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# *Research on Fault Diagnosis and Disposal Suggestions Method of Power Communication Network Based on Dynamic Event Driven Knowledge Graph*

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***Abstract:*** With the development of smart grids, the intelligent operation and maintenance of power communication networks urgently need to evolve from passive response to active warning. Although knowledge graphs provide a global perspective for this, their static characteristics are difficult to cope with real-time and changing network states. The article paper aims to address the limitations of static knowledge graphs in real-time fault diagnosis. The proposed method converts real-time monitoring data into timestamp events and constructs spatiotemporal correlation sessions, achieving active perception and collaborative analysis of multi-source asynchronous faults. Based on this method, the system can not only accurately locate the root cause of faults, but also generate interpretable disposal suggestions automatically based on topology and business logic, providing new ideas for building intelligent power communication operation and maintenance systems.

## 1. Introduction

As an indispensable nerve centre of smart grid[1], power communication network carries the production control data flow of key businesses such as relay protection, security and stability control, dispatching automation, and is closely related to the safe and stable operation of power grid. With the continuous improvement of the intelligent level of the power grid[2], the scale of the power communication network continues to expand, the terminals are more diversified, the network structure is becoming increasingly complex, and the coupling relationship between equipment and business is becoming increasingly close, which makes the operation and maintenance of the power communication network much more difficult.

At present, the mainstream intelligent monitoring system still relies on the traditional network management and dynamic ring monitoring platform to a large extent. Although these systems are automated at the data acquisition level, there are still significant bottlenecks at the intelligent level of data analysis and decision support. Firstly, there is a severe issue with storm warnings. A single fault in the bottom layer (such as an optical cable interruption or a power supply failure) will spread along the network topology to the upper layer, triggering a large number of derived alarms, making it difficult for the operation and maintenance personnel to quickly identify the real root cause among a large number of alarms. Secondly, multi-source data islands severely hinder integrated analysis. Transmission network management, power environment monitoring, resource management and other systems have become fragmented into information silos, primarily due to heterogeneous architecture and insufficient top-level design. The isolation of key operational parameters, such as equipment performance, room temperature and humidity, power status and service routing, hinders correlation analysis, crippling our ability to rapidly locate faults and provide clear diagnostics. Operation and maintenance personnel are forced to rely on experience to conduct tedious cross validation and manual association analysis between multiple independent systems. This approach is not only inefficient and time-consuming, but also prone to error. It renders the fault diagnose process a “black box” lacking a clear, traceable logical chain and effective fault solutions.

In recent years, Knowledge Graph technology, with its powerful capabilities in semantic interconnection and relevance reasoning, has offered a novel approach to addressing the correlation challenge within these complex systems[3]. The knowledge graph integrates heterogeneous data into a unified, machine-understandable network by building a formal model of equipment, links, systems and their interrelationships. This establishes a solid foundation for precisely tracing fault propagation paths and analysing their impact scope[4]. Current research has explored the application of knowledge graphs to communication network fault management, demonstrating their efficacy in topology query and simple association analysis[5, 6]. However, in most existing studies, the knowledge graph remains a static knowledge model of physical topology with infrequent updates and minimal integration with real-time data streams. Consequently, it cannot perceive instantaneous network changes or respond dynamically to evolving faults. This static framework confines its reasoning ability to post-event analysis, and is not competent for real-time, in-event diagnosis and disposal.

In order to break through the limitations of static knowledge graph, this paper aims to propose a dynamic event driven knowledge graph model. The core concept of the model is to convert the real-time monitoring data, such as fluctuates in optical power, voltage, temperature or humidity, into “dynamic events”. These events activate corresponding nodes in the knowledge graph, transforming it from a static knowledge base into a cognitive engine capable of real-time perception and reasoning. Then, a weighted random walk and rule-based reasoning algorithm are employed to analyse the fault impact chain and pinpoint the root cause. It automatically generates a fault reasoning chain and disposal suggestions based on topology and business logic, reducing the operational difficulty while enhancing decision credibility.

This paper is organized as follows. Section I introduces the background and significance of the research. Section II reviews related work. Section III presents the construction of dynamic event-driven knowledge graph model. Section IV details the fault diagnosis algorithm and automatic generation method for fault disposal suggestion.  Section V introduces its implementation results, and section VI concludes the paper and looks forward to future work.

## 2. Related Work

As a technical paradigm for abstract representation of the structure of the real world graph, knowledge graph uses "nodes" to represent entities and "edges" to represent the relationships between entities, providing a key data structure support for cutting-edge algorithms in the field of artificial intelligence, especially graph neural network (GNN)[4].

In recent years, knowledge graph technology has been widely applied in panoramic grid topology construction and power business[6-10]. In 2019, State Grid Zhejiang Electric Power Company built a grid simulation model based on Neo4j graphic database, and verified its significant advantages in query efficiency through simulations[8]. In 2021, State Grid Jiangsu Electric Power Company proposed a method to build knowledge graph of equipment in the field of power grid monitoring based on multi-source data fusion. However, this method does not cover communication related equipment[9]. In the same year, the company developed a knowledge graph for power communication network maintenance using a BERT-BiLSTM-CRF model. This approach effectively leverages contextual information from the text corpus, establishing a foundation for the deep application of graph computing in this field[11]. In 2022, NARI Group Co., Ltd in Nanjing proposed a machine learning-based method to construct an intelligent analysis rule base for distribution network monitoring. This framework enables real-time analysis, providing technical support for the immediate detection of distribution network faults[10]. In 2023, the State Grid Corporation of China (SGCC) officially released the Technical Guidelines for the Construction of Knowledge Graph of Power Grid Equipment (DL/T 2725-2023), which plays an important role in equipment fault diagnosis and management, power dispatching information processing, power grid material supply chain and other scenarios.

Research efforts have intensified throughout 2024. State Grid Information & Telecommunication Branch proposed a top-down methodology for constructing a fault knowledge graph of power communication network. Centred on a fault indicator graph, it built a knowledge service model and systematically explored its potential application in fault diagnosis[5]. In the same year, State Grid East Inner Mongolia Power Co., Ltd. developed a BERT-BiGRU-CRF method for entity recognition of power communication equipment. Leveraging Neo4j, they constructed a visual knowledge graph and integrated it with TFIDF-cos model. Experiments verified the method’s feasibility, showing significant improvements in both efficiency and accuracy of fault diagnosis [6]. In summary, current research has primarily centred on the construction methodologies for power communication equipment knowledge graphs and their application in individual fault diagnosis cases.

## 3. Knowledge Graph Construction

The knowledge graph construction process includes data acquisition, knowledge modelling, knowledge extraction, knowledge fusion and visualization[4], as shown in Figure 1.

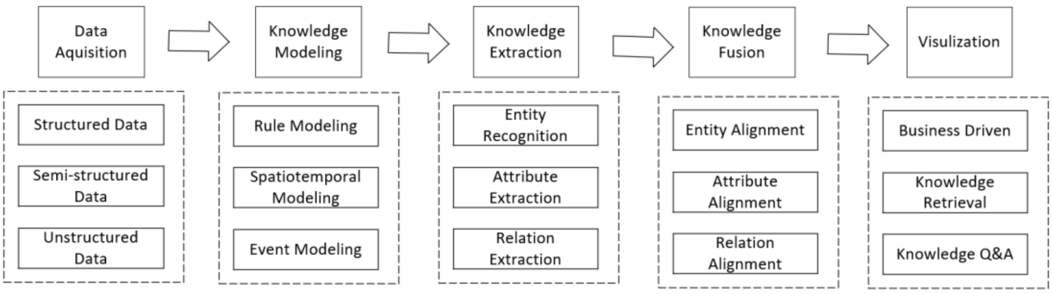


Figure 1 Process of Knowledge Graph Construction

### 3.1 Data Acquisition

Acquiring clean and unified data is a foundational step in building a knowledge graph. Four commonly employed methods for knowledge acquisition are crowdsourcing, data crawling, machine learning, and the expert method[12]. Knowledge bass, like Baidu Baike and Wikipedia, provide machine-readable structured data. Data collected from web pages, systems, devices and servers, whether structured, semi-structured and unstructured, usually need to be pre-processed and cleaned. Fundamental cleaning methods include rule-based imputation and deletion invalid samples, correction of erroneous formats, and removal of duplicates. Furthermore, machine learning techniques can be employed for data augmentation, key information extraction, automated cleaning, etc., transforming raw data into machine-understandable knowledge. Expert rules, another key method, formalize human expertise into structured knowledge, such as rule bases.

## 3.2 Rule Modelling

Performance monitoring relies on rules to identify equipment degradation or threshold violations. Traditionally, these rules are derived from expert knowledge, a process that involves converting documented experience into machine-understandable rules. Recently, machine learning has been integrated with rule modelling. As referenced in [13], techniques like Graph Neural Network (GNN) can generate rules automatically, significantly reducing the need for manual intervention. The rule modelling methodology is shown in Figure 2.

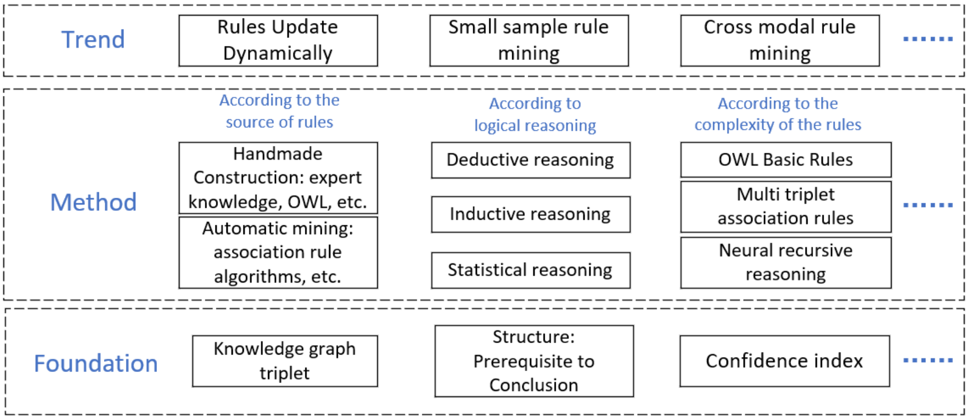


Figure 2 Method of Rule Modelling

For simple business rules, such as single-device threshold alerts, methods like SPARQL, SWRL, OWL axioms can be directly transformed into logical representations that knowledge graph can interpret. These rules are executed through the graph's rule engine and API, which leverage entity relationships and attributes if an alarm should be triggered. For complex business rules involving multi-entity associations hierarchical reasoning, the rule base must be logically embedded into the knowledge graph to utilize its native reasoning capabilities. Taking the rule modelling of the room temperature and humidity threshold as an example, the LSTM model can be trained on historical data to derive an optimal threshold. Then, it is formalized into an SWRL rule for the knowledge graph to execute.

## 3.3 Knowledge Extraction

Knowledge extraction technology converts heterogeneous, multi-format data into structured, machine-understandable data to facilitate the fusion and analysis in the next step. At present, knowledge extraction mainly focuses on entity extraction, attribute extraction, relationship extraction and event extraction from textual data, forming a triple group (entity, attribute, relationship). This is the basis of subsequent graph visualization.

In production activities, the power communication network monitoring scope encompasses two key aspects: the physical infrastructure, including optical cables, power supplies, equipment rooms and their topological connections, and the operational status of these devices, such as temperature, humidity, port optical power, optical power and supply voltage. The monitoring data is ingested into the knowledge graph. For instance, in optical power monitoring, optical power values and their time stamps are obtained from the network management system, such as the average power and attenuation per kilometre over recent half-month and quarterly periods, and finally generates a trend chart for following analysis. Any occurrence of a trend mutation or threshold overrun detected through methods like thresholds rules is labelled as an “event”.

## 3.4 Knowledge Fusion

In knowledge graph construction, the core objective of knowledge fusion is to address the heterogeneity, redundancy and conflicts present across multi-source knowledge, and integrate fragmented knowledge into a unified and consistent target graph. This process critically involves the alignment of entities, attributes and relationships. The goal is to eliminate semantic heterogeneity through the identification of equivalent elements in different data sources. Among them, entity alignment is the cornerstone, attribute alignment is the supplement of entity consistency, and relationship alignment is the crucial for graph structural consistency. Together, they collectively ensure the construction of a unified and high-quality knowledge graph.

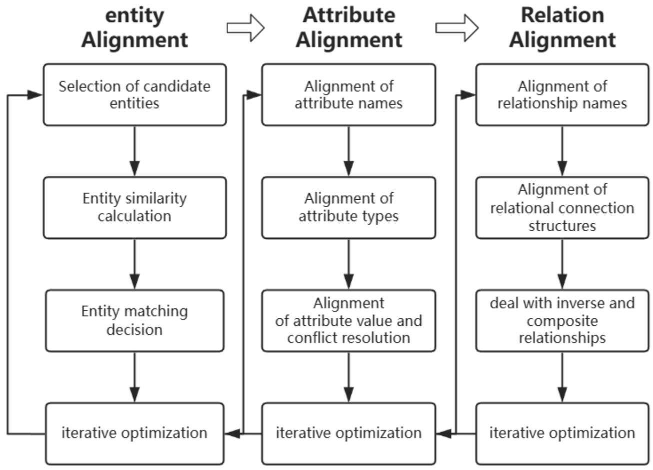


Figure 3 Process of knowledge fusion

Figure 3 illustrates the fundamental workflow of aligning entities, attributes and relationships. The entity alignment process begins with a preliminary filtering step to narrow the candidate set and retain potentially equivalent pairs. Subsequently, entities are converted into vectors using algorithms like SVM or BERT to calculate the semantic proximity. This quantified similarity directly informs the final equivalence decision. Attribute alignment is implemented through a three-stage methodology. It begins with leveraging domain knowledge to map attributes based on semantic or contextual similarity. This is followed by converting heterogenous data into a unified format and standardizing value representations. In the end, select and retain the most reliable value when multiple conflicting values exist for the same entity attribute. In parallel, relationship alignment proceeds through a structured, three-stage process. First, establish correspondence between relationship names that differ lexically but share the same semantics. Subsequently, verify whether the relationships from different sources connect semantically equivalent entity types. And finally, process inverse and composite relationships to prevent structural and semantic conflicts. Once the aligned and conflict-free knowledge is integrated into the domain knowledge graph, the quality must be validated. The results are systematically evaluated using quantitative metrics (e.g. precision, recall, F1-score, redundancy elimination rate) as well as through manual sampling.

## 3.5 Knowledge Fusion

Multi-source events in power communication faults, such as environment, performance and alarm data, are characterized by temporal asynchrony and propagation correlation, constructing an accurate fault subgraph through spatiotemporal association. First, each abnormal event is assigned a spatiotemporal tag that records its occurrence time, associated equipment, and position within the knowledge graph. A sliding time window is then established, within which incoming events are correlated based on their topological proximity in the knowledge graph. Events whose corresponding entities are topologically linked within a defined number of hops are grouped into a common fault session. This subgraph contains all relevant event information, establishes a local context for subsequent reasoning, and clearly depicts of potential faults within a specific network segment and time interval. Fault session generation effectively correlates temporally and spatially dispersed abnormal symptoms, such as gradual temperature increases, power fluctuations, and optical path performance degradation, which facilitates subsequent root cause diagnosis of complex faults.

## 4. Method

Based on the previously generated "fault session" subgraph, this module utilizes a hybrid reasoning mechanism that combines data-driven and knowledge-driven approaches. It accurately calculates the suspicion level of entities in the network, ultimately outputting a root cause localization result along with a human-readable reasoning chain. Additionally, it provides fault disposal suggestions based on expert knowledge. The algorithm flowchart is shown in Figure 4.


Figure 4 Flowchart of fault diagnosis and disposal suggestion algorithm

### 4.1 Fault Diagnosis Algorithm Based on Weighted Random Walk

The random walk algorithm is a method to simulate random paths on a graph or network. Its basic idea begins at a specified starting node and iteratively and randomly selects neighbouring nodes as the next step, thereby forming a random path. Random walk algorithm, encompassing unbiased (e.g. Deep Walk[14]) and biased (e.g. node2vec[15]), is widely used in tasks such as community detection and content recommendation[16]. To quantify the suspicion score, the likelihood of each entity being the root cause, we employ a weighted random walk algorithm to simulate fault probability propagation through the network topology.

Given a fault session:

$$S=[e_1,e_2,\ldots,e_n]^T \tag{1}$$

Among them, $e_i$ represents the event entity, the device entity directly connected to the event entity, and all the edges (relationships) connecting the entity. Define propagation weight $w_{uv}$ for each edge (u, v) on subgraph $G_s$, which is a linear combination of multiple influence factors of fault propagation:

$$w_{uv}=\alpha\cdot Severity(u)+\beta\cdot Criticality(u,v)+\gamma\cdot Topology\text{-}Bias(u,v) \tag{2}$$

Among them, *Severity(u)* represents the normalized value of event severity on node u. By taking the highest severity among multiple events, the model ensures that wandering gravitates towards areas with the most serious events. *Criticality(u, v)* indicates the importance of the service carried by the edge (u, v). For example, relay protection is assigned a higher weight than general management). This factor introduces the operation and maintenance priority into the model. According to node2vec, *Topology-Bias(u, v)* introduces topology bias (via parameters p and q) during the random walk. This factor governs whether the walk explores nodes within local communities or seeks out nodes with similar functions. α, β and γ are adjustable hyperparameters to balance the influence of different factors.

The weighted random walk algorithm starts from all event entities in the generated fault session to quantify the suspicion score of each entity. The transition probability is calculated based on the edge weight $w_{uv}$. After iteration, the algorithm converges to a stable probability distribution:

$$P=[p_1,p_2,\ldots,p_n]^T \tag{3}$$

Among them, $p_i$ represents the initial suspicion level of the corresponding entity, $e_i$, reflecting its topological proximity to the initial events and the weights of the connecting paths.

## 4.2 Validation and Correction Based on Rules

Following the rule modelling method introduced in Section 3.3, a rule library can be established for power communication operation and maintenance. Examples of partial rules are provided in the table 1.

Table 1: Partial judgement rules in the field of power communication operation

| Equipment | Judgment rules | Rules and regulations | Judgment Result |
|---|---|---|---|
| Transmission optical path | Degradation rules for optical path performance indicators | Within 15 days, the received optical power attenuation has exceeded the reference by ≥3dB on more than three times | Deterioration of optical path performance indicators |
| communication power supply | Deterioration rules for performance indicators of communication power supply | Within 30 days, the performance index of a power supply has exceeded the threshold (< 10%) three times in a row | Deterioration of performance indicators of communication power supply |
| | Rules for N-1 Capacity Verification | In an N-1 configuration for a single power, one of the SDH/OTN/PTN devices it supplies is interrupted | Capacity verification does not meet the standard |
| Computer room temperature and humidity | Rules for deterioration of temperature and humidity indicators in computer rooms | Within 30 days, the temperature and humidity index in the computer room have exceeded the threshold three times in a row | Deterioration of temperature and humidity indicators in the computer room |
| Communication optical cable | Discrimination rules for increased attenuation of fibre cores | Within 15 days, the fibre core attenuation is greater than the threshold by ≥3dB on more than three times | The attenuation of the fibre core increases |
| | Discrimination rules for fibre core interruption | A certain SDH/OTN/PTN device supported by a single optical cable interrupts completely or a single optical path interruption | Fiber core interruption |

After formulating the rule table, verify whether the high-ranking entities in section 4.1 meet the rules, and adjust the suspicion score based on the confidence level of the rules. If an entity with a moderate ranking is verified by rules as highly trustworthy, its suspicion score will be increased. Conversely, if an entity definitively excludes an entity as a root cause, its score is set to zero. Finally, this process produces a suspicion ranking calibrated by domain knowledge. The entity with the highest score is definitively identified as the root cause of the fault, R.

### 4.3 Explanation Chain Generation

Starting from the identified root cause node R, a breadth-first search (BFS) is performed on the knowledge graph to trace all paths leading to the event entities in the initial fault session S. The most critical fault propagation path is then selected based on a synthetic assessment of the weights and types of the components along the path:

$$Path=[path_1,path_2,\ldots,path_k]^T \tag{4}$$

The generation of the explanation chain requires predefined natural language templates for each relationship type in the knowledge graph. Then, the entities and relationships along the path are instantiated into the template and concatenated into coherent text. An example is provided below:

Input: Root Cause Node (Computer Room A-Air Conditioning); Transmission Path (Computer Room A-Air Conditioning ➞ located in ➞ Equipment B - Power Supply ➞ power supply ➞ Equipment C- Transmission ➞ bear ➞ Optical Path D ➞ Performance degradation ➞ Event E).

Output: The system detected a persistent high-temperature in Computer Room A, exceeding the critical threshold. This environmental failure directly caused voltage fluctuations in the power supply of Equipment B, located in the room. Consequently, it causes the abnormal transmission operations in the connected Equipment C. Ultimately, the Optical Path D carried by Equipment C received a serious power degradation alarm. The analysis infers the root cause to be the failure of the air conditioning system in Computer Room A.

### 4.4 Fault Disposal Suggestions Generation

After obtaining the root cause and the propagation chain of the fault, power communication operation personnel need to quickly handle the fault to maintain the normal operation of the network. In order to assist operation and maintenance personnel in quickly disposal faults, we also establish a corresponding rule base according to the expert knowledge, operational experience, and other resumes. Partial disposal suggestion rules are shown in Table 2. Based on this, the system can automatically generate fault disposal suggestions, providing effective assistance for operation and maintenance personnel in fault handling.

Table 2: Partial rules for fault disposal suggestions

| Equipment | Fault | Disposal Suggestions |
|---|---|---|
| Transmission fibre | Optical cable interruption | Fiber optic cable repair; Detect at the substation to locate the fault point, etc. |
| | Optic cable broken | Use spare fibre cores to restore the optical path, etc. |
| Power supply | a single power supply failure | Use a spare power supply; Emergency repair, etc. |
| | Module failure | Replace the module; repair the faulty module, etc. |
| Computer room | High temperature | using cooling measures blowing for high temperatures; Emergency repair of air conditioning, etc |

## 5. Verification

The network management system collects real-time device performance data, such as optical power, temperature and humidity in computer rooms from terminal equipment. With lengths and topology known, the monitoring system of transmission optical cables obtains the transmission/receive power values and the latest collection timestamps of the A/Z end. Subsequently, it calculates the average receive power and per kilometre attenuation over both the past half-month and the past quarter. To facilitate subsequent anomaly detection, these data are plotted into an optical power trend chart, providing an intuitive and clear visual basis for analysis.

Additionally, the system represents equipment status (e.g., performance degradation, exceeding limits) with bubbles. Based on the knowledge graph, we can query the location of alarm devices (power supply, transmission equipment, optical cables, etc.), the connected sites, the impacted services probably, etc. The system also gives fault diagnosis suggestions based on the type of fault to improve the response speed of faults, which greatly reduce the workload of operation and maintenance personnel.

## 6. Conclusions

This paper innovatively proposes a dynamic event driven knowledge graph model to address the core challenges of low fault diagnosis efficiency and poor interpretability in intelligent operation of power communication networks. We construct a spatiotemporal correlation model that integrates multi-source asynchronous events by automatically converting real-time monitoring data into events that activate the knowledge graph. A hybrid algorithm combining a weighted random walks and rule-based reasoning was designed, successfully achieving accurate fault diagnosis and automatic generation of interpretable reasoning chains and disposal suggestions. The practical application validates the effect of this method. In the future, we will focus on improving the adaptive learning ability of the model, introducing Graph Neural Networks (GNN) to enhance the capture of complex fault patterns, exploring predictive maintenance from diagnosis to warning, and promoting the construction of a unified knowledge graph across power grids and communication networks, laying a foundation for the intelligent power communication operation and maintenance system.

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