

Research on Knowledge Graph Construction and Intelligent Assisted Decision-Making of Power Grid Dispatching

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ABSTRACT

In view of the complex knowledge of power grid dispatching and the high real-time performance of dispatching decision, a study on the construction of power grid dispatching knowledge graph and intelligent assisted decision-making were proposed. Firstly, a BERT-BiLSTM entity recognition model is proposed to identify the data such as power grid dispatching procedures, fault plans and business processes. Then, a top-down ontology construction model for power grid dispatching is proposed to assist the construction of the knowledge graph for power grid dispatching. Finally, based on the knowledge graph of power grid dispatching, the intelligent assisted decision-making of power grid dispatching is realized. The validity and rationality of the model have been verified through actual operation data of power grid dispatching, and the assisted decision-making system can realize the rapid data processing and decision support.

Keywords: Power grid dispatching; Knowledge graph; BERT-BiLSTM; Data mining

1. INTRODUCTION

With the continuous development of the Internet of Things in power, big data in power has ushered in new opportunities [1]. Power grid dispatching is an effective management method used to make all kinds of power production work orderly, ensure the safe and stable operation of the power grid internally, and provide reliable power supply externally. The existing power grid dispatching system focuses on power system data acquisition, system monitoring, security verification, etc., but it is difficult to process natural language-based dispatching data information [2]. The dispatching system needs to convert the unstructured power grid dispatching data into data that can be recognized by the computer, and visualize the data to help the staff to quickly and comprehensively trace the fault causes and make auxiliary decisions when the power grid dispatching fault is handled, so as to improve the stability of the power system. In this context, it is necessary for power grid dispatching personnel to be familiar with field equipment and power regulations, and to repeatedly consult and memorize a large amount of non-(semi-) structured text information. Therefore, targeted and efficient natural language understanding technology should be studied to realize semantic analysis of scheduling text [3, 4].

Knowledge graph is a knowledge representation method, which is a visual mesh representation of entities and their interrelationships using triplets as a representation form [5, 6]. Power equipment, fault handling, business process and grid structure in power grid dispatching can be represented by graph structure, and power grid dispatching needs to integrate and analyze a large amount of data. By combining the natural language parsing technology of power text with knowledge graph technology, unstructured data in power knowledge can be integrated into the knowledge graph, which can reduce mistaken operations in intelligent decision support, optimize disposal strategies, and improve work efficiency [7].

At present, knowledge graph technology is still in the initial exploration stage in the power sector, and there is no research on knowledge graph in the field of power grid dispatching [8]. Literature [9] proposed the "neighborhood knowledge" model of power grid dispatching and the fine operation rule method of online discovery, but the content of knowledge graph is limited to the cross-section and its quantitative relationship. Literature [10] proposed the construction method of "one power grid diagram" to achieve comprehensive integration of power grid data, but did not consider the correlation with business scenario knowledge. Literature [11, 12] integrates existing power grid multi-

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source data to build power equipment knowledge graph and realize intelligent search and visualization, mainly focusing on integrated equipment management in the case of non-power grid faults. Literature [13] integrated the graph computing platform and proposed the integration method of power grid multi-source information system, which greatly improved the analysis level of complex systems on the power grid side, but ignored the improvement of the business knowledge level of regulators and the man-machine interaction of scenes. In terms of assisted decision-making for power grid dispatching, literature [14] aims to construct a knowledge graph for the basic platform of the dispatch system, assisting operation and maintenance personnel in completing business fault analysis of the dispatch automation system. It mainly focuses on the problem of automation operating system faults and does not involve power system faults. In general, the current research work mainly focuses on conceptual frameworks and has few specific implementation applications; Most of them are limited to partial map construction and single function implementation, and comprehensive scenarios are not considered insufficiently; Convenient human-computer interaction is missing, algorithm ignores the leading role of regulators.

Although knowledge graphs have been rapidly developed and applied in the field of electricity, research on the construction and intelligent assistance of knowledge graphs for power grid dispatch has not yet been conducted in depth. Therefore, this paper takes power grid dispatch data as the research object and designs and constructs a domain knowledge graph framework. Firstly, the BERT-BiLSTM-CRF model is proposed for entity recognition of power grid dispatching data. Then, a top-down ontology construction method is proposed to assist the construction of power dispatching group knowledge graph, and the visualization of power grid dispatching data is realized by using Neo4j graph database. Finally, the intelligent auxiliary decision-making is realized on the basis of power dispatching knowledge graph.

2. ANALYSIS OF CHARACTERISTICS OF POWER GRID DISPATCHING DATA

The power grid dispatching service needs to process a large amount of text information, such as power outage plans, operation tickets, work tickets, and fault alarm messages. The syntactic characteristics of these texts are similar, and this paper takes the more complex text of power outage and power transmission as an example to study computer natural language understanding algorithms. The structure of power grid dispatching data is shown in Figure. 1, which generally includes the name of applicant, application number, work location, work content, work time, job application unit, etc. Among them, the work content and opinions are generally written in natural language, containing a large number of professional electricity vocabulary, which is difficult for computers to accurately identify.

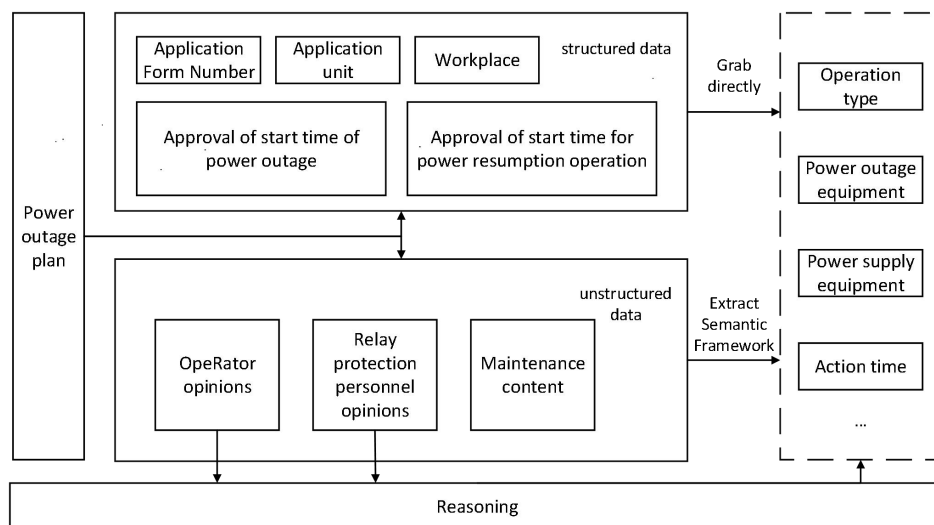


Figure 1. Data structure diagram of power dispatching.

The characteristics of power grid dispatching data are as follows:

(1) A large amount of dispatching data is saved on the power grid dispatching platform, but as training samples, there is a lack of label information that makes it difficult to directly apply machine learning algorithms such as deep learning.

(2) There are various types of dispatching operations, and their understanding requires professional knowledge of electricity power, lacking conventional and available resource and syntax knowledge bases.

(3) The description of operation objects is complex and there exist numerous types. They are often defined by multiple nouns such as power station, voltage level, equipment type, and number, and some elements are often omitted in actual expression, resulting in subject detachment, which requires to be understood in combination with multi-level context. Figure. 2 is a simplified version of TPOP content. There exist a lot of terms such as "110kV Secondary Line of Secondary Street" and "Automatic Takeover to Stand-by Supply", and each sentence needs to be accurately understood.

3. KNOWLEDGE ENTITY RECOGNITION MODEL OF POWER GRID DISPATCHING BASED ON PBERT-BILSTM-CRF

Entity recognition is an information extraction technology that determines the boundary of data such as person names and place names with specific meanings. Power regulation data has the characteristics of having a large number of unique location words and abbreviations, which belong to text in the field of expertise. Therefore, when recognizing entities, it is necessary to fully consider the characteristics of the text. In order to address the issue of difficulty in accurately identifying power regulation entities, this paper proposes the PBERT-BiLSTM-CRF model as a named entity recognition model for implementing the field of power grid fault handling. The BERT-BiLSTM-CRF power regulation entity recognition model mainly consists of three parts: BERT representation layer, BiLSTM feature extraction layer and CRF output layer. The entity recognition process is shown in Figure. 2.

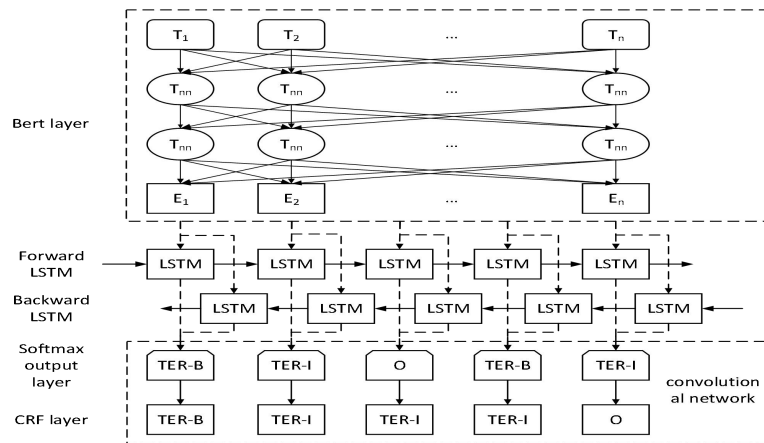


Figure. 2 BERT-BiLSTM-CRF entity recognition model.

3.1 BERT layer

The BERT layer is a knowledge representation model composed of multiple Transformer encoders that converts the input text sequence into a vector sequence representation, and each of which incorporates contextual information. The BERT layer captures word-level and sentence-level representations respectively through masking training and subsequent prediction training. Compared with traditional models that can only obtain semantic information in one direction, the BERT layer can obtain semantic information in any direction as the objective function. The addition of residual modules in the BERT layer improves the optimization ability of the model, which can effectively alleviate the gradient vanishing problem of the model. The BERT layer structure is shown in Figure. 3.

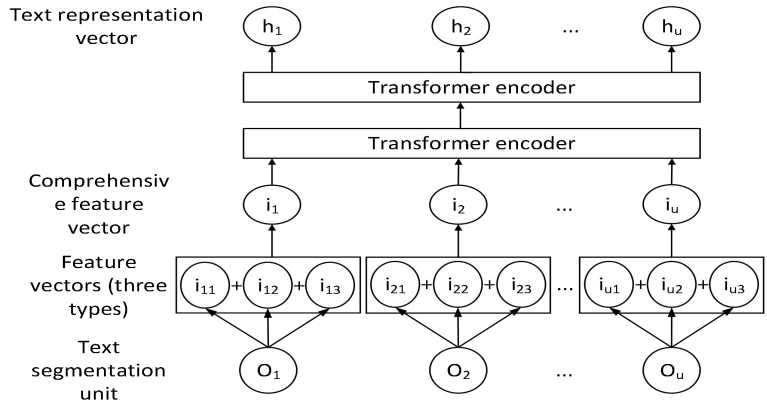


Figure. 3. BERT layer structure.

Firstly, power grid dispatching data texts after segmentation are input into the BERT layer in the form of segmentation units O_1, O_2, \dots, O_u , and semantic features of segmentation units, contextual position features, and position features in sentence fragments are extracted. Finally, the Transformer encoder outputs the texts in the form of vectors h_1, h_2, \dots, h_u represented by different class features.

(1) BERT overshadows the training process

Masking training is aimed at improving the model's efficiency in utilizing text and enhancing the range of text information acquisition. Masking training randomly covers 15% of the characters in the sentences as training samples, where 80% of the characters in the samples are replaced by masked token, 10% remain unchanged, and 10% replace randomly. Let the encoder predict the original vocabulary in the masked area after completing the replacement. Finally, the error between the actual characters and the predicted characters is calculated, and the model parameters are adjusted through backpropagation.

(2) BERT context prediction training

Context prediction is the optimization of a model at the sentence level, which involves randomly replacing some sentences and determining their order. During context prediction training, the output of BERT is 1, indicating the existence of context relationships. BERT realizes the process of extracting power text features at the sentence level through context prediction training, the model parameters is further optimized, achieving the goal of improving the accuracy of downstream natural language processing tasks.

With the increase of the number of network layers, the training error periodically expands, and the accuracy of neural network gradually decreases. Assuming that the output of a designed neural network is $H(x) = f(x) + x$. Network is more easily optimized by adding residual learning, which makes the output more sensitive.

3.2 BiLSTM feature extraction layer

When entity recognition is performed on power grid dispatch texts, there is a strong semantic correlation between contextual texts. Therefore, LSTM models with arbitrary length sequences can be processed by introducing a built-in gating mechanism. LSTM selectively forgets unimportant sequence information while retaining the current input information. In order to better obtain contextual semantic information and expand backward knowledge acquisition method, forward LSTM is added on the basis of backward LSTM in the article to obtain forward hidden state and backward hidden state. The results of BiLSTM layer are shown in Figure. 4.

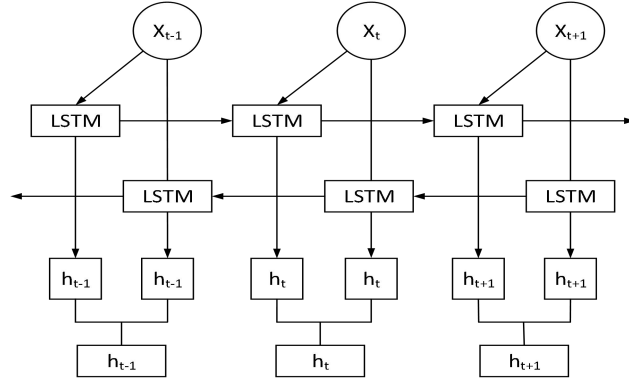


Figure. 4 BiLSTM layer.

At time t , the output sequence of the forward LSTM hidden layer is $\vec{h} = \{\vec{h}_1, \vec{h}_2, \dots, \vec{h}_n\}$, and the input of \vec{h}_1 is W_1 . Starting with \vec{h}_2 and $\forall \vec{h}_2 \in \vec{h}$, the input is $W_i \oplus \vec{h}_{t-1}$. At time t , the output sequence of the reverse LSTM hidden layer is $\vec{S} = \{\vec{S}_1, \vec{S}_2, \dots, \vec{S}_n\}$, and the input of s_1 is W_1 . Starting with s_2 and $\forall s_j \in s$, the input is $W_j \oplus s_{j-1}$. Performing technical output on W_k to obtain vector T_k , and $T_k = \vec{h}_k \oplus W_j \oplus s_{j-1}$. At this point, the normalization of output result means that only each location is independently classified, and no information that has been marked in the context is used. The LSTM state update expression is shown in the equation as follows.

$$a_i^{(t)} = \text{sigmoid}(w_i \vec{h}_{t-1} + u_i x_t + b_i) \quad (1)$$

$$a_f^{(t)} = \text{sigmoid}(w_f \vec{h}_{t-1} + u_f x_t + b_f) \quad (2)$$

$$a_o^{(t)} = \text{sigmoid}(w_o \vec{h}_{t-1} + u_o x_t + b_o) \quad (3)$$

$$\vec{h}_t = a_o^{(t)} \tanh(C_t) \quad (4)$$

$$C_t = a_f^{(t)} C_{t-1} + a_i^{(t)} \tanh(w \vec{h}_{t-1} + u x_t + b) \quad (5)$$

In the formulas, sigmoid is the activation function; \tanh is the activation function; a is the gate control unit of LSTM; w is the hidden layer weight matrix; u is the weight matrix of the input vector x ; b is the offset term; C_t is the text information at time t of LSTM unit.

3.3 CRF output layer

Although Bi-LSTM considers the context information of power text, it cannot take the dependency relationship between power entity labels into account. Therefore, the model can consider the correlation between class labels by adding the CRF layer to the Bi-LSTM layer, and obtain the global optimal annotation results through the transfer matrix for global scoring.

Firstly, the transfer matrix A is set that the transfer scores between adjacent labels in the statement of power safety hazards can be represented by matrix element $A_{i,j}$. The total score of a label sequence is determined by the transfer of each label. Given the input sentence $X = (x_1, x_2, \dots, x_n)$ and the output label sequence $Y = (y_1, y_2, \dots, y_n)$, the total score of the label sequence is shown in the formula.

$$S(X, y) = \sum_{i=0}^n A_{y_i, y_{i+1}} + \sum_{i=1}^n P_{i, y} \quad (6)$$

$P_{i,j}$ is the i -th character of hidden text in the formula and $P \in \mathbb{R}^{n \times k}$; y_i is the score of the label; n is sentence label type; $A_{i,j}$ is matrix element and $A \in \mathbb{R}^{(k+2) \times (k+2)}$.

Then, quotient the total correctly labeled score with the sum of all possible labeled scores, normalize the sequence path, and the sequence path is normalized to generate the probability of label sequence y under the condition of input sequence X . The probability is shown in the formula.

$$P(y|X) = \frac{e^{S(X,y)}}{\sum_{\tilde{y} \in Y_X} e^{S(X,\tilde{y})}} \quad (7)$$

During the training process, the logarithmic maximum likelihood estimation method is used to obtain the loss function and the logarithmic probability of the correct label sequence, as shown in the formula.

$$\log (P(y^*|X)) = S(X, y^*) - \log (\sum_{\tilde{y} \in Y_X} e^{S(X,\tilde{y})}) \quad (8)$$

Finally, the parameters are trained by the stochastic gradient descent learning algorithm. After obtaining the parameters, the dynamic programming algorithm Viterbi algorithm is used to obtain the output sequence with the maximum score, which is used as the final annotation result for the entities with safety hazards in power production, as shown in the formula.

$$y^* = \operatorname{argmax}_{\tilde{y} \in Y_X} S(X, \tilde{y}) \quad (9)$$

4. RESEARCH ON THE CONSTRUCTION OF POWER REGULATION KNOWLEDGE MAP AND ASSISTED DECISION MAKING

4.1 Ontology assisted construction

Due to the relatively fixed physical information of the power grid dispatch text, the core elements can be further subdivided into various types of unstructured information. Therefore, this paper adopts the top-down ontology construction method to assist in constructing a knowledge graph of power grid dispatching. The process of ontology construction is as follows:

- (1) Identifying the research fields and tasks. Knowledge graph is the mining and analysis of knowledge and its corresponding carriers by visualization technology, and the display of their internal relationships. Therefore, the characteristics of this field should be understood in detail during the construction process. When constructing an ontology, it should also be defined based on the characteristics of the field, and the levels and hierarchies should be clearly divided. The knowledge graph for power production safety hazards should be domain oriented, and the scope of ontology construction should be limited.
- (2) Investigating the existing power domain ontology and considering its reusability. Ontology refers to the formal and detailed description of concepts in a certain domain, which has the characteristics of abstraction and generality. Therefore, when constructing the ontology in the power field, it is necessary to draw on the existing third-party knowledge system or relevant information in the field, and analyze and select the contained ontology. At present, this paper has borrowed from power safety regulations, Baidu Encyclopedia, and International Grid Corporation's power safety work regulations.
- (3) Making statistics of power grid dispatching ontology. This article comprehensively summarizes the relevant concepts, attributes, and relationships of power grid dispatch ontology under the guidance of power system experts. The essential elements of equipment in the power field are listed, such as transformers, inverters, circuit breakers, protective devices, UPS, etc.
- (4) Constructing power grid dispatching ontology system. After the statistics of power grid dispatching ontology, the system construction of the power grid dispatch ontology can be carried out, and the superior concepts can cover the lower concepts. For example, transformer equipment includes booster transformers, inverters, voltage transformers, etc. All transformers and voltage transformers belong to the category of substation equipment.
- (5) Defining attributes and relationships. After determining the categories of power production safety hazards, it is necessary to define attributes and relationships for each category determined in the previous step. Attributes are used to describe the inherent characteristics of the concept, such as the rated capacity of the transformer, rated voltage, rated current, capacity ratio, voltage ratio, etc. Relations are used to represent the relations between different concepts, such as the phenomenon relation between transformers and excessively high temperatures.
- (6) Defining constraints on attribute values and relationships ensures that the consistency in the ontology, attributes, and relationships of safety hazards in power production, and the data quality can be improved.

In the construction of the knowledge graph for power grid dispatching, the construction of the power grid dispatching ontology system provides conceptual relationships for the construction of the knowledge graph. The effectiveness of

constructing a knowledge graph for power grid dispatching is enhanced by the improvement of constraining entities, relationships and attributes.

4.2 Construction of knowledge graph

Knowledge storage is the storage of data generated in power dispatching texts. Power dispatching texts requires a high-performance database for storage management because of characteristic of long-term preservation and huge quantity. Therefore, Neo4j graph database is used to store safety hazards in power production using the Cypher operating language. Neo4j has all the characteristics of mature database such as atomicity, consistency, isolation and persistence. The graph structure can be used to store data more efficiently. Query and display functions can be provided through Neo4j Web visual interface.

The system takes user dialogue interaction as the main operation mode integrates the characteristics of MATLAB with high computational efficiency, knowledge graph Neo4j with high search efficiency and excellent visualization effect, and Python with friendly interface. Using Python equipped with AIML technology to complete MATLAB calculation, Neo4j display and search. The specific development process is shown in Figure. 5.

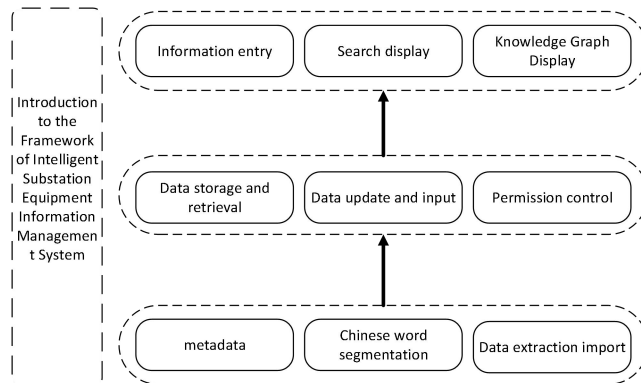


Figure. 5 Development process.

4.3 Scheduling assistance question answering based on knowledge graph

In order to meet the demand for auxiliary Q&A in power grid dispatching, this paper combined the characteristics of power system operation, and designed the processing process of a dispatching auxiliary Q&A based on the knowledge graph of power grid dispatching and AIML. The example are shown in Figure. 6.

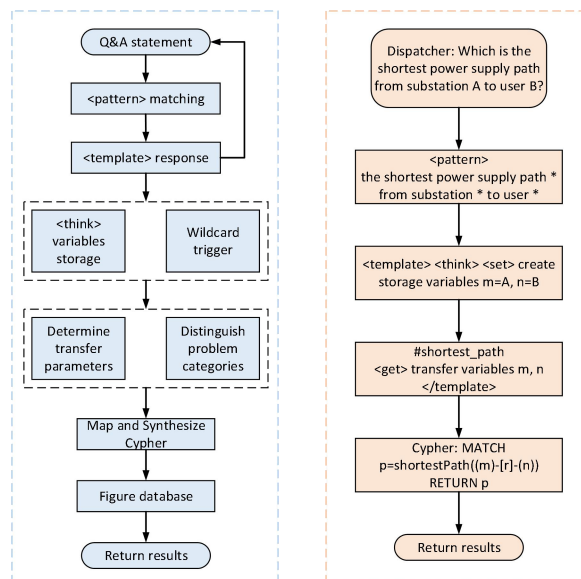


Figure. 6 Q&A processing flow.

paper, a total of 28863 words were selected to form a professional dictionary for power outage planning in power grid dispatching. Among them, there are 975 transformer related words, 32 inspection anomalies, 783 circuit related words, 5335 switches, 949 busbars, 15,340 tool brakes, 684 substation names, 88 generators, and 1847 other commonly used words.

(1) Evaluation of entity recognition mode

In this paper, Precision (P), Recall (R) and F1 Score are taken as evaluation indicators to evaluate the effectiveness, and the calculation formula is as follows.

$$P = \frac{TP}{TP+FP} \tag{10}$$

$$R = \frac{TP}{TP+FN} \tag{11}$$

$$F1 = (2 \times P \times R)/(P + R) \tag{12}$$

The effectiveness and rationality of the entity identification model for power production safety hazards can be evaluated through the evaluation index system.

In order to verify the validity and rationality of entity recognition model for power production safety hazards based on BERT-BiLSTM-CRF proposed in this paper, the dataset that consists of grid dispatching records are compared with dictionary-rule, BiLSTM-CRF and BERT-BiLSTM-CRF models. Table 1 shows the comparison of entity recognition on different models.

Table 1. Comparison of three entity recognition models.

Contrast model	Score of P	Score of R	Score of F1
Dictionary - Rules	0.7023	0.6059	0.6505
BiLSTM-CRF	0.7417	0.6255	0.6787
ATT-BiLSTM-CRF	0.7287	0.6698	0.6980
BERT-BiLSTM-CRF	0.8025	0.8106	0.8065

The experimental results showed that the dictionary-rule based recognition method depends on the integrity and accuracy of the power grid dispatching dictionary. Incorrect recognition will be caused in the presence of typos in the power grid dispatching records. BiLSTM-CRF entity recognition model, ATT-BiLSTM-CRF entity recognition model and BERT-BiLSTM-CRF entity recognition model are developed on the basis of deep learning, which can explore the relationship the characters between themselves and the context of hidden text with higher accuracy. The performance of the BERT-BiLSTM-CRF entity recognition model is greatly promoted compared with the dictionary-rule recognition mode, increasing F1 score by about 0.16, recall rate by about 0.20 and accuracy rate by about 0.1. The entity recognition model of Bert-BiLSTM-CRF added the BERT vector expression layer based on the BiLSTM-CRF model, increasing F1 score by about 0.13, recall rate by about 0.19, and accuracy rate by about 0.06. The entity recognition model of ATT-BiLSTM-CRF has a certain improvement in performance compared with BiLSTM-CRF entity recognition model after incorporating attention mechanism. However, there is still some gap in accuracy, recall rate and F1 score compared with BERT-BiLSTM-CRF entity recognition model. The power grid dispatching named entity recognition model based on BERT-BiLSTM-CRF utilizes BERT vector representation layer to obtain abstract features of text, fully considering the impact of context information on entities, and achieving the best entity extraction effect. Table 2 shows the experimental results of identifying various types of entities in power grid dispatching based on the BERT-BiLSTM-CRF model.

Table 2. Comparison of entity recognition by category

Entity class	Score of P	Score of R	Score of F1
Unit name	81.89	85.79	83.79
Device name	88.72	85.69	87.18
Discovery location	72.43	76.18	74.25
phenomenon	55.79	68.79	61.61
Personnel name	92.46	95.77	94.09

6. CONCLUSIONS

This paper proposed a research on the construction of power grid dispatching knowledge graph and intelligent assisted decision-making. Considering characteristics of regulation and operation tasks in actual scenarios and the power grid electroplating data, the power grid dispatching knowledge graph is constructed. Based on this, the power grid dispatching assisted decision-making system is established and developed to achieve the functions of data management, intelligent interaction and auxiliary decision-making. The validity of the entity recognition model was verified through the actual operation data of the power system, and the scientific and practical nature of each functional module of the developed system was effectively verified through decision query. The fault regulation ability of dispatchers and the safe operation level of the distribution network are improved by conducting knowledge guidance and recommendation decision-making in the task scenario, which can provide a certain reference for other provinces and cities to improve the ability of dispatching assisted decision-making.

7. ACKNOWLEDGMENTS

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