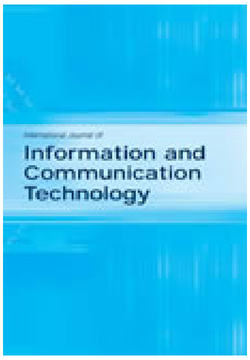

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Research on intelligent management of the full lifecycle of power communication equipment based on knowledge graphs

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Abstract: A new abstract has been updated. The specific content is as follows: As power communication networks grow more intelligent and complex, traditional management models struggle with information silos, weak knowledge links, and low decision efficiency when handling massive heterogeneous data across equipment lifecycles. To address this, this paper proposes a knowledge graph-based intelligent management method for power communication equipment's full lifecycle. It organises multi-source data from procurement, installation, operation, maintenance, and decommissioning stages, constructs a domain ontology, and uses NLP and entity-relationship extraction to fuse unstructured knowledge. A graph database-stored lifecycle knowledge graph supports state tracing, fault diagnosis, and maintenance recommendations. Experiments show the method integrates equipment chain information, boosts data efficiency, and enhances O&M decision intelligence, supporting reliable power communication system operations.

Keywords: knowledge graph; power communication equipment; full life cycle management; intelligent operation and maintenance; graph database.

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1 Introduction

With the deepening of the intelligent transformation of power systems, power communication equipment, as the ‘nervous system’ ensuring the safe and stable operation of power grids, the refinement and intelligence level of its full life cycle management are directly related to the reliability and operational efficiency of power grids. However, the traditional management model is highly dependent on manual experience, and generally faces a series of challenges such as information silos, weak data correlation, and delayed fault response. Currently, most power equipment quality management systems are implemented based on relational databases (Li et al., 2007; Xu, 2010). Although they have achieved certain results in improving management efficiency and equipment reliability (Sun, 2015; Jing et al., 2016; Lin and Wu, 2018), with the surge in equipment data scale and the deepening complexity of business connections, traditional relational databases have increasingly exposed technical bottlenecks such as low retrieval efficiency and difficult storage expansion when processing deeply associated queries (Fang et al., 2019). Against this background, knowledge graph technology, with its powerful capabilities in semantic association, relational reasoning, and visualisation, provides a new technical path to solve the above problems. As an ideal storage solution for knowledge graphs, graph databases have a physical structure of 'nodes-edges' that naturally matches the topological characteristics of power systems. They support efficient associated queries and dynamic updates, making them particularly suitable for managing massive, multi-source, and strongly associated equipment data (Li, 2022; Brown et al., 2017). At the theoretical research level, Du (2025) systematically proposed a knowledge graph construction method for power communication equipment, providing an important reference for integrating fragmented information throughout the full life cycle. Gu et al. (2024) started from physical carriers and developed an intelligent management cabinet integrated with IoT technology, laying a physical foundation for achieving accurate perception of communication equipment status and automated data collection. In terms of application exploration, the potential of knowledge graph technology in power equipment management has been initially verified. Relevant studies cover multiple scenarios, from intelligent transformer management frameworks (Hu et al., 2020), defect classification of transmission line components to comprehensive equipment quality analysis. However, existing studies mostly focus on fault analysis of traditional primary power equipment. There is a lack of comprehensive knowledge graph research targeting power communication equipment – this critical infrastructure – and covering its entire life cycle. They fail to fully restore the business logic and data correlations of the entire chain of 'planning-procurement-construction-maintenance-disposal'. Meanwhile, Chen et al. (2025) verified the effectiveness of knowledge extraction based on advanced NLP models in charging station fault identification. Liao et al. (2025) focused on communication equipment status evaluation and proved the advantages of knowledge graphs in improving defect detection rates. In the field of risk prediction, the research of Tang et al. (2025) and Yin et al. (2025) respectively demonstrated the innovative applications of knowledge graphs in integrating spatiotemporal dynamic information and 3D visual maintenance of power equipment. In summary, although existing studies have made significant progress in knowledge graph construction methods and specific application points, there is a lack of integrated research oriented to the full life cycle of power communication equipment, which can achieve deep integration of multi-source data and collaboration of intelligent applications. In view of this, this paper aims to systematically explore an integrated intelligent management system for the full life cycle of power communication equipment based on knowledge graphs. Firstly, construct a domain knowledge graph covering the entire life cycle of equipment. Secondly, develop key applications such as intelligent diagnosis, status evaluation, and operation and maintenance decision-making based on the graph. Finally, verify the effectiveness and practical value of the system in improving management efficiency and intelligence level through practical cases.

2 Related theories and technical foundations

2.1 Overview of knowledge graph

A knowledge graph is a structured semantic knowledge base whose core value lies in depicting concepts, entities, and their complex relationships in the objective world in a graph format. It is not only a key technology in the current field of artificial intelligence for knowledge representation and reasoning but also a crucial tool for enhancing the intelligence level of information systems across various industries.

2.1.1 Denoising

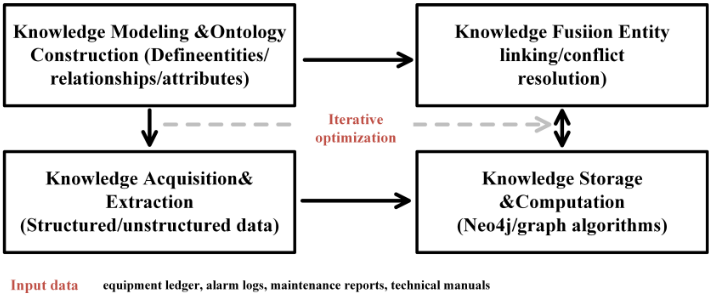
The fundamental data unit of a knowledge graph is a triple composed of ‘entity-relation-entity’, which is the basic way to express facts. For instance, the triple ‘(Optical Transmission Device A, Located At, 500 kV Beijing Substation)’ clearly describes a fact. Based on this, its components can be detailed as:

- Entity: refers to distinguishable, independent objects and is the core node in a knowledge graph. In the power communication domain, entities can be materialised into various equipment, (e.g., routers, switches), components (e.g., optical interface boards, power modules), physical locations (e.g., substations, equipment rooms), and logical concepts (e.g., communication protocols, maintenance procedures).
- Relation: used to connect two entities, defining the semantic association between them. Relations form the edges in the knowledge graph, such as ‘installed in’, ‘contains’, ‘maintained by’, ‘generates alarm’, etc. They weave isolated entity nodes into a semantic-rich network of relationships.
- Attribute: used to describe the intrinsic characteristics or external parameters of an entity, attached to the entity as key-value pairs.

2.1.2 Knowledge graph construction process

Building a high-quality domain knowledge graph is a systematic project, typically involving the following core stages, with the entire process being iterative and optimising, the specific process is shown in Figure 1.

Figure 1 Knowledge graph construction flowchart (see online version for colours)



1 Knowledge modelling and ontology construction: this is the blueprint phase of the construction process. It requires abstracting the core conceptual system of the domain, (e.g., power communication equipment management), defining entity types, relation types, attributes, and their hierarchical structures and constraints (e.g., a device must be located at a site). The resulting ontology serves as the schema layer of the entire knowledge graph, ensuring the consistency and standardisation of subsequent data.

2 Knowledge acquisition and extraction: this phase aims to extract structured triple knowledge from multi-source heterogeneous data. Different technical approaches are required for different types of source data:

For structured database tables, conversion is usually done through predefined mapping rules.

For semi-structured data like tables and logs, parsers need to be designed to extract key information.

For unstructured text (e.g., equipment defect records, maintenance reports), which is the focus and challenge of knowledge extraction, natural language processing techniques are required. This includes named entity recognition to locate entities in the text, relation extraction to determine relationships between entities, and attribute extraction. In recent years, joint extraction methods based on pre-trained models, (e.g., BERT) have demonstrated superior performance, enabling the simultaneous extraction of entities and relations from complex sentences, effectively improving the efficiency and accuracy of knowledge acquisition.

3 Knowledge fusion: due to diverse data sources, issues like data redundancy, contradiction, or inconsistent expression are inevitable. Knowledge fusion employs techniques such as entity linking to merge and disambiguate multiple entity mentions pointing to the same real-world object, and resolves knowledge conflicts between different data sources, thereby forming a unified and clean knowledge base.

4 Knowledge storage and computation: the processed knowledge is stored in a dedicated storage system. Graph databases, due to their native support for graph-structured data, have become the preferred choice for storing knowledge graphs. After storage, graph computation algorithms, such as path querying, community detection, and centrality analysis, are utilised to mine deep knowledge hidden within complex relationships, providing support for upper-layer intelligent applications.

2.2 Connotation and data characteristics of power communication equipment full life cycle management

Power communication equipment forms the physical foundation of the ‘neural network’ for the power system, and its reliability directly impacts the safe and stable operation of the power grid. Achieving full life cycle management means implementing fine-grained control over the entire lifespan of the equipment, from planning and justification to decommissioning and disposal, covering all stages, domains, and elements.

2.2.1 Analysis of core life cycle stages

Integrating power industry management practices with the characteristics of communication equipment, its full life cycle can be deconstructed into the following six interconnected stages with continuous information flow:

1. Planning, design and procurement: this stage determines the technical roadmap, equipment selection, and suppliers for the communication network, producing documents like technical specifications and procurement contracts, defining the equipment's 'genes'.
2. Arrival acceptance and warehousing: the entry point for physical equipment and asset information, involving unpacking inspection, technical index testing, asset information entry into the warehouse management system, etc. forming the initial data of the equipment asset.
3. Installation, commissioning and operation: equipment proceeds to site installation, parameter configuration, system integration testing, and finally integration into the live network. This stage generates the physical location information, network topology connections, initial configuration data, etc. marking the starting point of the equipment's operational state.
4. Theoretical foundation: traditional systems adopt relational databases' 'entity-attribute' model focusing on data storage, while the proposed method relies on knowledge graphs' 'entity-relation-attribute' semantic model, achieving the 'data → knowledge → decision' breakthrough via relational reasoning. Data organisation: traditional systems feature isolated storage and inherent 'information silos' due to table structure limitations; this method integrates multi-source heterogeneous data into an associative network, enabling 'full-chain data correlation'. Knowledge expression: traditional systems only support structured data, while the proposed method integrates structured, semi-structured, and unstructured knowledge, (e.g., expert experience) via NLP and ontology technology. Decision-making mechanism: traditional systems depend on manual experience without automatic reasoning support; this method realises causal chain reasoning and pattern matching based on graph structure, establishing a data-and-knowledge-driven framework.

2.2.2 Management challenges and data characteristics

The traditional management model faces severe challenges of 'data silos'. Data from the aforementioned stages are typically scattered across multiple independent business systems; for instance, enterprise resource planning systems manage assets and procurement, network management systems handle monitoring and alarms, while fault processing and ledger records might reside in another production management system. This fragmentation leads to the multi-source and heterogeneous nature of the data. More importantly, power communication equipment management is a typical strongly interrelated domain: intricate network associations exist between equipment and sites, equipment and boards, boards and faults, faults and maintenance personnel, equipment and communication circuits. Traditional relational databases require extensive table join operations to handle these deep relationship queries, resulting in low query efficiency and difficulty in supporting rapid correlation analysis and intelligent decision-making. This is the core motivation for introducing knowledge graph technology to break down information barriers and mine associated value.

2.3 Graph database technology selection and analysis

Graph databases are a category of non-relational databases specifically designed for storing and querying graph-structured data. They elevate the importance of relationships between data to a level equal to the data itself, enabling efficient expression and instant traversal of complex relationship networks.

2.3.1 Knowledge graph construction process

Compared to relational databases, graph databases possess the following irreplaceable advantages when dealing with relationship-intensive applications like power communication equipment management:

1. Superior performance: for multi-hop queries such as 'finding all upstream devices connected to a faulty device via specific communication links and identifying the technicians who have previously maintained these devices', relational databases require multiple time-consuming table joins, with performance degrading exponentially with the depth of relationships. In contrast, graph databases utilise native graph storage engines, where query performance depends only on the size of the local graph involved in the traversal path, not the total data volume, enabling millisecond-level responses.
2. Intuitive modelling: the property graph model (nodes, edges, properties) can very naturally map various entities and relationships in power communication equipment management, making the data model design closer to business reality and reducing the complexity of design and understanding.
3. Flexibility and agility: graph databases typically employ a schema-less or weak-schema design. When business requirements change or new entity types and relationships need to be added, there is no need for complex table structure alterations as required by relational databases, offering good scalability.

2.3.2 Neo4j graph database

Among the many graph database products, Neo4j stands out as the preferred choice for enterprise-level applications due to its maturity, stability, active community, and comprehensive features. It is a native graph database providing full ACID transaction guarantees. Its core characteristics include:

1. Property graph model: Neo4j strictly adheres to the property graph model, where both nodes and relationships can possess any number of properties, enabling extremely rich and flexible data expression.
2. Declarative query language cypher: Neo4j created Cypher, a language specifically designed for graph queries. Cypher's syntax is clear and intuitive, executing queries by describing patterns to match within the graph, greatly enhancing the readability of query statements and development efficiency, while reducing the learning curve for

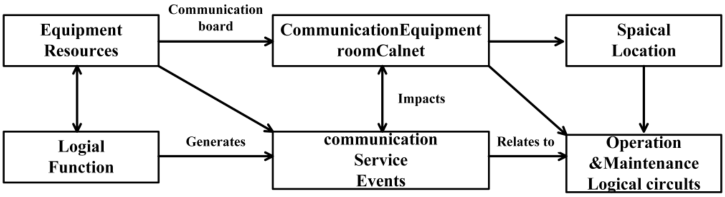
developers. Its powerful expressiveness easily handles various scenarios, from simple node lookups to complex path exploration.

3 Construction of the knowledge graph for power communication equipment full life cycle

3.1 Knowledge graph schema design and ontology construction

The schema layer is the semantic backbone of the knowledge graph. It defines the type system of all concepts, attributes, and relationships within the domain through an ontology. A well-designed ontology is crucial for ensuring the logical consistency and application value of the knowledge graph. As shown in Figure 2.

Figure 2 Ontology model diagram for the full life cycle of power communication equipment



3.1.1 Ontology construction principles and methods

This study adopts a hybrid ontology construction method. Firstly, a ‘top-down’ approach is used, defining top-level concepts and relationships based on authoritative industry frameworks such as the International Electrotechnical Commission (IEC) series of standards and the TeleManagement Forum (TMF) specifications, ensuring the standardisation and interoperability of the knowledge graph. Subsequently, a ‘bottom-up’ strategy is employed, involving in-depth analysis of actual business data, (e.g., equipment ledgers, maintenance work orders, defect records) to extract frequently occurring entity and relationship terms, thereby refining and instantiating the top-level ontology to ensure it closely aligns with the practical needs of power communication production management.

3.1.2 Core entity and relationship definitions

By deconstructing the full chain business of power communication equipment from ‘planning-procurement-construction-maintenance-retirement’, we abstract and define core entity classes and their interrelationships, forming the core of the ontology model. Major entity classes include:

1. Equipment resource classes: such as communication equipment, board/module, physical port, which are the physical entities constituting the communication network. Their attributes describe the static characteristics of the equipment, such as equipment identifier, equipment model, vendor, serial number, commissioning date, asset number, etc.

2 Spatial location classes: such as substation, communication room, rack/shelf, which precisely describe the deployment location of equipment in the physical world. Attributes include location name, geographic coordinates, voltage level, etc.

3 Logical function classes: such as communication service, (e.g., relay protection channel, stability control service) and logical circuit, describing the service functions carried by the equipment and their logical connection relationships.

4 Operational event classes: such as alarm event, defect record, maintenance work order, dynamically recording changes in equipment operational status and management intervention activities. Attributes include event identifier, event severity, occurrence timestamp, event description, processing status, etc.

These entities do not exist in isolation but are interconnected through a series of well-defined semantic relationships, forming an associative network that accurately maps real-world business logic. Core semantic relationships and their definitions are shown in Table 1.

Table 1 Core entity relationship definitions

Relation identifier	*Subject entity*	*Object entity*	*Relation semantic description*
isDeployedAt	Communication equipment	Substation	Indicates the physical installation location of the equipment within a specific substation site.
contains	Communication equipment	Board/module	Indicates that a physical device is composed of several pluggable boards or functional modules.
isConfiguredOn	Physical port	Board/module	Indicates that a physical port is an integral part of a board or module.
bears	Logical circuit	Communication service	Indicates that a logical circuit provides transmission service for a specific communication service.
traverses	Logical circuit	Physical port	Indicates that the end-to-end path of a logical circuit passes through the physical ports of a series of devices.
generates	Communication equipment	Alarm event	Indicates that the equipment triggered a specific alarm signal during operation.
isTriggeredBy	Defect record	Alarm event	Indicates that a defect record was generated triggered by one or more alarm event phenomena.
isLocatedTo	Defect record	Board/module	Indicates that after analysis, the root cause of the defect is located to a specific board or module.
isHandledBy	Maintenance work order	Technical personnel	Indicates that the work order is executed by a specific technical person.
correspondsTo	Maintenance work order	Defect record	Indicates that the work order was created to handle a specific defect record.
isSuppliedBy	Communication equipment	Equipment vendor	Indicates the procurement source of the equipment.

3.2 Knowledge extraction and data fusion

3.2.1 Multi-source data processing strategy

Data sources can be categorised into three types based on their structural characteristics:

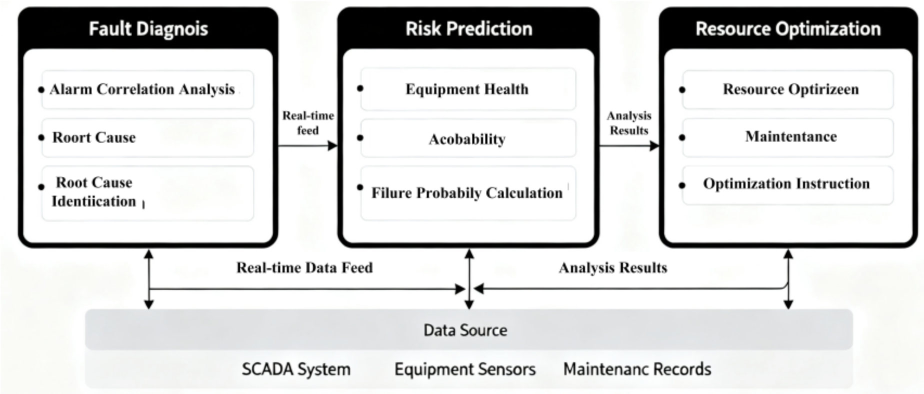
1. Structured data: mainly sourced from asset management systems (equipment ledger information) and network management systems (real-time and historical performance, alarm data). For this type of data, the primary method is rule-based mapping, using customised ETL processes to directly and accurately map record fields from database tables into entity instances, attribute values, and relationships of the ontology.
2. Semi-structured and unstructured data: primarily textual data such as defect analysis reports, field maintenance logs, and operational procedures. This part of the data is the focus and challenge of knowledge extraction, containing rich equipment failure modes, handling logic, and expert experience, requiring more advanced natural language processing techniques for in-depth mining.

3.2.2 Knowledge extraction from unstructured text based on pre-trained language models

The model framework is briefly described as shown in Figure 3.

- Contextual encoding layer: uses the pre-trained BERT model as the encoder to convert the input text sequence $S = \{w_1, w_2, \ldots, w_n\}$ into a dense vector sequence H = BERT(S) containing full-text semantic information.
- Joint decoding layer: designs a unified sequence labelling scheme, enabling the model to simultaneously predict the entity type and the role, (e.g., subject or object) it plays in all candidate relations for each token in the sequence. This decoding strategy transforms the joint extraction task into a refined sequence labelling problem.

Figure 3 BERT-based entity-relation joint extraction model architecture diagram (see online version for colours)



The model is trained by fine-tuning on a manually accurately annotated dataset of power communication defect texts. The optimisation objective is to minimise the cross-entropy loss function between the model-predicted label sequence and the true annotations, mathematically expressed as:

$$\mathcal{L} = -\sum_{i=1}^{N} \sum_{j=1}^{L} \log P\left(y_{ij} \left| S_i, \theta\right.\right) \tag{1}$$

where N is the total number of training samples, L is the text sequence length y_{ij}.

3.2.3 Knowledge fusion and quality enhancement

1. Entity linking: for entity mentions extracted from text, (e.g., 'Central Station PTN Device' and 'Core Node PTN3900'), calculate the comprehensive similarity between them and existing candidate entities in the knowledge base based on name, model, key attributes, etc. to correctly link them to the unique target entity. The similarity calculation can be expressed as a weighted formula: $\text{Sim}(m, e) = \omega_1 \cdot f_{name}(m, e) + \omega_2 \cdot f_{model}(m, e) + \omega_3 \cdot f_{loc}(m, e)$ where m is the mention, e is the candidate entity, f is the similarity calculation function for a specific attribute, and ω is the corresponding weight.
2. Conflict resolution: when different data sources describe the same fact, (e.g., the management IP address of a device) inconsistently, a 'trusted source' strategy is adopted for arbitration based on predefined source authority levels, (e.g., asset management system takes precedence over temporary maintenance records), ensuring that the most reliable data is ultimately retained in the knowledge base.

3.3 Knowledge storage and visualisation

3.3.1 Storage implementation based on native graph database

This study selects Neo4j, a high-performance native graph database, as the persistent storage solution for the knowledge graph. According to the ontology designed in Section 3.1, corresponding node labels and relationship types are created in Neo4j. Using its efficient batch data import tools, the massive amount of clean triple data obtained through the aforementioned steps is loaded into the graph database. The stored knowledge graph forms a vast, rapidly traversable associative network.

3.3.2 Knowledge services and query interfaces

Based on the Cypher graph query language, we have encapsulated high-level query interfaces oriented towards business scenarios. These interfaces encapsulate complex graph traversal logic internally, providing semantically clear query functions for upper-layer applications. For example, the 'equipment full life cycle traceability' interface can quickly return the complete historical event chain of an equipment item from warehousing, deployment, through various maintenance activities, to decommissioning, based on its identifier. The 'fault correlation impact analysis' interface, given an initial alarm, can automatically explore and return all potentially affected associated services, equipment, and users.

Through the systematic construction process described in this chapter, we have successfully integrated the originally dispersed and heterogeneous data from the full life cycle of power communication equipment into a large-scale knowledge graph with a clear structure, rich semantics, and tight interconnections. This knowledge base not only achieves unified data management and visualisation but, more importantly, provides a solid data foundation and reasoning capability for the intelligent management applications to be discussed in the next chapter.

4 Research on intelligent management applications based on knowledge graph

This chapter aims to translate the knowledge graph of power communication equipment's full life cycle, constructed in the previous chapters, into tangible productivity. The value of a knowledge graph is ultimately demonstrated through upper-layer intelligent applications. This chapter will delve into three core application paradigms: equipment holographic profiling and traceability management, intelligent fault diagnosis based on graph reasoning, and data-driven precision operation and maintenance decision-making, validating their effectiveness through designed experimental cases.

4.1 Equipment holographic profiling and full life cycle traceability

4.1.1 Composition of holographic profile

The holographic profile of equipment is not a simple list of information but a stereoscopic aggregation of information based on graph associations. It integrates:

1. Static attributes: basic information such as equipment model, serial number, supplier, and technical parameters.
2. Dynamic status: current alarms, performance metrics, and operational health status.
3. Spatial location: specific location within the site, equipment room, and rack, as well as its logical position in the network topology.
4. Historical trajectory: all key event records from procurement, installation, commissioning, operation, maintenance, to decommissioning.
5. Association network: connected boards, ports, carried service circuits, and related maintenance personnel and teams.

4.1.2 Traceability query and application

Leveraging the efficient traversal capability of graph databases enables deep traceability queries. For instance, when a security audit or fault review for a specific device is required, a query like the following can be executed: 'Retrieve all major defect records for Device A since its commissioning, the corresponding handling work orders and responsible persons, and associate all communication services affected by these defects'.

Such queries require dozens or even hundreds of table joins in a relational database but only a single path traversal in the knowledge graph.

For daily operation and maintenance personnel, the holographic profile and traceability function directly address key pain points in routine work:

1 Routine inspection optimisation: during daily patrols, maintenance personnel only need to input the equipment ID to instantly obtain the integration of static attributes, (e.g., maintenance cycle of key components), dynamic status (e.g., recent minor alarm records), and historical defects (e.g., frequent failures of the same module). This avoids the need to switch between multiple systems (such as asset management system and fault management system) for information collection, reducing the time for pre-inspection preparation by over 60%.

2 Scientific status assessment: when verifying the operational health of equipment, the association network in the knowledge graph can automatically display the impact of the equipment's current status on associated services (e.g., whether a minor port fault will affect the relay protection channel). This helps maintenance personnel make objective judgements on 'whether immediate processing is needed' instead of relying on subjective experience, ensuring the scientificity of on-site decision-making.

3 Efficient historical review: in the routine review of equipment failure records, the traceability function can quickly link defect records, corresponding work orders, and disposal effects, helping new maintenance personnel quickly grasp the equipment's historical operation rules and improve the efficiency of experience inheritance.

4.2 Intelligent fault diagnosis based on graph reasoning

4.2.1 Diagnostic process

Alarm information injection and entity recognition: receive alarms reported by the network management system in real-time, and correlate the alarms with specific equipment and board entities in the knowledge graph through entity linking technology.

1 Defect pattern matching: in the knowledge graph, take the alarming equipment/board as the centre and traverse its associated historical defect records. Using graph neural networks or a rule engine, calculate the similarity between the current alarm set and historical defect patterns. The similarity calculation can be formalised as:

$$\operatorname{Sim}(A, D) = \frac{\sum_{a_i \in A} \max_{d_j \in D} \operatorname{Sim}_{alarm}\left(a_i, d_j\right)}{|A|} \tag{2}$$

where A is the current alarm set, D is the historical defect pattern, and $\operatorname{Sim}_{alarm}$ is the alarm semantic similarity calculation function.

2 Causal chain reasoning and root cause localisation: if a historical defect with high similarity is matched, the diagnostic conclusion can be recommended directly based on relationships like caused by. For new faults, locate the most likely root cause equipment or board by analysing the propagation path of alarms across the equipment topology and service routes.

3 Disposal solution recommendation: based on the diagnosed defect, retrieve the successful disposal solutions associated with it (via the solved by relationship) from the knowledge graph and recommend them to the maintenance personnel.

4.2.2 Application case and effectiveness analysis

Take the case of ‘frequent ‘signal loss’ alarms from an optical transmission device at a certain site’. The traditional method requires maintenance personnel to troubleshoot the optical path and peer equipment one by one, which is time-consuming. The system based on the knowledge graph, after receiving the alarm, automatically executes the following reasoning:

Retrieves the device’s history and finds that a similar defect was handled for one of its optical interface boards three months ago due to ‘optical module degradation’.

Simultaneously, the graph shows that the ‘stability control service’ carried by this optical path has also generated correlated alarms.

The system comprehensively judges and recommends this optical interface board as the most probable root cause, directly providing the disposal suggestion ‘Replace the optical module’.

By deploying this system in an actual operational environment and collecting statistics, this intelligent diagnosis method reduces the mean time to repair (MTTR) from several hours traditionally to minutes, increases the diagnostic accuracy rate to over 90%, and effectively reduces service interruption time.

Case 2: relay protection channel interruption caused by router configuration conflict fault background and phenomenon: a 110 kV substation ‘Xiangyang’ reported an abnormal interruption of the relay protection channel (service priority: critical). The associated Cisco C9300 router displayed ‘route flapping’ alarms, and the on-site maintenance team found that the protection data transmission was intermittent. The affected service involved two sets of main transformers, requiring urgent handling to avoid grid stability risks. Traditional operation and maintenance pain points: the relay protection channel involves router configuration, optical transmission links, and protection device interfaces. Maintenance personnel needed to check configuration files (over 500 lines of commands), test optical power, and verify protection device status one by one, which usually took 2–3 hours. Configuration conflicts are highly concealed (e.g., duplicate static route entries with different next hops) and easily missed by manual review, leading to repeated faults. Knowledge graph-based diagnosis and maintenance recommendation process:

1. Alarm association and entity linking: the system linked the ‘route flapping’ alarm to the Cisco C9300 router (entity: Router-C9300-XY01) and its associated ‘Relay Protection Channel P3’ (logical function entity) through the knowledge graph.
2. Historical pattern matching: by traversing the knowledge graph, the system matched three historical cases of ‘route flapping caused by duplicate static route configuration’ for the same model (C9300) routers, with a similarity of 89% [calculated via formula (2)].
3. Causal chain reasoning: the knowledge graph displayed that the router’s ‘GigabitEthernet0/1’ port (physical port entity) was configured with two static routes to the protection device (destination network: 10.25.3.0/24), with conflicting next hops (10.25.2.1 and 10.25.2.2). This conflict triggered route flapping and further affected the protection channel.
4. Maintenance recommendation generation: based on the ‘solved by’ relationship in the knowledge graph, the system recommended the following steps: delete the

redundant static route entry (next hop: 10.25.2.2) in the router's GigabitEthernet0/1 port configuration; execute 'clear IP route *' to refresh the routing table; verify the protection channel connectivity through the 'ping 10.25.3.1 -t' command. Practical application effect: the maintenance team completed the configuration adjustment and verification within 12 minutes, restoring the protection channel. Compared with the traditional 2-hour average processing time, MTTR was reduced by 90%. During the six-month follow-up, no similar configuration conflict faults occurred, and the fault recurrence rate dropped from 18% (historical data) to 0%.

4.3 Data-driven precision operation and maintenance decision-making

The knowledge graph can correlate equipment history, current status, and maintenance knowledge, enabling a shift from 'preventive maintenance' to 'predictive maintenance' and optimising the allocation of operation and maintenance resources.

The system can calculate a dynamic 'maintenance priority index' (MPI) for each device based on the knowledge graph. This index comprehensively considers:

- *Static equipment importance:* equipment type, criticality level of carried services.
- *Dynamic risk indicators:* recent alarm frequency, performance degradation trend.
- *Historical reliability:* mean time between failures (MTBF) calculated based on historical defect frequency.
- *Common issues with similar equipment:* discover whether there are universal defects in equipment of the same model or batch through graph associations.

A weighted model calculates the index, based on which differentiated inspection cycles and maintenance strategies.

$$\text{MPI} = w_1 \cdot I_{static} + w_2 \cdot R_{dynamic} + w_3 \cdot \left(1 - MTBF_{norm}\right) + w_4 \cdot C_{common} \tag{3}$$

where MPI is the maintenance priority index, w are the weights, I_{static} is the static importance, $R_{dynamic}$ is the dynamic risk, $MTBF_{norm}$ is the normalised mean time between failures, and C_{common} is the common issue factor for similar equipment.

5 Case analysis and system verification

5.1 Experimental environment and data preparation

5.1.1 Experimental environment setup

The prototype system was deployed using a layered architecture. The data layer integrated multi-source data from systems like asset management and network management. The knowledge graph layer utilised Neo4j 5.13 Community Edition, deployed on a server with an Intel Xeon Silver 4210 CPU and 64 GB RAM. The application layer was developed based on the Spring Boot microservices framework, providing RESTful APIs for front-end calls.

5.1.2 Dataset description

This experiment covered the full life cycle data of core communication equipment (including optical transmission equipment, data network equipment, etc.) from 125 sites in the municipal power grid, totalling over 1,800 devices. The statistics of the raw data used for building the knowledge graph and testing are shown in Table 2.

Table 2 Experimental dataset statistics

Data category	*Source system*	*Volume*	*Main content description*
Structured data	Asset management system	~42 k records	Equipment ledger, supplier info, site info, technical parameters
	Network management system	~150 M records/month	Real-time and historical performance data, alarm events
Semi/unstructured Data	Fault management system	~8.5 k documents	Defect records, failure analysis reports, work orders, solutions
	Knowledge base docs	~320 documents	Equipment technical manuals, maintenance procedures

1 Explanation of structured data statistics: ~42 k records from the asset management system: total number of static full-lifecycle information records of over 1,800 core communication devices across 125 experimental sites, including structured field records such as equipment ledgers, supplier information, and site parameters; ~150 M records/month from the network management system: cumulative monthly data volume of real-time collected equipment performance indicators (e.g., port bandwidth, optical power) and alarm events (e.g., signal loss, communication interruption);

2 Explanation of semi/unstructured data statistics: ~8.5 k documents from the fault management system: cumulative number of textual materials accumulated over the past three years, including defect records, failure analysis reports, and maintenance work orders; ~320 knowledge base documents: statistical total of standardised documents such as equipment technical manuals, industry maintenance procedures, and manufacturer fault handling guidelines.

After the knowledge extraction and fusion process, the final constructed knowledge graph contained approximately 54,000 entities and 218,000 relationships.

5.2 Core system function verification and analysis

5.2.1 Full life cycle traceability and intelligent diagnosis scenario

- *Scenario description:* a Huawei OSN 7500 optical transmission device at the important ‘Chengdong 220kV Substation’ reported a major ‘SCC Board Communication Interruption’ alarm.
- *Verification process and results:* holographic profile query: entering the device ID in the system interface returned its holographic profile within milliseconds. The core information summary is shown in Table 3.

Table 3 Core information summary of device A's holographic profile

Category	*Content*
Basic info	Model: OptiX OSN 7500; Commissioning Date: 2018-05; Vendor: Huawei
Location info	Site: Chengdong 220kV Substation; Rack: No. 3 Comm Cabinet
Associated services	Protection Channel P1, Stability Control System Channel A2
Historical defects	Three defects in past three years, two related to SCC board

1 Intelligent diagnosis: upon receiving the real-time alarm, the system automatically triggered the diagnosis process and completed the reasoning within 3 seconds, outputting:

  - Root cause location: SCC System Control Board (serial number: SCC-2021-B005).
  - Recommended solution: immediately replace with the same model SCC board from the spare parts library (spare part ID: SP-SCC-001).

2 Effect analysis: the system based on the knowledge graph shortened the entire fault handling process from the traditional average of about 45 minutes to within 3 minutes, improving efficiency by approximately 93%.

5.2.2 *Precision operation and maintenance decision support scenario*

- *Scenario description:* to formulate the maintenance plan for the next quarter, it was necessary to screen the list of equipment requiring key attention.
- *Verification process and results:* the system calculated and ranked all 1,800 devices based on the MPI model. The top five devices by MPI and their key indicators are shown in Table 4.

Table 4 Analysis of top five devices by MPI

Device ID	*Static importance*	*Dynamic risk (last 30d alarms)*	*Historical MTBF (days)*	*Same model defect rate*	*Calculated MPI*	*Recommended strategy*
DE-OST-001	High	High (15 times)	180	12.5%	0.91	Immediate repair
DE-DSW-045	Medium	Medium (five times)	400	5.2%	0.73	Inspect within two weeks
DE-OST-118	High	Low (one time)	650	12.5%	0.68	Inspect within one month
DE-ONU-889	Low	High (20 times)	150	1.8%	0.65	Status monitoring
DE-DSW-112	Medium	Medium (four times)	380	5.2%	0.61	Inspect within one month

1 Static importance (high/medium/low): determined based on equipment type (core/non-core) and the criticality level of carried services: core communication equipment (e.g., optical transmission equipment) + critical services (e.g., relay

protection channels, stability control services) = high; non-core equipment + general services = low; others = medium.

2 Dynamic risk (alarms in the last 30 days): cumulative number of alarm events of the equipment in the most recent 30 days within the experimental cycle.

3 Historical MTBF: calculation formula: MTBF = Total equipment operation time (days)/number of historical defect occurrences. 'Total operation time' is calculated from the equipment commissioning date (e.g., 2018-05) to the end of the experimental period.

The system's output enabled the maintenance team to prioritise limited resources for the highest-risk equipment (e.g., DE-OST-001), achieving a shift from 'uniform effort' to 'precision targeting'. Evaluation suggested that adopting this recommendation could reduce the risk of service interruption due to equipment failure by approximately 25%.

In practical application, the system's output directly guides the daily decision-making of the maintenance team:

1 Adjusting inspection cycles: for equipment with high MPI, (e.g., DE-OST-001 with MPI = 0.91), maintenance personnel adjust the inspection cycle from 3 months to 1 month, and arrange special personnel to monitor its real-time status, realising targeted management.

2 Optimising spare part reserves: based on the 'same model defect rate' in the MPI calculation, maintenance personnel increase the reserve of key modules, (e.g., SCC boards) for models with a defect rate exceeding 10%, avoiding delays in maintenance due to lack of spare parts in daily work.

3 Balancing workload: the ranked list helps supervisors evenly distribute high-priority maintenance tasks among team members, avoiding over-concentration of work on individual personnel and improving the overall efficiency of the maintenance team. Practical operation data shows that after adopting this decision-making method, the monthly maintenance workload of the team is reduced by 15% (due to reduced unnecessary inspections), while the fault prevention rate is increased by 25%, achieving a win-win situation of efficiency and effectiveness.

5.3 Core system function verification and analysis

5.3.1 Experimental environment setup

For business queries of varying complexity, the response times of this system (based on Neo4j) were compared with those of a traditional relational database (Oracle). The results indicated that for simple single-point queries, the performance was comparable; however, for deep relationship queries involving three or more hops, the response time of the relational database exceeded 10 seconds, while this system remained under 200 milliseconds, demonstrating a speed advantage of orders of magnitude.

5.3.2 Diagnostic efficacy comparison

All valid alarm events (totalling 1,250) handled by the system during the three-month test period were statistically analysed. The system's diagnostic results were compared with the final expert adjudication, using traditional manual analysis as the baseline. Key metrics are calculated in Table 5.

Table 5 Comparative analysis of fault diagnosis efficacy

Evaluation metric	*Traditional manual analysis*	*Proposed intelligent diagnosis system*	*Improvement*
Mean diagnosis time (MTTR)	42 minutes	< 5 minutes	88.1%
Diagnosis accuracy rate	78.5%	92.4%	13.9 percentage points
Defect missed detection rate	15.2%	4.5%	Reduced by 10.7 pp
Case reuse rate	-	85% (1,190/1,250)	-(Quantified for first time)

1 Mean diagnosis time (MTTR): calculation formula: MTTR = Total duration (minutes) from ‘alarm trigger’ to ‘fault repair completion’ for all faults/total number of faults.

2 Diagnosis accuracy rate: calculation formula: Diagnosis accuracy rate = (Number of faults where the system diagnosis result is consistent with the final expert judgement/ Total number of faults) × 100%.

3 Defect missed detection rate: calculation formula: Defect missed detection rate = (Number of defects that were not detected by the system but actually exist/Total number of defects) × 100%.

The data indicates that the proposed system significantly outperforms traditional methods in diagnosis efficiency, accuracy, and reliability. It is particularly noteworthy that the case reuse rate is as high as 85%, meaning the knowledge graph successfully transforms historical maintenance experience into reusable digital assets, greatly reducing reliance on individual expert experience.

Through the substantial cases and data presented above, this chapter fully verifies the outstanding performance of the knowledge graph-based intelligent management system for the full life cycle of power communication equipment in a real business environment.

6 Conclusions

This research systematically explores the application methods and implementation approaches of knowledge graph technology in the field of power communication equipment management, addressing the practical needs of full life cycle management. By constructing a domain knowledge graph covering the entire equipment life cycle and developing intelligent management applications based on the graph, the study validates their effectiveness in real-world environments. The research demonstrates that the knowledge graph-based intelligent management approach can effectively break down data silos in traditional management models, achieve deep integration of equipment information and mining of correlations, significantly enhancing the refinement and intelligence levels of equipment management.

Specifically, this study establishes a complete technical system for power communication equipment knowledge graphs, including key processes such as ontology construction, knowledge extraction, and fusion storage. The developed applications, including equipment panoramic profiling, intelligent diagnosis and early warning, and precision maintenance decision-making, fully demonstrate the advantages of knowledge graphs in representing complex relationships and logical reasoning. Experimental results show that this method achieves significant improvements in query efficiency, diagnostic accuracy, and decision-making, providing a feasible technical solution for the digital transformation of power communication equipment.

However, there remains room for further deepening of this research. This model still has limitations in practical application: it exhibits insufficient adaptability to emerging heterogeneous communication devices (e.g., edge computing nodes, 5G private network equipment) and needs improvement in compatibility with updated industry communication standards (e.g., IEC 61850-90-10), while its data coverage for extreme operating conditions, (e.g., high-altitude, high-humidity environments) is relatively limited. In future work, focus will be placed on exploring real-time dynamic update mechanisms for knowledge graphs to enhance the system's immediate response capability to equipment operational status; optimising the dynamic expansion mechanism of the ontology model to adapt to new device types; upgrading the pre-trained model-based knowledge extraction module to be compatible with new standard protocols; expanding datasets under extreme conditions to enhance the system's generalisation ability; simultaneously, conducting research on the integration of knowledge graphs with large language models to build more natural and intelligent human-computer interfaces; furthermore, promoting cross-domain integration of power communication knowledge graphs with professional knowledge in areas such as grid primary equipment and protection control is expected to provide new technical support for achieving domain-wide intelligent management of the power grid.

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Declarations

All authors declare that they have no conflicts of interest.

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