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Automated Construction of Knowledge Graphs: Advancing Intelligence in Electrical Power Systems through Fault Diagnosis, Optimization, and Decision Support

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Abstract

The introduction of knowledge graphs (KGs) in the electric power system aims to leverage the extensive data generated by the electric power Internet of Things (IoT). By structuring concepts, entities, events, and their interrelationships, KGs enhance the organization, management, and cognitive processing of cross-media big data within the electrical power industry. This paper presents an innovative approach to automatically constructing knowledge graphs. Furthermore, it delves into detailed applications of KGs in power equipment inspection and explores their potential directions and challenges in future implementations within the sector.

Keywords: knowledge graph; electric power system; power equipment;entity extraction

1. Introduction

A. Conventional Power Knowledge Initiative

The power system constitutes an integrated network encompassing power generation, transmission, transformation, distribution, and consumption, along with the associated auxiliary systems. The relevant business knowledge originates from industry standards, guidelines, and the expertise and experience of professionals and technicians. Over the last three decades, power companies have focused on creating numerous application systems tailored to the operational requirements of different business units. These efforts aim to enhance the progression from raw data to actionable knowledge and from basic awareness to deeper understanding, covering areas such as dispatch, inspection, marketing, infrastructure, and materials management [1-2]. The open structure enabled by knowledge acquisition tools has facilitated the integration of knowledge engineering technologies into numerous application systems within power systems. These systems aim to address complex scientific and engineering challenges, with particular emphasis on adopting expert system frameworks. Expert systems leverage the strengths of knowledge engineering; including knowledge refinement, logical reasoning, and control mechanisms, to enhance decision-making and problem-solving capabilities in the power sector [3-4], the application system based on power knowledge engineering met the business needs of the time, and access to hundreds of millions of types of terminals such as smart meters. The daily increment of collected data exceeds 60TB, and the world's largest Internet of Things has been successfully operated.

As the Internet gradually advances within China's traditional power industry, supporting sectors such as power design, construction, and equipment supply have increasingly become integral components of the overall power industry. Moreover, in recent years, the power sector has expanded its collaboration across industries, partnering with companies in the home appliance and insurance fields. This has led to a more open, streamlined, and interconnected knowledge system within the power domain. However, traditional information systems remain limited to basic applications of power data and knowledge, lacking a comprehensive understanding of the entire knowledge framework and the ability to perform cognitive reasoning related to power business. Consequently, their simplistic construction models no longer fully meet the evolving development requirements of power companies.

B. New Cognitive Methods: Knowledge Graph

In recent years, experts and scholars have proposed technical frameworks and application cases based on domain-specific knowledge graphs to help China's electric power companies overcome knowledge silos, enable business collaboration, and integrate data effectively. These efforts aim to support the development of emerging power grid businesses across areas such as power dispatch, transportation inspection, and marketing. In the field of power inspection, the adoption of artificial intelligence technologies like image analysis for power inspections over the past three years has provided a solid foundation for the research and application of knowledge graphs. By focusing on power equipment as the central element, researchers have conducted in-depth studies on domain-specific knowledge graphs, particularly within segmented business processes For example, Liu et al.[5] used the equipment defect record corpus to construct a power equipment defect knowledge graph, and proposed a method for graph search for power equipment defect retrieval. Yang et al.[6] used domain knowledge graph to comprehensively display the life cycle data of power equipment, and revealed the relationship between equipment entities and business object entities. Tang et al. [7] proposed a method for constructing a knowledge graph of power equipment defects based on multi-source heterogeneous power equipment data, and improved the graph search to show the expected information of the retrieval results. Tang et al.[8] used the domain knowledge graph to perform rule inference, and realized efficient analysis and query involving equipment, manufacturers, stations/lines, companies, and quality events.

This paper will introduce the application of power equipment inspection.

2. Representation of Knowledge and Automated Construction of Graphs for Electric Power Systems

A. Knowledge Representation

The knowledge in the electric power field is derived from both structured data, such as traditional power knowledge engineering systems and expert knowledge bases, and semi-structured or unstructured data, including power standards, guidelines, specifications, procedures, and the experience of experts and technicians. This knowledge spans multiple business domains and can be categorized into general knowledge and specialized knowledge based on its degree of reuse.

General knowledge includes information like the names, voltage levels, capacities of power equipment,

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and organizational structures, which are utilized across various areas such as customer service, power dispatch, operation inspection, and safety quality. In contrast, specialized knowledge pertains to specific fields; for example, customer service data like user names, electricity fees, and prices are rarely relevant to dispatching, inspection, or safety operations. However, the distinction between general and specialized knowledge is often unclear. In practical applications, statistical analysis based on actual business needs is required to define the boundaries between these two categories.

Building on the knowledge representation practices of open domain knowledge graphs, the ontology for the power domain primarily consists of entities, concepts, relationships, attributes, attribute values, functions, and constraints. Since different levels of knowledge vary in complexity, most domain knowledge graphs focus mainly on modeling entities, concepts, relationships, and attributes. Typically, the ontology structure is divided simply into a concept layer and an instance layer, with only a few domain knowledge graphs incorporating simple rule descriptions. However, in real-world power business scenarios, many terms such as "payment," "tripping," and "elimination" do not fit neatly into either the concept or instance categories. These terms, representing actions, events, and regulatory boundaries closely tied to business processes, cannot be accurately classified within the concept or instance layers. To address this, this paper introduces a business layer in the power domain ontology modeling. Acting as a bridge between the concept and instance layers, this business layer maps knowledge elements like actions and events, creating a three-layer knowledge representation framework for the power domain. When performing ontology migration within specific power business verticals, it is necessary to simultaneously update the data in the concept, business, and instance layers according to the domain-specific knowledge.

At present, the two primary graph data models are the Resource Description Framework (RDF) graph model and the attribute graph model. The RDF graph model, established by the W3C for the Semantic Web, is designed to represent and exchange machine-understandable information. It features robust logical foundations and well-defined model characteristics. On the other hand, the attribute graph model, rooted in graph theory, is widely adopted in the graph database industry. While RDF effectively describes entities, their attributes, and their relationships, it cannot represent relationships between entity categories. Therefore, this paper employs the attribute graph model to represent knowledge in the electric power domain.

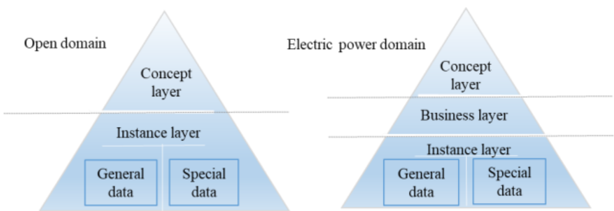

Figure 1. Diagram of knowledge representation in electric power system

B. Knowledge Graph Construction

With the ongoing digitization of power business operations, the data and knowledge in the electric power field have experienced rapid growth. Constructing a domain-specific knowledge graph for the electric power sector from scratch, with detailed and comprehensive knowledge, poses a significant challenge for industry experts and engineers. This chapter focuses on the ontology construction and graph development of knowledge graphs in the power domain.

Methods for constructing domain knowledge graph ontologies primarily include knowledge-driven top-down approaches, data-driven bottom-up approaches, and hybrid approaches combining both. The top-down approach involves manually preparing or utilizing existing structured knowledge bases to extract structural information for the ontology in the power field. Conversely, the bottom-up approach extracts entities, concepts, relationships, attributes, and attribute values from unstructured data, selects high-confidence objects as candidates, analyzes and organizes them into foundational structural information, and incrementally builds the knowledge ontology layer by layer to integrate it into the knowledge base.
Many experts and scholars have conducted a lot of research on domain knowledge graph construction technology. For example, Li et al. used hierarchical learning, fact learning and other related technologies to achieve bottom-up graph construction[10]. Liu et al. combined with the artificial intelligence technology of domain experts' experience to carry out a combination of top-down and bottom-up of Chinese professional dictionary and knowledge graph construction[11]. By analyzing the existing research results, it can be found that although the technical framework of domain knowledge graph construction of different research teams is slightly different, the core modules include knowledge extraction, knowledge fusion, and knowledge processing, as shown in Figure 2.

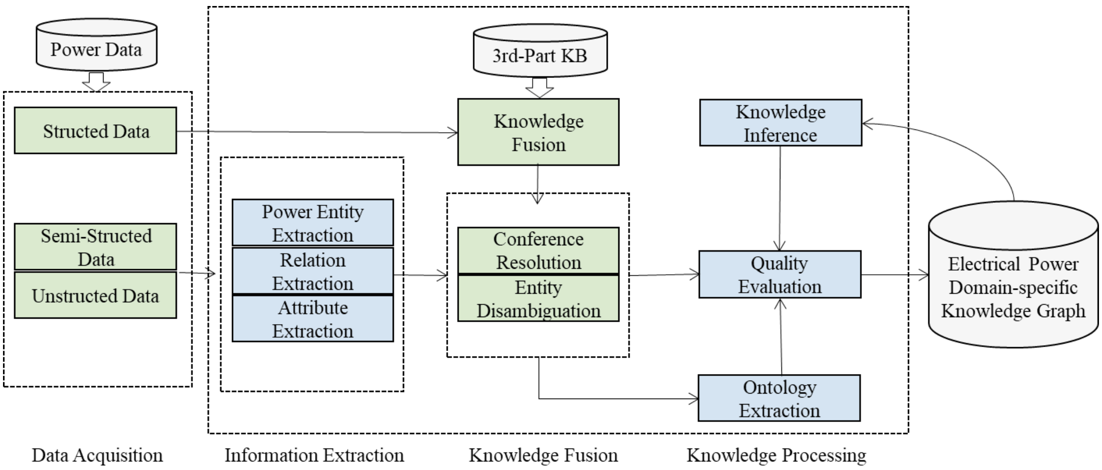

Figure 2. Automatic construction architecture of knowledge graph in electric power system.

Among the widely studied technologies in knowledge graphs are knowledge extraction, fusion, and processing. Knowledge extraction involves automatically identifying and extracting relevant information from text, transforming unstructured data into structured formats. It primarily focuses on extracting entities, relationships, and attributes. Common entity recognition techniques include LSTM-CRF models, LSTM-CNNs-CRF models, and neural network models utilizing attention mechanisms. For relationship extraction, methods range from template-based approaches to supervised learning techniques such as CR-CNN models, Attention CNNs models, Attention Bi-LSTM models, and BERT+GRU joint extraction methods.

Knowledge fusion pertains to integrating multi-source heterogeneous data for decision-making and knowledge services. Supported by ontology and rule databases, it identifies hidden associations within data resources through extraction and conversion, enabling semantic-level inference and creation of new knowledge. Entity disambiguation is a key area within knowledge fusion, employing technologies like entity-mentioned probability generation models, entity-topic models, and deep neural network-based semantic correlation calculation models.

Knowledge reasoning involves deriving new knowledge from existing information using specific strategies to enhance the quality of the knowledge graph. By enabling deeper insights into data, reasoning capabilities allow knowledge graphs to uncover intrinsic value and support downstream applications effectively.

3. Equipment Inspection Application in Distribution System

In the equipment inspection application in distribution system, our team collected business data such as account tables, work orders, work tickets, repair and test records, standard documents for Power equipment inspection. The equipment inspection knowledge ontology framework for electric power distribution system covering equipment, components, parts, defects, faults, descriptions, causes, solutions, fields/stations/lines, units, personnel, ticket types and other information was constructed manually. Bi-LSTM- CRF、Bi-GRU-CRF and other algorithms were used to build the bottom-up map from business data and standard documents. Among them, there are more than 27,000 entities and more than 114,000 relationships, the accuracy rate of entity recognition is about 83.26%, the accuracy rate of entity relationship recognition is about 80.19%, and the accuracy rate of attribute relationship recognition is about 86.77%.

Based on the application architecture of equipment inspection application in distribution system shown in Fig.3 above, a hybrid database was used to store the power operation and inspection domain knowledge graph and its associated data. In addition, through the combination of network crawler, entity and relationship mining algorithm, the knowledge graph of power operation and inspection field could be updated and improved.

When the business data such as power operation inspection image or work order is input into the system, firstly, the cross media data is unified into the text data under the work order template through computer vision, natural language processing and other technologies. The knowledge computing engine looks for the matching knowledge path in the knowledge graph of power operation and inspection field, and clarifies the asset path "field/station/line - centralized management/responsible unit - responsible person - ticket type" and business path "field/station/line - equipment/component/part - defect/fault - solution - ticket type". After getting the relevant knowledge, through the information analysis, work ticket generation, repair and test record comparison three modules to study and judge, and realized the automatic disassembly from work order to work order, as well as match the repair and test record with the work order and work order defect elimination progress. For the judgment and operation of key business links of power operation and inspection, it is necessary to conduct artificial secondary audit to ensure the safety of intelligent decision- making. Taking work order splitting as an example, two optimal paths of "event - field/station/line - responsible unit - maintenance personnel" and "event - equipment – component - part - fault/defect - solution - qualification requirements" were found through optimal path search.A simple application example is shown in the Fig.4.

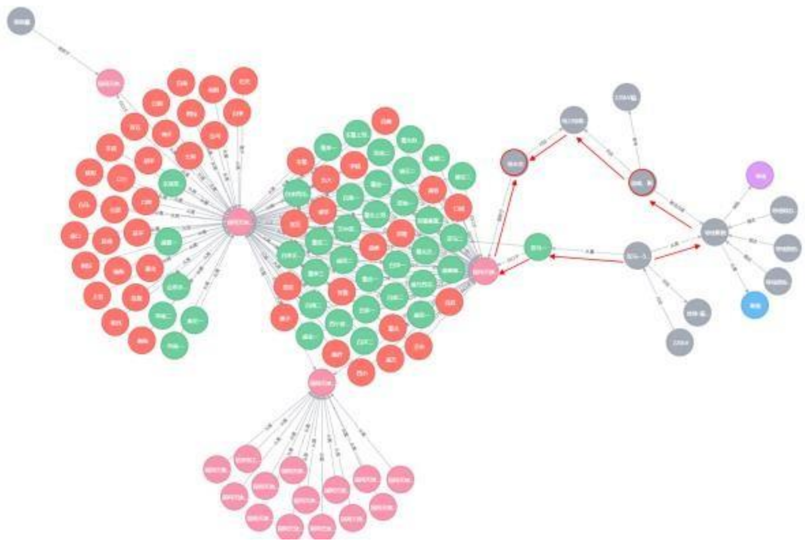

Figure 3. Automatic construction architecture of knowledge graph in electric power system

4. Conclusion and Discussion

The knowledge graph in the power domain seeks to fully utilize data from the electric power Internet of Things to structure concepts, entities, events, and relationships within the power system. It aims to enhance cross-media big data organization, management, and cognitive capabilities across the power industry chain. By integrating big data and artificial intelligence technologies, domain-specific knowledge graphs are becoming key drivers of electric power AI development. This paper introduces an automatic construction method for knowledge graphs and discusses their application in power equipment inspection based on the electric power domain knowledge graph.

Knowledge graph technology acts as a vital link between digital and semantic spaces in artificial intelligence, facilitating knowledge representation and cognitive reasoning, and serving as a foundational resource for intelligent systems. However, its application in power systems faces four major challenges: (1) extracting knowledge and constructing knowledge graphs from mixed data; (2) performing cognitive reasoning and decision-making while accounting for power grid topology; (3) developing a quality evaluation system for power domain knowledge graphs; and (4) creating an efficient, cost-effective mechanism for building domain-specific knowledge graphs in the power sector.

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