Intelligent Auxiliary Operation and Maintenance System of Power Communication Network based on Knowledge Graph

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Abstract—With the deepening application of knowledge graph technology, in order to solve the problems that it is difficult to quickly obtain knowledge and complete the maintenance task, an intelligent auxiliary operation and maintenance system of power communication network based on knowledge graph is designed and implemented. The proposed system addresses effectively the two mentioned challenges accordingly by aggregating semantic information of different granularity in the constructed knowledge graph. Specifically, a Relation-Tuple-Entity Heterogeneous Graph Neural Network (SG-HGNN) is proposed to model effectively the different granularities of semantic information for knowledge reasoning. Comprehensive experiments which are conducted on the constructed knowledge graph demonstrate the effectiveness of the proposed framework. After the pilot application of the system, the problem hit rate and problem response time are significantly reduced, which greatly improves the operation and maintenance efficiency of power communication network.

1. INTRODUCTION
In recent years, with the rapid technological development of mobile Internet, cloud computing, and big data and Internet of things have been widely deployed and applied in the new products, new technologies, and new services of power information and communication. In view of the complex and diverse information and communication operation and maintenance site with various equipment, the operation and maintenance personnel need to consult a large number of technical documents and equipment information during the field inspection and fault handling, which requires higher business level and technical requirements. In the face of such a large and complex information set, how to quickly obtain information and discover knowledge is an urgent problem to be solved to quickly complete the maintenance task and improve maintenance efficiency [1-3].

In past decades, researchers have proposed different approaches to meet the increasingly complex processing needs. Babak et al. [4] examined several proposed methodologies and synthesized them into a new methodology that they demonstrated through a case study of an electric power distribution company. First, the research approach for creating the knowledge graph was process-oriented and the processes are considered as the main elements of the model. The Delphi method was used for the research model validation. Some of the important outputs of this research were mapping knowledge flows, determining the level of knowledge assets, expert-area knowledge graph, preparing knowledge meta-model, and updating the knowledge graph according to the processes. Chuning et al. [5] suggested that they designed the operation of the system to solve the problem that a variety of automated equipment to coordinate the operation of instability, monitoring was not timely. Yun et al. [6] analyzed
the development of the smart grid, combined with the latest ICT technology development results, demonstrated the important role of information and communication network for new applications in smart grid, put forward the integrated framework of operation and maintenance which was based on resource integration, supported by standardized processes and centered by an integrated evaluation. The paper pointed out the key technical problems such as the resource model, the monitoring data fusion, intelligent alarm indicator evaluation system, and running state assessment in the building of operation and maintenance system for the integration of smart grid information and communications. In addition, some methods explore features from the constructed knowledge graph and perform the knowledge reasoning, for example, NTN [7], DKRL [8], ProjE [9], and MT-KGNN [10], etc. Such approaches, however, have failed to make full use of the different granularities of semantic information for knowledge reasoning.

Furthermore, other researchers [11-18] have also done a lot of research in this area, and they made a very remarkable and effective contribution which is meaningful for the present research. This will help to deal with the problems of the application of the intelligent auxiliary operation and maintenance system of power communication network through the application of Knowledge Graph technology.

In this paper, we first introduce the system architecture and core modules. Then we present a Relation-Tuple-Entity Heterogeneous Graph Neural Network (SG-HGNN) for knowledge reasoning, which considers the interaction among three types of nodes. And the information of different granularity in the constructed knowledge graph is fully utilized.

2. SYSTEM ARCHITECTURE
The data structure retrieval technology based on knowledge graph could realize the essential association between semantic understanding and knowledge, and build an intelligent auxiliary operation and maintenance system of power communication network, provide comprehensive knowledge support for field operation and maintenance personnel, and improve the timeliness and reliability of operation and maintenance personnel to deal with fault maintenance.

2.1. Overall Structure
The knowledge graph is the key to the intelligent auxiliary operation and maintenance system. The main overall structure of the knowledge graph can be divided into five layers: data collection layer, knowledge extraction layer, knowledge fusion layer, knowledge storage layer, and knowledge service layer. The overall structure is shown in Figure 1.

Data collection layer: this layer provides basic data. The source data of power communication network comes from multiple dimensions and types of data, which can be divided into two categories according to data source channels. The one data source channel is collected from monitoring system, including environment data, device operation data, and inspection data. The other data source channel is knowledge data. It mainly comes from the discrete collection and history data. In the process of data collection, it needs a lot of advanced technology support, especially image recognition technology, equipment communication technology, and large-scale data storage technology.

Knowledge extraction layer: this layer is used to extract knowledge from collected business data of power communication network, which includes structured data, semi-structured data, and unstructured data.

Knowledge fusion layer: this layer mainly solves the problem of multi-source heterogeneous data integration in power communication network. It mainly adopts entity relationship analysis, synonym construction, semantic analysis, keyword extraction, and other technologies. This layer is used to further integrate the complex knowledge acquired from multi-source data and expand the original knowledge base. Traditional knowledge fusion methods include string-based matching method and divide and conquer algorithm. With the development of machine learning, especially in-depth learning, some scholars have introduced word embedding and topic model into knowledge fusion.
Figure 1. Overall structure

Knowledge storage layer: this layer provides one-stop storage, query, analysis and mining platform services for the whole business of electric power communication network, which takes graphic data as the main body and multiple data coexists. It is mainly responsible for storing knowledge in NoSQL and DB.

Knowledge service layer: this layer realizes the function of unified service. It aims to achieve business objectives, solve user problems, and improve the production of electric power information network. It provides different services for managers and operators. In intelligent auxiliary operation and maintenance system, this layer mainly provides knowledge modeling, intelligent interaction, knowledge operation and maintenance, and other services.

2.2. Knowledge Extraction Layer
The purpose of knowledge extraction layer is to extract knowledge from collected business data of electric power communication network, and extract relevant entities, attributes, relationships, events, and other knowledge. The knowledge extraction layer structure is shown in Figure 2.

From the division of data structure, the collected data is divided into structured data, semi-structured data, and unstructured data, and the processing methods of each kind of data are different. The three types of data includes operation guidance base, maintenance guidance base, relevant rules and regulations, network management platforms, TMS, IMS, and other system, network management platform, video conference system, etc. This layer is mainly responsible for extracting triples similar to (entity a, entity b, relationship) or (entity, attribute, attribute value).
3. **CORE MODULES**

The intelligent auxiliary operation and maintenance system of electric power communication network is based on all kinds of data and operation management mode, and integrates multiple data to break through the barriers between multi-system, multi-dimensional and multi-structure data, so as to realize the intelligent auxiliary operation and maintenance of power communication network based on knowledge graph. The system includes three modules: knowledge modeling module, intelligent interaction module, and knowledge operation and maintenance module.

### 3.1. Knowledge Modeling Module

Knowledge modeling refers to the establishment of a data model of Knowledge Graph. That is a kind of way to express knowledge and build a model to describe knowledge. The process of knowledge modeling is the basis of Knowledge Graph. High quality data model can avoid many unnecessary and repetitive knowledge acquisition work, effectively improve the efficiency of Knowledge Graph construction, and reduce the cost of domain data fusion.

The data of electric power communication network has the characteristics of large quantity, complex structure and many types. Aiming at the disadvantages of traditional artificial knowledge modeling, such as time-consuming, labor consuming and low efficiency, the top-down method is adopted to model. In this paper, we firstly define the top-level concept, and then gradually refine to form a 4-element classification hierarchy structure.

Firstly, the knowledge entity meta set is established.

\[
S = \{K_1, K_2, \ldots, K_n\}
\]  

(1)

Among them, \(K\) is the knowledge entity, \(n\) is the number of knowledge entity, and \(S\) is the knowledge entity meta set.

Next, natural language processing, semantic analysis, keyword extraction, semantic annotation and other technologies are used to process and analyze the knowledge source. The near end entity \(K\), entity feature \(a\), entity relationship \(R\), and remote entity \(K'\) form an ordered 4-tuple. The equation is as follows:

\[
Q = \begin{bmatrix}
S & A_1 & C_1 & K'_1 \\
A_2 & C_2 & K'_2 \\
\vdots & \vdots & \vdots \\
A_m & C_m & K'_m \\
\end{bmatrix} = \begin{bmatrix}
Q_1 \\
Q_2 \\
\vdots \\
Q_m \\
\end{bmatrix}
\]  

(2)

In the above equation, \(m\) is the number of features of the proximal entity pair, and \(Q\) is called m-dimensional knowledge entity, \(Q = (S, A, R, K')\). Under normal circumstances, the knowledge source is processed and analyzed to construct a triplet such as (entity a, entity b, relationship) or (entity, attribute, attribute value). This strategy constructs a four tuple, which can not only be split into corresponding triples, but also better express the association between the three tuples. Based on the above semi-automatic method, the existing structured knowledge model can be quickly integrated to
support the expression mode of complex knowledge forms such as events, time series, etc. In addition, the knowledge model with more perfect function and stronger expression can be established.

### 3.2. Intelligent Interaction Module

Power communication network provides a safe information transmission channel for power grid dispatching, automation, security automatic control and power market transaction in the whole power system. Its high-quality management is the key to keep the whole power grid smooth. The intelligent interaction module realizes the research of data structure retrieval technology based on knowledge graph, realizes the essential relationship between semantic understanding and knowledge, builds intelligent question answering system applied in the field of power communication operation and maintenance. It can provide comprehensive knowledge support for field operation and maintenance personnel, and improve the timeliness and reliability of operation and maintenance personnel to deal with troubleshooting. It mainly adopts the following three steps to improve the intelligent interaction ability based on knowledge graph.

**Step 1: Key node classification**

According to the corresponding business classification of power communication network operation and maintenance, the core nodes in the knowledge graph are labeled with service tags, and the output results are feature atlas database. In this way, in the face of a certain type of operation and maintenance problems, we can give priority to retrieval in the counterpart business nodes, so as to improve the efficiency of node retrieval.

**Step 2: Node importance evaluation**

For the key nodes in the feature map database, the following algorithm is used to calculate the node importance.

\[
M = \frac{p \sum_{i=1}^{n} T(i)}{\max \left[ \sum_{i=1}^{n} T(i) \right]} + q \frac{2/n \sum_{i=1}^{n} T(i)}{n(n+1) \max \left[ T(i) \right]}
\]

In the above equation, \( M \) is the importance of nodes, \( n \) is the number of statistical cycles, \( j \) is the sorting of nodes, and \( T \) is the number of hit nodes. In addition, \( p \) and \( q \) represent the weight of the front end and the back end respectively, and \( p > 0, q > 0, p + q = 1 \).

Through the knowledge graph key node importance evaluation algorithm, we can evaluate the importance of the node. After a certain operation and maintenance problem is input into the system, it can search from high to low according to the node importance, which can greatly improve the hit efficiency and save the intelligent interaction time.

**Step 3: Knowledge reasoning**

Knowledge reasoning can be defined as the process of deriving new knowledge from existing knowledge according to a certain strategy. A knowledge graph with knowledge reasoning ability will dig out the deeper intrinsic value of data. In this paper, we present a Relation-Tuple-Entity Heterogeneous Graph Neural Network (SG-HGNN) for knowledge reasoning, leveraging full advantage of the different granularities of semantic information in the constructed knowledge graph. Here, we consider three types of information i.e., relation types, tuples, and entities. As shown in Figure 3, we construct the heterogeneous graph \( G = (V, E) \) containing the relation types \( R = \{r_1, \ldots, r_g\} \), tuples \( T = \{t_1, \ldots, t_w\} \), and entities \( E = \{e_1, \ldots, e_y\} \) as nodes, i.e., \( V = R \cup T \cup E \). The set of edges \( E \) represent their relations. The details of constructing the network are described as follows.
Figure 3. Relation-Tuple-Entity Heterogeneous Graph

For graph edges, we connect every tuple node to its two entity nodes and its relation type nodes. To further capture the semantics of knowledge graph and advance the information propagation, we consider the relations between entities. Particularly, if the similarity score (cosine similarity) between two entities, computed based on their entity feature, is above a predefined threshold $\delta$ (The $\delta$ between entities is set $\delta = 0.5$ in this paper), we build an edge between them.

Typically, given a specific node, different types of neighboring nodes may have different impacts on it. Additionally, different neighboring nodes of the same type could also have different importance. To capture both the different importance at both node-level and type-level, we update these node representations in our constructed heterogeneous graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ via dual-level attention mechanism as shown in Algorithm 1, which mainly consists of two parts: the Node-level Attention for aggregating neighbor of the same type and Type-level Attention for aggregating different types of neighbors. Finally, the representations of nodes are extracted for entity prediction and relationship prediction. The detail processes of message passing are described as follows.

Algorithm 1: Relation-Tuple-Entity Heterogeneous Graph Neural Network

**Input:** Heterogeneous Graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$

**Output:** The final node representations that aggregated the different granularities of semantic information in the constructed knowledge graph.

1. for $l = 1 ... L$
2. // Node-level Attention
3. for $v \in \mathcal{V}$ do
4. \[ u_i^l = \tanh(W^l_i u_i^{l-1} + b^{l}_i) \] (4)
5. \[ \alpha_i = \frac{\exp(u_i^l)}{\sum_{i\neq i} \exp(u_i^l)} \] (5)
6. \[ h_r, h_t, h_e = \sum_{i \in \mathcal{R}} \alpha_i v_i, \sum_{i \in \mathcal{T}} \alpha_i v_i, \sum_{i \in \mathcal{E}} \alpha_i v_i \] (6)
7. end
8. // Type-level Attention
9. \[ u_i^l = \tanh(W^l_i h_i^l + b^{l}_i) \] (7)
10. \[ \beta_i = \frac{\exp(u_i^l)}{\sum_{i \in \mathcal{C}} \exp(u_i^l)} \] (8)
11. \[ h_e = \sum_{i \in \mathcal{C}} \beta_i h_i^l \] (9)
12. \[ v_i^{l+1} = \text{ReLU}(W^l_i [h_e; v_i] + b^{l}_e) \]
13. end

3.2.1. Node-level Attention: We design the node-level attention to capture the importance of different neighboring nodes and reduce the weights of noisy nodes. Formally, given a specific node $v \in \mathcal{V}$, we sample all its 1-order and 2-order neighbors, and then group different types of neighbors. Formally,
the node-level attention is presented by Equations 4, 5, and 6 in Algorithm 1. In this way, we can get three neighbor type vectors $\mathbf{h}_r, \mathbf{h}_t, \mathbf{h}_e$.

### 3.2.2. Type-level Attention
In order to further capture the importance of different types of neighboring nodes, the type-level attention learns the weights of different types representation after the node-level attention. With the similar treatment to the node-level attention, a type-level attention is utilized to model the semantic relationships among types. Formally, the type-level attention is presented by Equations 7, 8, and 9 in Algorithm 1. Then, we transform the concatenation of the type vector $\mathbf{h}_e$ and the specific node representation through a fully connected layer (e.g., one-layer MLP) with ReLU function, which are used as input of the next Relation-Tuple-Entity heterogeneous graph layer.

Finally, the representations of nodes are extracted for entity prediction and relationship prediction after the $L$th Relation-Tuple-Entity heterogeneous graph layer.

#### 3.3. Knowledge Operation and Maintenance Module
Knowledge operation and maintenance refers to the process of evolution and improvement of knowledge graph based on the feedback of operation and maintenance personnel and new knowledge sources after the initial construction of operation and maintenance knowledge graph of power communication network. The quality control and gradual enrichment and evolution of knowledge graph need to be ensured in the process of operation and maintenance. The operation and maintenance process of knowledge graph is an engineering system, covering the whole life cycle of knowledge graph. This module adopts the knowledge operation and maintenance method based on incremental data, which is responsible for the construction, statistics, analysis, reasoning, version, security, backup, and other processes of power communication network operation and maintenance knowledge graph. Finally, an intelligent question answering system based on Knowledge Graph technology is established. The operation and maintenance personnel interact with the system through keyword query, systematically analyze keywords, and intelligently provide relevant knowledge of various forms in the system.

### 4. Simulation and Experiments

#### 4.1. Performance of SG-HGNN
For investigating the performance of our proposed knowledge reasoning algorithm, we select several representative methods as baselines: NTN[13], DKRL[14], ProjE[15], and MT-KGNN[16]. Table I depicts the performance of our proposed model on the constructed knowledge graph, in comparison with the selected baselines. Following convention, we use Mean Rank and HITS@10 as evaluation metrics. Mean rank measures the average rank of correct relationships. HITS@10 measures if correct relationships appear within the top-10 elements. The filtered mean rank and filtered HITS@10 ignore all other true relationships in the result and only look at the target relationship. Note that the smaller the mean rank, the better. It is found that our method SG-HGNN derives the best results in all evaluation measures.

| Method   | Mean Rank | HITS@10 |
|----------|-----------|---------|
| SG-HGNN  | 1.2       | 95.34   |
| MT-KGNN  | 2.01      | 72.51   |
| ProjE    | 2.33      | 61.21   |
| DKRL     | 3.55      | 61.46   |
| NTN      | 3.10      | 57.41   |
In addition, Figures 4 and 5 depict the relationship prediction performance of the SG-HGNN on the constructed knowledge graph, in comparison with the selected baselines. Note that for baselines whose source codes are not available, we re-implement the methods based on the published papers. For each baseline, the parameters are tuned accordingly and the parameter setting deriving the best results is used for performance comparison. To make a fair comparison, training and testing setups are completely same across different methods.

![Figure 4. Mean rank comparison with selected baselines.](image1)

Figures 4 and 5 show that the proposed method outperforms existing methods in most cases. We attribute the performance improvement to the effective modeling of the aggregation of different granularity information in the constructed knowledge graph.

![Figure 5. HITS@10(%) comparison with selected baselines.](image2)

### 4.2 Overall Performance

The intelligent auxiliary operation and maintenance system of power communication network based on knowledge graph breaks through the barriers between multi-system, multi-dimensional, and multi-structure data, and realizes the knowledge support for on-site operation and maintenance. Before the system deployment, there are only simple operation and maintenance knowledge base in each pilot area, which has limited support for power communication network managers. After the system is deployed,
the management efficiency of power communication network is greatly improved, as shown in the following table:

| Pilot area | Hit rate / response time | growth rate |
|------------|--------------------------|-------------|
|            | Before                   | After       |            |
| Nanjing    | 57.3% / 25.1s            | 89.1% / 3.9s | 55.5% / 84.5% |
| Suzhou     | 55.4% / 25.3s            | 89.3% / 3.8s | 61.2% / 85.0% |
| Wuxi       | 53.1% / 25.1s            | 88.7% / 4.1s | 67.0% / 83.7% |
| Nantong    | 49.7% / 25.2s            | 88.3% / 4.2s | 77.7% / 83.3% |
| Changzhou  | 46.9% / 25.5s            | 88.4% / 4.9s | 88.5% / 80.6% |
| Average    | 52.5% / 25.2             | 88.7% / 4.2  | 69.0% / 83.3% |

The intelligent question answering system based on Knowledge Graph technology is designed and implemented. At present, the system has been applied in Nanjing, Suzhou, Wuxi, Nantong and Changzhou. According to the pilot results, the problem hit rate increased from 52.5% to 88.7%, with an increase rate of 69.0%; the problem response time increased from 25.2 seconds to 4.2 seconds, with an increase rate of 83.3%. With the deployment and application of the system, the barriers between multi-system, multi-dimensional and multi-structured data are broken through, and the knowledge support for field operation and maintenance is realized, and the operation and maintenance efficiency of power communication network is greatly improved.

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