Question Answering Algorithm for Grid Fault Diagnosis based on Graph Neural Network

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***Abstract*—Due to the existence of uncertain factors such as the power grid system itself, natural climate change and human factors, various faults will still occur in the power grid system. If the fault alarm is not responded to in time, it is likely to cause grid instability or even collapse, resulting in inestimable losses. By building a knowledge graph for massive power grid operation and maintenance information, we can achieve fast and accurate fault information reasoning and traceability, and retrieve reasonable fault resolution measures. Use artificial intelligence technology and big data to assist power grid systems to achieve more efficient operation and maintenance. Realizing the intelligent fault diagnosis of power grid is an urgent problem to be solved at present. With the rapid development and application of artificial intelligence technology, if artificial intelligence and big data technology can be applied to the fault diagnosis and analysis of power grids, this situation of relying on manual analysis will be broken, and the efficient processing of massive operation and maintenance data will be realized.**

Keywords*—*Power grid system; Fault diagnosis; Graph neural network amplifiers

I. Introduction

With the rapid development of the national economy, the demand for electric energy is becoming more and more vigorous. The reliability and stability of the power system operation are very important to the national economy and people's production and life. At present, the scale of my country's power system continues to expand and the structure is increasingly complex, which also means that the probability of actual failures in the power grid continues to increase. Although the construction of power grid systems at home and abroad continues to advance, due to the existence of uncertain factors such as the power grid system itself, natural climate change and human factors, various faults will still occur in the power grid system. If the fault alarm is not responded to in time, it is likely to cause grid instability or even collapse, resulting in inestimable losses. For example, the blackouts in the U.S. and Canada power systems in 2003, and the blizzard disaster in southern China in 2008 all caused widespread power system failures, all of which seriously affected industrial development and national life. However, the causes of power grid failures are very complex, not only the influence of human factors, but also the influence of natural environment, unknown factors, and emergencies, and even some of these factors are difficult to prevent and unavoidable. Relying on the State Grid "Cloud Data Center Intelligent Operation and Maintenance Knowledge Construction and Decision-making Technology Research and Application" project, this topic can achieve fast and accurate fault information reasoning and traceability, and retrieve reasonable fault solutions by building a knowledge map of massive power grid operation and maintenance information. measure. Use artificial intelligence technology and big data to assist power grid systems to achieve more efficient operation and maintenance.

In recent years, most of my country's medium-sized power grids have realized real-time monitoring and information collection of power grid faults [1]. However, the current power grid fault diagnosis technology is far from enough at the intelligent level, and some advanced power grid systems only realize the remote unattended mode. If a fault occurs during operation, manual assistance is still required. Because the power grid is extremely complex, usually when a fault occurs[2], there are various types of fault signals. Fault analysts and maintenance engineers often need to retrieve a large number of maintenance manuals, spend a lot of time processing textual information, reasoning about the principles of power grid lines and equipment, and determining the cause and location of the fault. It is difficult to diagnose the fault accurately and efficiently. State Grid Corporation of my country has put forward the development plan of "smart grid" according to China's national conditions[3]. "Intelligence" is the top priority, and the realization of intelligent fault diagnosis of the power grid is an urgent problem to be solved at present. With the rapid development and application of artificial intelligence technology, if artificial intelligence and big data technology can be applied to the fault diagnosis and analysis of power grids, this situation of relying on manual analysis will be broken[4], and the efficient processing of massive operation and maintenance data will be realized[5].

II. Related works

Knowledge Graph (KG) is a large-scale semantic network based on big data[6]. It originated in the middle of the twentieth century and developed from knowledge engineering and the semantic web. In 1995, Swanson proposed to build a document map based on document citation relationships. Use citation index to achieve literature search. Since then, Feigenbaum proposed knowledge engineering in 1997, and established an expert system based on expert knowledge and reasoning ability[7]. In 1998, Tim Berners Lee proposed a semantic network[8], which uses nodes and edges to describe

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the relationship between resources and data in the World Wide Web, and proposes a knowledge representation method that can be understood and processed. Until 2012, the concept of knowledge graph was proposed by Google[9], and a semantic-based search engine was established, which truly announced that knowledge engineering has entered the era of big data.

The history of knowledge graphs can be traced back to the early days of expert systems. The early knowledge graph is realized by manual editing by experts, that is, the knowledge base part in the expert system, which has high knowledge accuracy. Since 1989, the emergence of the World Wide Web has brought a new revolution[10] to the acquisition and organization of knowledge. Extracting knowledge information and building relationships from open Internet resources has become a new direction for knowledge graphs. Open resources have greatly promoted the development of general knowledge graphs[11]. Such knowledge graphs generally emphasize the breadth of knowledge, but are not suitable for professional fields that require high knowledge accuracy[12]. In recent years, with the advancement of intelligence in various industries, the deep integration of knowledge graphs with various fields and industries has become mainstream[13]. Therefore, for the field of power grid failure, the general knowledge graph is far from meeting the needs of the professional field, so the domain knowledge graph came into being. The construction of this type of knowledge graph requires the guidance of a professional ontology model layer to ensure that the organizational form of knowledge meets industry requirements.

Power grid fault diagnosis began in the 1940s. It refers to the analysis of massive fault information, including alarm information of protection devices, circuit breaker action information, and electrical quantity information, to determine the location and type of faults, so as to guide operation and maintenance personnel to analyze the power grid. fault for repair. Before the power grid fault occurs, the power grid is in a stable operation state. When the power grid fails, the first change is the electrical quantity information such as voltage and current, and then the relay protection device performs protection actions according to the state of the electrical quantity, and sends a trip signal to the circuit breaker. The circuit breaker trips the circuit breaker so that the faulty element can be disconnected from the grid, thereby protecting the grid from greater losses. To sum up, after a grid fault occurs, the main changes are the two types of information, electrical quantity and switching quantity. Therefore, most power grid fault diagnosis solutions are to collect these two types of fault symptom information, analyze and judge the two types of information, so as to determine the fault. Type and location of failure. Nowadays, with the rapid development of deep learning, there have been many excellent results. Based on these new results, deep learning can be applied to more places. The deep neural network has strong learning ability, can automatically extract abstract features of data, and has strong feature robustness. Therefore, this topic weighs the advantages and disadvantages of each algorithm, and uses the deep learning method to realize accurate and efficient knowledge reasoning of power grid fault operation and maintenance, and establish a solid foundation for power grid fault diagnosis.

A knowledge graph is a multi-relational graph that contains millions of entities, and the relationships that connect the entities. Question Answering over Knowledge Graph (KGQA) is a research field that uses knowledge graph information for reasoning. Given a natural language question and a knowledge graph, KGQA tries to give the correct answer by analyzing the information contained in the question and KG[14]. This topic uses the constructed power grid fault knowledge graph to conduct knowledge reasoning and search question and answer, aiming to trace the source of the fault in time after the fault occurs and complete the fault troubleshooting.

III. Method

From the perspective of the modeling method of knowledge graph question answering, there are mainly two categories: template and semantic retrieval (Semantic Parsing and Information Retrieval). The template approach is more traditional and aims to parse a question into an executable graph database query statement (such as SPARQL), and then execute that statement to find the answer. For the semantic retrieval method of Simple QA, the aim is to parse the question into a head entity and a relation, where is the question indicator, and then obtain the question answer through the query entity. For the semantic retrieval method of Complex QA, Microsoft Research defines a query graph (Query Graph) [15], which directly maps complex questions into a searchable logical form. The semantic retrieval problem is reduced to a query graph generation and staged search problem, narrowing the search space of the knowledge base. Another idea of the semantic retrieval method is to extract their semantic features from questions and candidate answers, and design a corresponding scoring function based on these features to measure the semantic relevance of the ”question-candidate answer”, and finally the candidate with the highest score The answer is output as the predicted answer. The Amazon Web Services team proposed a unified deep learning architecture and end-to-end variational learning algorithm [16] to achieve noise processing and multi-hop inference in complex problems.

Design a reasoning neural network model that can be used for complex question answering in the field of power grid fault diagnosis. In order to avoid the error layer-by-layer transmission of problem entity recognition and entity linking technology, an end-to-end graph neural network is used for training and reasoning. The two modules of subject entity recognition and knowledge reasoning are integrated in an end-to-end manner, so that the loss in the training process will be directly fed back to the subject entity recognition module, which helps to more accurately identify the correct subject entity in a noisy environment . After the knowledge inference process generates the answer candidates of the question, then based on the knowledge graph context where the answer candidates are located, the vector representation corresponding to the answer candidates is generated, and the correlation

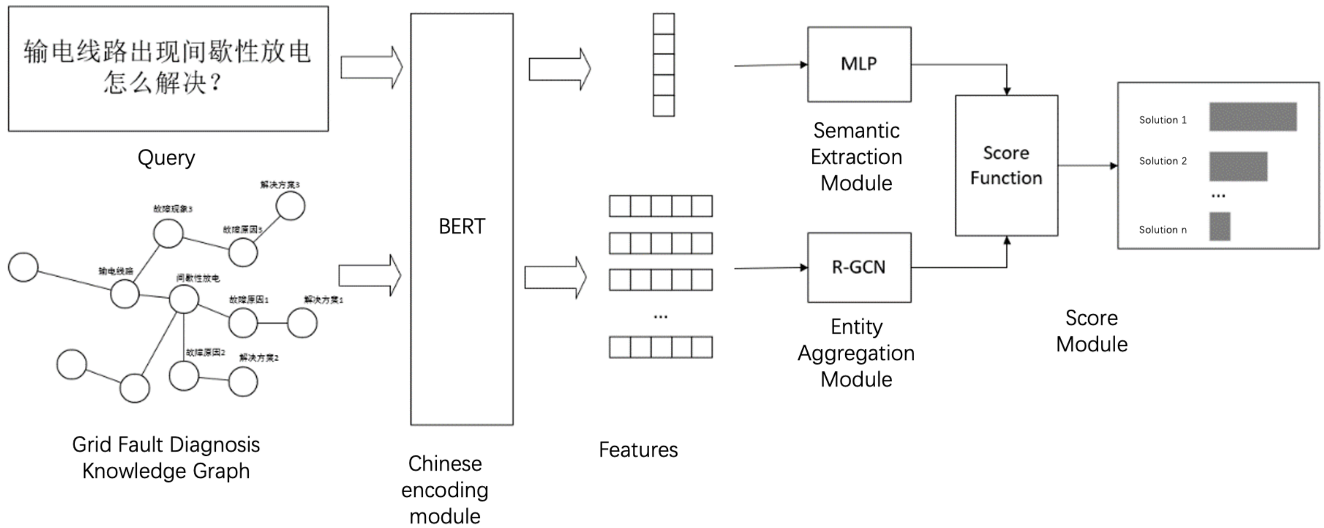

Figure 1. Model structure

between the input question and the answer candidates is calculated. Finally, the different answer candidates are scored, and the answer candidate with the highest score is returned as the result of the power grid fault diagnosis reasoning question and answer.

As a form of knowledge storage, one of the most important drawbacks of knowledge graphs is that they are usually incomplete, which poses a higher challenge for reasoning question answering. Question answering reasoning requires a long path, and the absence of any triples along the path will result in the true answer not being searchable. Therefore, it is helpful to predict the missing links in the knowledge graph in some way to improve the performance of question answering reasoning. Graph neural network (GNN) transmits messages by aggregating the neighbor entities of each entity in the knowledge graph, and is currently the mainstream method of knowledge graph reasoning based on deep learning. The method based on graph neural network has stronger expressive power when processing knowledge graph data, and can fully consider the relevant entities and relationship information of the target entity in the problem in the graph. This topic proposes a graph neural network architecture suitable for the power grid field. Realize accurate multi-hop reasoning of knowledge graph.

A. *Grid fault reasoning question and answer*

In knowledge graph question answering, the primary goal of question understanding is to identify the topic entity in the question, which is also the starting point of reasoning in the subsequent reasoning process [17]. Some previous works have used text matching to identify topic entities, but this approach is susceptible to noise (natural language ambiguity and typos) in practical application scenarios [18]. In these cases, if we divide the knowledge graph question answering into two independent stages: topic entity recognition and knowledge reasoning, the errors generated in the topic entity recognition stage are often passed on to the knowledge reasoning stage, so that the final Predictions have serious consequences.

However, knowledge graphs in real application scenarios often have the problem of missing links [19], that is, some correct triples are not included in the knowledge graph. And these missing triples may be critical to answering a given question accurately. This topic mainly studies the reasoning algorithm in the real scene of knowledge graph link missing (incomplete) and link prediction. In the knowledge graph reasoning task, the relational graph convolutional neural network model is used to convolve each dimension in the triplet to obtain the global embedding property, and can effectively avoid overfitting in the model training.

The knowledge graph reasoning question answering method proposed in this subject consists of four modules: Chinese encoding module, entity aggregation module, semantic extraction module, and scoring module. The overall structure is shown in Figure.

B. *Chinese encoding module*

The Chinese encoding module performs two tasks: 1. Extract the Chinese text encoding of question sentences and knowledge graph nodes, and train word vectors and sentence vectors through BERT. The Chinese text is mapped to the same semantic feature space to realize the quantification of the Chinese text, which is convenient for subsequent processing. 2. Extract the head entity in the question sentence (simple entity extraction task), and then associate the head entity with an entity node in the knowledge graph.

The BERT model is an NLP pre-training technique [20], an important role of which is to generate word vectors, which can solve the word polysemy problem that cannot be solved in word2vec. When BERT calculates the Chinese vector, it can directly input the entire sentence without advance word segmentation. Because in Chinese-BERT, the corpus is processed in word units, so the output is a word vector for the Chinese corpus. The BERT structure is shown in Figure.

C. Entity Aggregation Module

The entity aggregation module aggregates the information of the knowledge graph nodes, so that the expression vector of each entity is integrated into the information of the surrounding nodes, which is convenient for subsequent multi-hop reasoning. The knowledge graph aggregates node features through a Relational Graph Convolutional Network (R-GCN) model [21], and nodes express predictable and implicit links between vectors. In this topic, the implicit link between prediction nodes is equivalent to predicting the relationship mentioned in the question between the question node and the answer node, so the link prediction task is equivalent to the knowledge reasoning question answering task

The R-GCN model originated from the graph convolutional neural network GCN (Graph Convolutional Network, GCN). GCN can be viewed as a special case of a simple and differentiable messaging framework:

$$h_i^{l+1} = \sigma\left(\sum_{m \in M_i} g_m\left(h_i^l, h_j^l\right)\right) \tag{1}$$

Among them, h_i^l represents the node of the hidden layer l, $g_m(\cdot)$ represents the incoming message, $\sigma(\cdot)$ represents the activation function. More specific representation:

$$g_m\left(h_i, h_i\right) = W h_j \tag{2}$$

Equation 10 is the classical expression of GCN [22]. Based on Equation 2, define a forward propagation model:

$$h_i^{l+1} = \sigma\left(\sum_{r \in R} \sum_{m \in N_i^l} \frac{1}{c_{i,r}} W_r^l h_j^l + W_0^l h_i^l\right) \tag{3}$$

Among them, N_i' represents the set of neighbor nodes of node i under relation r, and $c_{i,r}$ is a standardized constant, which can be specified or learned. It can be seen from formula that the node features of each layer of R-GCN are obtained from the relationship (edge) between the node features and nodes of the previous layer; Features; R-GCN will consider self-loops in order to preserve the information of the node itself. The difference from GCN is that R-GCN considers edge type and orientation [23]. R-GCN utilizes sparse matrix multiplication to efficiently implement forward propagation, while to avoid explicit summation of neighborhoods, multiple layers can be stacked to achieve dependencies across multiple relational steps.

D. Semantic Extraction Module

The semantic extraction module extracts the semantic information of the question sentence, and processes the sentence vector extracted by BERT through the full connection layer and the ReLu activation function in turn, in order to unify the expression vector dimension of the knowledge graph node. The structure of the grid fault question and answer dataset to be constructed is described here.

Question is the original sentence of the question. Path is the triple path of the reasoning process. In this question, the fault tracing idea is fault location - fault phenomenon - fault mode - solution. $Head_text$ and $Head_id$ represent the text content of the head entity in the question and the index value in the knowledge graph. The difference from the head entity extracted by BERT in the first part is that the head entity here is a labeled label, and this label is used to train the classifier. Perform the extraction of the first part of the head entity. $answer_text$ and $answer_id$ represent the text content of the answer entity in the question and the index value in the knowledge graph. The semantic extraction module processes the content of the sentence in the question and extracts the semantic vector in the natural language sentence.

E. Scoring module

A knowledge graph is usually a directed and labeled graph $G = (V, E, R)$, where V represents nodes, E represents edges, and R represents relationships. Usually E is incomplete. The goal of this project is to realize the reasoning question answering of the knowledge graph by predicting the missing edge between the question entity and the answer entity. Just inferential question answering models the question as a triple (head, query, answer), where query e_q is the sentence vector of the natural language question after the BERT model, head e_h is the question header entity extracted in the first part, and answer e_a is the answer Entity set, this topic sets the answer entity set to contain all entities of the knowledge graph. A scoring function $f = (s, r, o)$ is used to determine whether the requirements (s, r, o) are met. The scoring function f is to be implemented using DistMult decomposition [24], each question q is related to a diagonal matrix, and formula 12 is the score calculation formula:

$$f(h, q, a) = e_h^T R_q e_a \tag{4}$$

It is intended that among all the answer candidates, the answer candidate with the highest score by the scoring function is judged as the answer (positive example), and the rest are negative examples. When training the entire model, use binary cross entropy for optimization.

$$loss = -\frac{1}{N} \sum_{i=1}^{N} y_i \cdot \log(p(y_i)) + (1 - y_i) \cdot \log(1 - p(y_i)) \tag{5}$$

Among them, N is the number of all entities in the knowledge graph, yi is the label of the ith answer candidate, when yi is the answer to the question, yi=1, otherwise yi=0. p(y) represents the probability that the answer candidate belongs to a positive example, that is, the score of the answer candidate.

In the overall evaluation of the model, the MRR and HITS@1 evaluation indicators are used. The full name of

MRR is Mean Reciprocal Ranking.

$$MRR = \frac{1}{|S|}\sum_{i=1}^{|S|}\frac{1}{rank_i} \tag{6}$$

$$\sum_{i=1}^{|S|}\frac{1}{rank_i} = \frac{1}{rank_1} + \frac{1}{rank_2} + \cdots + \frac{1}{rank_{|S|}} \tag{7}$$

Where $|S|$ is the number of triples sets, and $rank_i$ refers to the link prediction ranking of the i-th triplet. The larger the index, the better. HITS@1 refers to the average proportion of triples that rank less than 1 in link prediction. The specific calculation method is as follows:

$$HITS@1 = \frac{1}{|S|}\sum_{i=1}^{|S|} I(rank_i \leq 1) \tag{8}$$

Among them, the function I is an indicator function. If the condition is true, the function value is 1, otherwise it is 0. The larger the indicator, the better.

IV. Conclusion

Fault diagnosis based on knowledge graph requires inference with the help of the already constructed knowledge graph, which requires us to build a knowledge graph that meets the inference requirements. In terms of knowledge graph construction, in addition to the extraction of required entities and relationships, the difference between domain knowledge graphs and general knowledge graphs should also be considered. When building a domain knowledge map, it is necessary to extract features and design algorithms according to the characteristics of the domain. In the field of power grid fault diagnosis, such as relative words such as ”occur” and ”cause”, and professional terms such as ”transmission line” and ”transformer” occur frequently. In addition, the domain knowledge graph also involves the problem of insufficient labeled data.

The key of knowledge graph reasoning question answering technology lies in accurate question understanding and designing appropriate reasoning algorithm for the corresponding data source. From the perspective of problem understanding, the difficulty of multi-hop question answering on knowledge graphs lies in how to accurately identify entities and relationships in the question. Most question descriptions are highly colloquial, and it is difficult to perform domain template matching. How to reduce natural language and normalize structured data gap between. From the point of view of reasoning algorithm, the main difficulty lies in: computing the correlation between the input question and the answer entity candidate is the core task. Using the ¡question, answer¿ paired dataset to directly train this type of question answering model can achieve good results on existing datasets. With the rapid development of deep learning today, most KGQA methods use neural networks for model training. How to add a multi-hop reasoning mechanism to the model and how to combine the deep learning model with linguistic knowledge are the problems that need to be solved at present.

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References

[1] Liang C, Tong X. Research on power grid fault diagnosis based on artificial fish swarm algorithm[C]//2017 2nd International Conference on Power and Renewable Energy (ICPRE). IEEE, 2017: 1047-1051.

[2] Zhong Q, Tang Y. An Attention-Based BILSTM-CRF for Chinese Named Entity Recognition[C]//2020 IEEE 5th International Conference on Cloud Computing and Big Data Analytics(ICCCBDA). IEEE, 2020.

[3] Li Fulin, Song Yuanbin, Shan Yongwei. Joint Extraction of Multiple Relations and Entities from Building Code Clauses[J]. Applied Sciences,2020,10(20).

[4] Zheng S, F Wang, Bao H, et al. Joint Extraction of Entities and Relations Based on a Novel Tagging Scheme[J]. Association for Computational Linguistics.2017.

[5] Giannis B, Johannes D, Thomas D, et al. Joint entity recognition and relation extraction as a multi-head selection problem[J]. Expert Systems with Application, 2018, 114(DEC.):34-45.

[6] Xiao C, Dymetman M, Gardent C, et al. Symbolic priors for RNN-based semantic parsing[C]//International Joint Conference on Artificial Intelligence, 2017:4186-4192

[7] Chen Y, Wu L, Zaki M J, et al. Bidirectional attentive memory networks for question answering over knowledge bases[J].arXiv:2019:1903.02188.

[8] Devlin J, Chang M W, Lee K, et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding[J]. arXiv preprint arXiv:2018:1810.04805.

[9] Bauer L, Wang Y, Bansal M. Commonsense for Generative Multi-Hop Question Answering Tasks[J]. arXiv, 2018.

[10] Peters M, Ammar W, Bhagavatula C, et al. Semi-supervised sequence tagging with bidirectional language models[J]. Association for Computational Linguistics, 2017.

[11] Vaswani A , Shazeer N, Parmar N, et al. Attention Is All You Need[J]. arXiv, 2017.

[12] Das R, Zaheer M, Reddy S, et al. Question answering on knowledge bases and text using universal schema and memory networks[J]. arXiv preprint arXiv:1704.08384, 2017.

[13] Hao Y, Zhang Y, Liu K, et al. An end-to-end model for question answering over knowledge base with cross-attention combining global knowledge[C]// Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2017: 221-231.

[14] Chen Yu, Wu Lingfei, et al. Bidirectional Attentive Memory Networks for Question Answering over Knowledge Bases[C]// Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers). 2019: 2913-2923.

[15] Yih S W, Chang M W, He X, et al. Semantic parsing via staged query graph generation: Question answering with knowledge base[C]//Proceedings of the Joint Conference of the 53rd Annual Meeting of the ACL and the 7th International Joint Conference on Natural Language Processing of the AFNLP. 2015.

[16] Zhang Y, Dai H, Kozareva Z, et al. Variational reasoning for question answering with knowledge graph[C]//Thirty-second AAAI conference on artificial intelligence. 2018.

[17] Karlinsky L, Shtok J, Harary S, et al. Repmet: Representative-based metric learning for classification and few-shot object detection[C]//Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2019: 5197-5206.

[18] Haj-Yahia Z, Sieg A, Deleris L A. Towards unsupervised text classification leveraging experts and word embeddings[C]//Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. 2019: 371-379.

[19] Vaswani A, Shazeer N, Parmar N, et al. Attention is all you need[J]. Advances in neural information processing systems, 2017, 30.

[20] Sarzynska-Wawer J, Wawer A, Pawlak A, et al. Detecting formal thought disorder by deep contextualized word representations[J]. Psychiatry Research, 2021, 304: 114135.

[21] Malkov Y A, Yashunin D A. Efficient and robust approximate nearest neighbor search using hierarchical navigable small world graphs[J]. IEEE transactions on pattern analysis and machine intelligence, 2018, 42(4): 824-836.

[22] Lei K, Deng Y, Zhang B, et al. Open domain question answering with character-level deep learning models[C]//2017 10th International Symposium on Computational Intelligence and Design (ISCID). IEEE, 2017, 2: 30-33.
[23] Zhou B, Sun C, Lin L, et al. LSTM based question answering for large scale knowledge base[J]. Beijing Da Xue Xue Bao, 2018, 54(2): 286-292.
[24] Sarzynska-Wawer J, Wawer A, Pawlak A, et al. Detecting formal thought disorder by deep contextualized word representations[J]. Psychiatry Research, 2021, 304: 114135.
[25] FERREIRA V H, ZANGHI, FORTES M Z, et al. A survey on intelligent system application to fault diagnosis in electric power System transmission lines[J]. Electric Power System Research,2016, 136: 135-153.
[26] Xuechen J, Dazhi W, Yi N, et al. Query method for optimal diagnosis of power system faults [J]. High Voltage Engineering, 2017, 43(4): 1311-1316.
[27] Xiong X, SHI D, ZHU L, et al. Fuzzy cellular fault diagnosis of power grids based on radial basis function neural network[J]. Automation of Electric Power Systems, 2014, 38(5): 59-65.
[28] Wei XIA, ZHANG L, Qiushi Y. Improved extreme learning machine applied in power system fault diagnosis[J]. Power Systemand CleanEnergy, 2015, 31(4): 15G19.
[29] Zhang Y, Chung C Y, Wen F, et al. An analytic model for fault diagnosis in power systems utilizing redundancy and temporal information of alarm messages[J]. IEEE Transactions on Power Systems, 2016, 31(6): 4877-4886.
[30] Dong M, Zhang Y, Zhang Y, et al. An analytic model for power system fault diagnosis employing electrical data[J]. Dianli Xitong Zidonghua (Automation of Electric Power Systems), 2013, 37(6): 55-62.
[31] Fellbaum C. WordNet: An Electronic Lexical Database[J]. Cambridge: MIT Press,1998. Pal A R, Saha D. Word sense disambiguation: a survey[J]. International Journal of Control Theory and Computer Modeling, 2015, 5(3).
[32] Niu X, Sun X, Wang H, et al. Zhishi. me-weaving chinese linking open data[J]. The Semantic Web–ISWC,2011:205–220.