + b_0) \tag{3}$$

$$\widetilde{c}_t = \tanh(w_c[h_{t-1}, x_t] + b_c) \tag{4}$$

$$c_t = f_t * c_{t-1} + i_t * \widetilde{c}_t \tag{5}$$

$$h_t = o_t * \tanh(c_t) \tag{6}$$

where i_t, f_t, and o_t represent the input gate, forget gate, and output gate outputs in the time slot t. Furthermore, x_t and h_t represent the input and output gates in the period t.

CRF Layer. Take its features and obtain the corresponding sequence vector. To ensure the accuracy of entity recognition, a layer of computational constraints is placed on the sequence vectors using the CRF layer to ensure the correspondence with the predefined labels. For sentence X, the predicting probability of the sequence $Y = (y_1, y_2, ..., y_n)$ is

$$P(X|Y) = \frac{e^{s(x,y)}}{\sum\limits_{y} e^{s(x,y)}} \tag{7}$$

$$s(X, Y) = \sum_{i=1}^{n} (P_{i,y_i} + W_{y_i,y_{i+1}}) \tag{8}$$

The output sequence of the BiLSTM layer is processed by the CRF layer. The CRF layer processes the output sequences of the BERT-BiLSTM layer, which can calculate the fit scores of subsequences and output labels, making the results of entity recognition more accurate.

3.2 Entity Recognize

In this paper, we select the case of hydropower plants in the past 20 years and the related literature on hydropower plant fault on the website as the corpus to be analyzed. Through text pre-processing, such as PDF text extraction, and sentence division to obtain the statements. The labeling rules of the data set are as follows. First, we classify the entities into four categories: system, component, fault, and fault signs, and learn the working principle of hydropower plants before labeling them. Second, the components contained in faults and fault signs are not labeled, and the labeling can only exist in one layer. Therefore, the fault diagnosis system pays more attention to faults and fault signs.

4 Relation Exaction

After obtaining the entity nodes, we analyze the relationship between the sentence and the entity pairs in the sentence. In this paper, we use the widely used BERT model as the base network and add a word attention layer into the network model to improve the accuracy of relationship extraction.

4.1 Word Attention with BERT

Figure 3 shows the structure of the Word-Attention-BERT, which includes the BERT coding layer, word attention layer, and relationship classification layer. Each word of the input sentence is converted into a token, and the token is input into the BERT encoding layer to obtain the vector representation of the sentence. In the relationship extraction process, the relationship between entities is determined by a certain word. Hence, the attention layer in the BERT relationship extraction network can emphasize the role of keywords and improve the accuracy of relationship extraction.

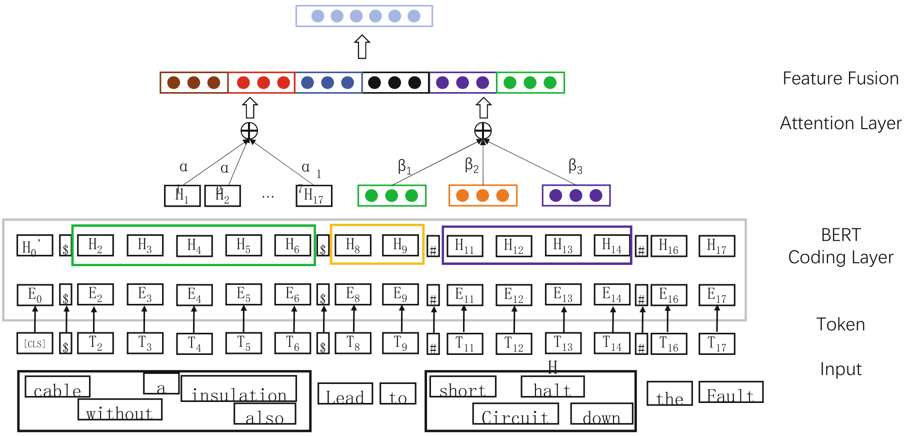

Fig. 3. The LSTM with Attention Model

BERT Coding Method. To enable the BERT model to obtain the position and boundary information of two entities in a sentence, "$" and "#" are used to mark the entities in the sentence. Sentence and entity are encoded in the BERT coding layer to obtain $H = \{H_0', H_1, H_0', H_0'\}$, where H_0' is the output corresponding to the token "[CLS]". As the semantic representation of the whole sentence with H_0', it is obtained by adding the tanh activation function to H_0' and undergoing a linear transformation. The entity information is obtained by calculating the average value of H_t contained in the entity, which is then transformed linearly by the tanh activation function. The word vectors are computed directly by calculating the average value of Ht contained in the words. The procedure is as follows.

$$H_0{}' = W_0\left(\tanh(H_0)\right) + b_0 \tag{9}$$

$$e_1 = W_1\left[\tanh\left(\frac{1}{\mathrm{j-i+1}}\sum_{t=i}^{j} H_t\right)\right] + b_1 \tag{10}$$

$$e_2 = W_2\left[\tanh\left(\frac{1}{\mathrm{m-k+1}}\sum_{t=k}^{m} H_t\right)\right] + b_2 \tag{11}$$

$$Word = \frac{1}{s-r+1}\sum_{t=s}^{s} H_t \tag{12}$$

where W_0, W_1, W_2 denote trainable weight matrices of dimension $d \times d$; b_0, b_1, b_2 denote trainable weight vectors of dimension $d \times 1$; and d denotes a trainable weight vector of dimension $d \times 1$; and b_0, b_1, b_2 denote the trainable weight vectors of dimension $d \times 1$; d denotes the word vector dimension; e_1 and e_2 denote the entities; i and j denote the weights of entity 1, respectively. k and m denote the start and end positions of entity 2; r and s denote the start and end positions of words. r and s denote the starting and ending positions of words. The word denotes the generalization of words in a sentence.

Attention Mechanism of Word. In the fault diagnosis field, words such as “due to”, “brought about”, “because of” often determine the relationship between entities, and thus the word attention layer is added in the fusion of sentence features to enhance the accuracy of the relationship extraction. Therefore, a word attention layer is added in the fusion of sentence features to enhance the keyword features to improve the accuracy of relationship extraction. The sentence is encoded as $H = \{H_0, H_1, ..., H_{n+4}\}$ in the BERT coding layer, and the keyword features are enhanced by using the word attention mechanism. Taking $H_1, ..., H_{n+4}$ as input, a two-layer neural network is used to obtain an importance vector α with a dimension of $1 \times (n + 4)$and a value range of $(0, 1)$. Similarly, an importance vector β is obtained on the word scale. Finally, the word vectors are weighted, and the weighted vectors are cascaded together to obtain the final word vector β after linear transformation and activation by the tanh activation function. Finally, the weighted vectors are cascaded and activated by the tanh activation function, and then linearly transformed to obtain the final sentence fusion feature representation. The calculation process is given by

$$\alpha = Softmax(q_c \tanh(Q_c H_c)) \tag{13}$$

$$\beta = Softmax(q_w \tanh(Q_w H_w)) \tag{14}$$

Relation Categorize. The input Softmax function for relationship classification to get the final result. The specific calculation process is given by

$$r = W_r \left[concat(H_0', e_1, e_2, h'', w'')\right] + b_r \tag{15}$$

$$outcome = Softmax(r) \tag{16}$$

where r denotes the fusion feature vector, W_r denotes the trainable weight matrix with dimension $L \times 5d$, b_r denotes the trainable weight vector with dimension $L \times 1$, and L denotes the number of relation types.

5 Experimental Result

To evaluate the proposed method, we have built a fault diagnosis method by using the knowledge graph. First, we design an algorithm for extracting historical fault cases and implement the build of the knowledge graph to diagnose the faults for Hydro-power plants. The Neo4j graph database is used for storing and managing the knowledge graph. Accuracy probability, recall rate, and F1 are adopted to evaluate the extractions.

The accuracy probability can be given by

$$P = \frac{T_P}{T_P + F_P}, \tag{17}$$

where T_P represents the character numbers manually labeled for a given label, and F_P is the character numbers labeled manually that were not extracted.

Second, the recall rate can be expressed as

$$T = \frac{T_P}{T_P + F_N}, \tag{18}$$

where F_N represents the character numbers extracted for a label rather than manually labeled.

Third, F1 can be calculated by

$$F1 = \frac{2 \times P \times R}{P + R}. \tag{19}$$

5.1 Entity Recognize Experiment

We adopt the BERT Chinese pre-training model released by Google, which contains 12 hidden layers, 768 hidden layer units, 12 encode layer headers, and 110M parameters, the maximum sequence length is set to 128, and the number of hidden units in LSTM is set to 200. The other settings are default. The experimental environment relies on the TensorFlow library. Then, we choose BERT and Word-Attention-BERT to compare with each other in terms of precision rate, recall

Table 2. Entity Recognize Results with Different Algorithms

Model	Accuracy	Recall rate	F1
BiLSTM	61	58	60
BiLSTM-CRF	76	54	65
Bert-BiLSTM	81	58	68
Bert-BiLSTM-CRF	86	65	75

rate, and F1 score in the domain of hydro-power plant fault diagnosis, and the specific results are shown in Table 2.

Table 2 shows that the BERT-BiLSTM-CRF model outperforms the other three models in terms of recognition accuracy. Moreover, the BERT Chinese word training to the BiLSTM-CRF model significantly improves the effectiveness of the entity recognition model for hydropower plant fault diagnosis.

5.2 Relation Recognize Experiment

The relationships between entities in hydro-power plant faults are defined into four categories: composition, occurrence, cause, and unknown. The data is divide into a training set and a test set in an 8:2 ratio., which are 11,885 and 2,971 items respectively. In the relationship extraction experiments, we also use the BERT pre-training model and fine-tune it for the relationship extraction task on this basis. The learning rate is set to 0.0005 and the maximum sequence length is 128. The specific results of relation recognition are shown in Table 3.

Table 3. The Recognition Results of Relations

Model	Accuracy	Recall rate	F1
BERT	84.54	79.25	86.19
Word-Attention-Bert	92.81	90	91

From Table 3, we can see that Word-Attention-BERT outperforms the ordinary BERT relational extraction model in terms of accuracy, recall, and F1 score. Moreover, we can observe that the Word-Attention-BERT can better utilize the key information in the sentence to improve recognition accuracy.

5.3 Fault Diagnosis for Different Types

Figure 4 shows the accuracy of fault extraction for different fault types.

From Fig. 4, the proposed method incorporates relationships between device structures into diagnostic reasoning by leveraging the knowledge map. First, the proposed method achieves an accuracy of around 90.6% by effectively utilizing device structure relationships. Second, we can observe that fault recognition outperforms fault location and status detection due to random position descriptions leading to lower detection accuracy.

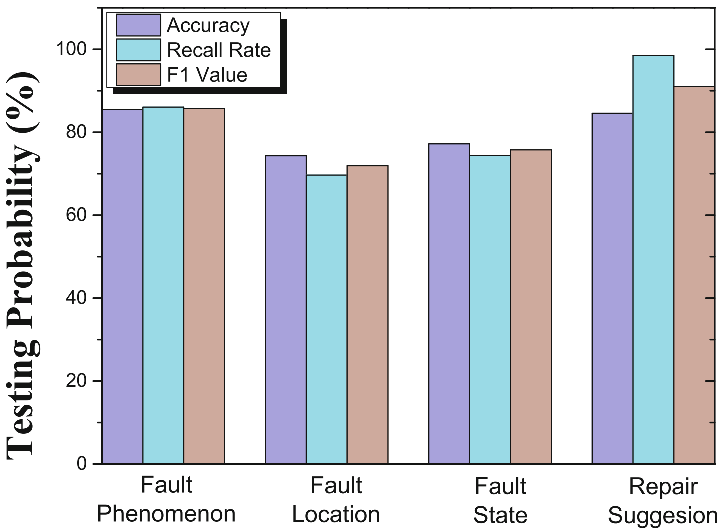

Fig. 4. The comparison of the optimal trajectory with the initial trajectory of the UAV.

6 Conclusions

To solve the problem of fast and accurate fault diagnosis for hydropower plants, we have proposed a knowledge-based knowledge graph to diagnose faults that occur in hydropower plants. We have designed a BiLSTM aided by the CRF algorithm to automatically recognize the entities and the BERT-BiLSTM is used to extract the relationship between the entities in hydropower plants. Experimental results validate the performance of the proposed method. In the future, we can focus on the construction of large-scale corpus data in the hydropower plants fault domain to improve the model.

Acknowledgement. This work is supported by the science project of State Grid Xin Yuan Company Limited (No. SGXYKJ-2023-012).

References

1. Buaphan, I., Premrudeepreechacharn, S.: Development of expert system for fault diagnosis of an 8-mw bulb turbine downstream irrigation hydro power plant. In: 2017 6th International Youth Conference on Energy (IYCE), pp. 1–6 (2017)

2. Chi, Y., Dong, Y., Wang, J.: Knowledge-based fault diagnosis in industrial internet of things: a survey. IEEE Internet Things J. **93**(2), 107–118 (2022)
3. Deng, J., Wang, T., Wang, Z., Zhou, J., Cheng, L.: Research on event logic knowledge graph construction method of robot transmission system fault diagnosis. IEEE Access **10**, 17656–17673 (2022)
4. Gou, B., Xu, Y., Xia, Y.: An intelligent time-adaptive data-driven method for sensor fault diagnosis in induction motor drive system. IEEE Trans. Industr. Electron. **66**(12), 9817–9827 (2018)
5. Jiang, J.: Reliability test and analysis of electrical automation control equipment. Appl. Mech. Mater. 2380–2383 (2014)
6. Lemes, D.A.M., et al.: Low runtime approach for fault detection for refrigeration systems in smart homes using wavelet transform. IEEE Trans. Consum. Electron. 1–1 (2023). https://doi.org/10.1109/TCE.2023.3328147
7. Nor, N.M., Hussain, C.: A review of data-driven fault detection and diagnosis methods: applications in chemical process systems. Rev. Chem. Eng. **36**(4), 513–553 (2020)
8. Qu, X., Cai, Y.: Conve-bio: knowledge graph embedding for biomedical relation prediction. In: 2023 International Conference on Intelligent Supercomputing and BioPharma (ISBP), pp. 10–13 (2023). https://doi.org/10.1109/ISBP57705.2023.10061292
9. Scharpf, P., Schubotz, M., Gipp, B.: Mining mathematical documents for question answering via unsupervised formula labeling. In: 2022 ACM/IEEE Joint Conference on Digital Libraries (JCDL), pp. 1–11 (2022)
10. Sousa, D., Couto, F.: Biomedical relation extraction with knowledge graph-based recommendations. IEEE J. Biomed. Health Inform. **26**(8), 4207–4217 (2022)
11. Wu, J., et al.: Fault diagnosis of the HVDC system based on the catboost algorithm using knowledge graphs. Front. Energy Res. **11** (2023)
12. Yuan, L., Qin, L., Zhang, W., Chang, L., Yang, J.: Index-based densest clique percolation community search in networks. IEEE Trans. Knowl. Data Eng. **30**(5), 922–935 (2018)
13. Zhang, Z., et al.: Knowledge graph construction method for power grid infrastructure. In: 2022 7th Asia Conference on Power and Electrical Engineering (ACPEE), pp. 633–637 (2022). https://doi.org/10.1109/ACPEE53904.2022.9783665