Framework and Key Technologies of Intelligent Operation and Maintenance of Traction Transformer Based on Knowledge Graph

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Abstract. With the rapid development of China's economy and high-speed railway, the operation scale of the traction power supply system is continuously increasing, which simultaneously enables the traction transformer and its components guarantee the improvement of the operational reliability. Moreover, the traditional operation and maintenance system is difficult to deal with the complicated traction transformer failure patterns. Therefore, this paper proposes a general knowledge graph framework for the intelligent operation and maintenance of traction trans-former, which utilizes a unified knowledge representation model to integrate multi-source heterogeneous data with respect to the operation and maintenance of traction transformer into the structured knowledge network. In addition, to cope with scenarios and business requirements, several significantly critical technologies are introduced, namely, data acquisition, knowledge graph construction, condition assessment, and intelligent services. Finally, knowledge entity map, concept map, fault treatment map and fault case map are constructed respectively, to realize the multi-source state data fusion and correlation analysis, multi-dimensional differentiated state assessment and intelligent auxiliary maintenance decision-making.

Keywords: Intelligent operation and maintenance · Traction transformer · Knowledge graph · Knowledge reasoning · Condition assessment · Auxiliary maintenance decision-making

1 Introduction

Traction transformer, as a significant equipment of intelligent traction power supply system (TPSS), provides power source for the high-speed trains, whose operational state is directly related to the safety of TPSS. Traction transformer is vulnerable to high voltage, high current, mechanical stress and other environmental factors, which may cause heating, discharging, poor insulation and other faults. Herein, it is necessary to

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analyze the real-time operational risks, carry out condition assessment, quantify the risk level and develop a reasonable operation and maintenance (O&M) strategy.

The online dissolved gas analysis (DGA) monitoring system was widely implemented in TPSS to monitor the operating condition of the traction transformer [1]. The collected chromatographic data can be utilized to analyze the operating condition and diagnosis fault type of traction power. The most common applied method for fault diagnosis is three-ratio method, which can help operators to determine the fault type [2]. However, there are several shortcomings existed in three-ratio method, for instance, inaccurate and incomplete fault coding, rough classification, etc. Although machine learning algorithms [3], including artificial neural network [4], support vector machine [5], fuzzy theory [6], Bayesian network [7], are widely applied to identify traction transformer faults more efficiently, they mainly rely on chromatographic data and fault coding, which cannot enable maintenance personnel clearly understand the correlations between transformer faults and a single state quantity and identify fault location.

For traction power supply equipment, the traditional periodic preventive maintenance and corrective maintenance are adopted by railway maintenance management institutions. However, this maintenance mode with fixed interval has shortcomings of high cost, low efficiency and heavy workload, which is unable to ensure the reliability and safety performance of transformer operation to the greatest extent [8]. Moreover, these problems also existed in the maintenance of traction transformer. In addition, reliability-centered maintenance (RCM) [8] and condition-based maintenance (CBM) [8] cannot predict the future trend of a traction transformer's status and failure time, minimizing inadequate or redundant maintenance [9].

To overcome these shortcomings, a feasible idea is to apply knowledge graph (KG) technology in this knowledge-intensive field, which can integrate multiple-source state information with the unified knowledge representation way. KG provides a feasible and practical means to combine traction transformer big data with robust semantic technologies, making a new step towards the new generation of artificial intelligence (AI) in TPSS [10]. In railway field, KG has become an optimal tool among the top concerned AI technologies, considering the necessary flexibility and the network nature of railway systems [11]. In [12], a new knowledge graph-based approach to explore railway operational accidents was introduced, aiming at revealing the potential rules of accidents by depicting accidents and hazards in a heterogeneous network. Reference [13] used the ontology model to analyze the logical relationships between railway train devices and faults and established the knowledge graph-based railway train device fault causality model.

To the best of our knowledge, there has been none study on the O&M of traction transformer based on KG. Herein, this paper investigates and explores the framework and key technologies of KG-based intelligent operation and maintenance (IO&M) of traction transformer. Firstly, a flowchart of domain knowledge graph toward IO&M of traction transformer is devised. And then critical technologies associated with construction and application of the proposed KG are investigated. Besides, the paper explores how to apply KG in fault treatment and maintenance decision-making.

2 The Overview of Knowledge Graph-Based IO&M for Traction Transformer

2.1 Overview of Knowledge Graph

KG, as another important research direction in the field of artificial intelligence, is proposed by Google in 2012 and widely applied in various fields, such as semantic search, recommendation system, automatic question-and-answer, and so on. In general, KG manages knowledge and information through a semantic network way and describes the entities and properties via relations in real word, in which each node refers to an entity and each edge represents the relationship between entities. The basic elementary unit can be represented as a triple of "entity-relation-entity" or "entity-property-property value", which can be denoted as $G = (E, R, S)$, where $E = \{e_1, e_2, e_3, \ldots e_n\}$ is a set of entities, $R = \{r_1, r_2, r_3, \ldots, r_m\}$ refers to a set of relations, S represents a set of triples, $S \subseteq E \times R \times E$. In particular, the entities are basic elements in KG, which are characterized by the specific property and property value. Moreover, the associated information between entities are recorded by relations [14].

The overall flowchart of KG construction technology is depicted in Fig. 1, which is a dynamic and iterative procedure. The whole construction process is composed of four key components: 1) data acquisition; 2) knowledge extraction; 3) knowledge fusion; 4) knowledge processing.

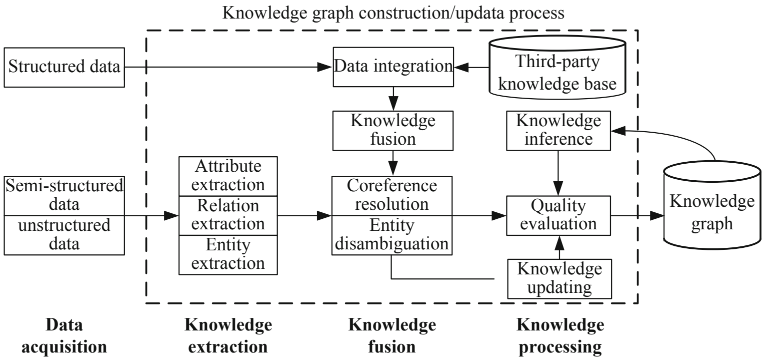

Fig. 1. The flowchart of knowledge graph construction technology.

2.2 IO&M of Traction Transformer

In order to better understand the well-devised KG platform applied in O&M of traction transformer, the high-level design of KG-based intelligent operation and maintenance (IO&M) of traction transformer and the relevant specific functions are depicted and presented as shown in Fig. 2. The whole flowchart of KG-based IO&M procedure consists of four key layers, namely, data acquisition, KG construction, condition assessment and intelligent services. The data flow of KG-based IO&M is: 1) obtaining a variety of heterogeneous data from all scattered data systems with respect to traction transformer, including manufacturing enterprises, supplies, operational units, online monitoring data, maintenance record, history data, etc.; 2) utilizing the critical technologies of KG construction to integrate all information and establish the KG for transformer through ontology modeling, knowledge extraction and knowledge representation technologies; 3) comprehensively using all state parameters to carry out condition assessment; 4) enabling various intelligent services aiming at disparate business scenarios, such as critical information tips, reliability and risk assessment, maintenance decision-making, etc.

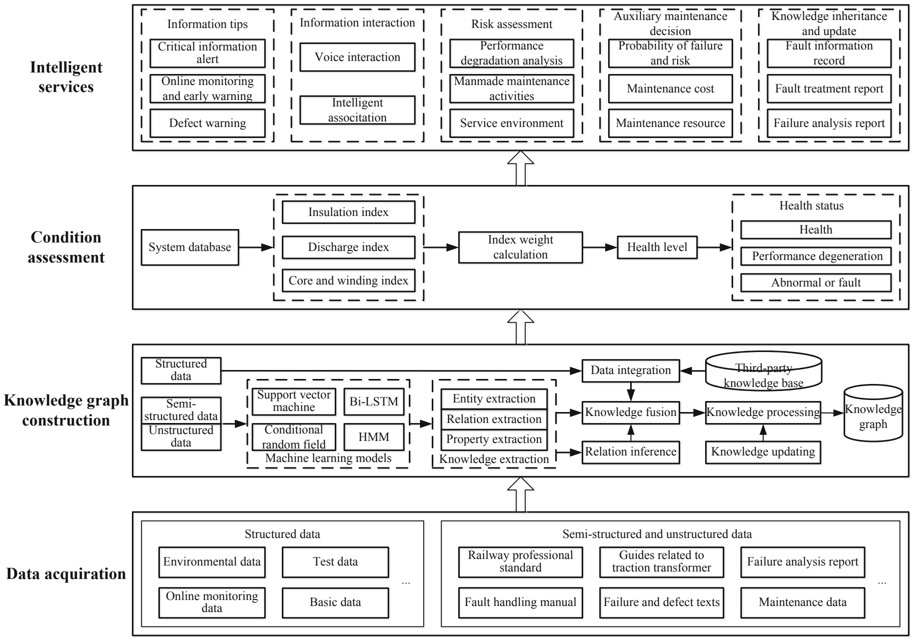

Fig. 2. The framework of KG-based IO&M of traction transformer.

3 Critical Technologies

3.1 Data Acquisition

The multisource transformer data is composed of three basic data sources, namely online monitoring data, offline data and nameplate data (as shown in Fig. 2).

3.2 Knowledge Graph Construction

As for KG construction for IO&M of traction transformer, the “bottom-to-up” construction method is applied to iteratively update the corresponding information and knowledge and the concerned knowledge technologies as described in Sect. 2.1, including knowledge extraction, knowledge fusion and knowledge processing.

Knowledge Extraction. Knowledge extraction is a text processing technique, which extract entities, relationships and entity properties from natural language texts and forms structured data output.

Entity Extraction. Entity extraction, also called named entity recognition, is to extract named entities hidden in the information and categorize the entity types. With respect to traction transformer, named entities can be transformer component, run time, fault time, and so on.

Relation Extraction. Relation extraction is to discover the relationships between named entities and categorize the relation types, which is always represented in terms of binary relation. Regarding traction transformer, oil storage and insulator bushing are components of transformer, that is “the whole and parts” relation.

Property Extraction. Compared with relation extraction, property extraction not only identifies the attributes of the entity, but also identifies its property value. The property value structure is uncertain, depending on rule extraction. For instance, the operating voltage of traction transformer is 220 kV.

Knowledge Fusion. Due to traction transformer big data coming from disparate data sources, the diversity of information description may lead to redundant information and errors existed in the extracted entities, relations and properties. To ensure the quality of constructed KG, it is indispensable to eliminate the disambiguation and errors through entity disambiguation and co-reference resolution technologies.

Entity Disambiguation. Entity disambiguation is to solve the problem of one entity being characterized by polysemy, which means that one entity refers to different objects in different contexts. The key point of this technology relies in the calculation of the similarity between entity objects and predefined referent according to contextual information via spatial vector model and semantic model.

Co-reference Resolution. Co-reference resolution is to analyze and make judgement whether entities from different data sources point to the same object in real world. The typical co-reference resolution methods include deep reinforcement learning [15] and end-to-end model [16].

Knowledge Processing. Knowledge processing is to integrate and refine the extracted information and knowledge, forming relatively complete knowledge system. To establish KG with high-level logical and high quality, knowledge processing is also indispensable and the involved technologies include: ontology construction, knowledge inference and quality assessment.

Ontology Construction. Ontology is a standardized representation of concepts and the semantic basis for describing the field, which provides a clear definition of concepts and their relations in a formal way. The main process of ontology construction consists of entity similarity calculation, upper and lower level relation extraction of entity and generation of ontology. In O&M of traction transformer, entity map, concept map, fault treatment map and fault case map should be constructed based on ontology modeling.

Knowledge Inference. Knowledge inference uses existing entities, relationships or factual information to discover new relationships between entities through machine learning, expanding and enriching knowledge networks. For example, according to historic failure analysis, the single fault or multiple faults and relevant fault characteristics can be discovered, so that summarizing new knowledge. Representative methods include neural tensor network model [17], Path Ranking method [18], etc.

Quality Assessment. Due to continuously increased data size and restricted data processing techniques, there are noises, conflicts and incompleteness existed in the transformer data obtained from substation prognostics and health management (PHM) platform. When new information and knowledge are integrated into the constructed KG, it is necessary to access their credibility and discard the knowledge with low confidence to ensure the quality of KG.

3.3 Condition Assessment

The objective of condition assessment is to calculate the weighted sum values of state parameters (including insulation, discharge, core and winding index) that can reflect the health status and obtain the health score of traction transformer. Different health scores reflect the health status, and the health status can be divided into five grades: normal, attention, abnormal, serious abnormal and failure. In addition, transformer condition assessment can provide powerful technical support for transformer condition-based maintenance and asset management.

3.4 Intelligent Services

When traction transformer happens a fault, the PHM platform would issue a warning. If the information prompt mode is not friendly enough to help operators sort out the key information, it will be unable to intelligently push the fault-related site map, equipment information, disposal principles and suggestions, etc., which still forces operators or maintenance personnel to done information enquiry and procedure browsing. In the future, with advancement of KG-based information query, voice interaction, semantic understanding and decision making, human-computer interaction has a wide application prospects in automatic information prompt and push, query intention understanding, natural language interaction, operating condition evaluation and so on.

Information Tips. KG technology can provide failure mode, failure analysis and fault treatment for operators and filter out the redundant information and interference. In addition, the key knowledge nodes are linked to traction transformer entities and the related operation rules and risk information are displayed, ensuring the efficiency of fault analysis and reliability of decision making.

Information Interaction. A human-computer interaction association method based on KG is devised to obtain the speech signals input by users, convert the speech signals into text signals, extract the core entities of the text signals, and identify the candidate associative entities from the preset KG according to the core entities. After sorting all the candidate associative entities, the K candidate associative entities with the strongest relevance are defined as the association results and the reply information is generated according to the association results. The method can imitate human's ability of association and generate a reply to user's input according to the result of association, which can not only realize the robot's autonomous conversion between topics, but also guarantee the relevance between the newly changed topic and the current topic. At the same time, the intelligent degree of the robot is improved, and the user can feel that the reply of the robot is more realistic and anthropomorphic.

Reliability Analysis and Risk Assessment. As the increased complexity of transformer fault analysis, reliability evaluation and risk assessment are to analyze the reliability and risk of the transformer and obtain the reliability and risk index, considering transformer performance decline, service environment, and manmade maintenance activities, combined with online monitoring data, offline testing data, historical fault and maintenance information.

Auxiliary Maintenance Decision. Decision-making is an important technical content of KG in transformer fault management, which provides decision basis, suggestions and tips to the maintenance personnel in the whole process of fault initiation, development and recovery. The maintenance decision function takes the minimum maintenance cost and highest overall reliability of the system as the optimization objective in the whole life cycle, and obtains the optimal maintenance scheme by optimizing the comprehensive maintenance period and maintenance mode, reducing maintenance manpower and cost, planned inspection and failure rate and improving system reliability. With the long-time accumulation of catenary fault cases and expert experience knowledge, the precision of machine decision-making can be gradually improved.

Knowledge Inheritance and Update. One of the important functions of KG is to realize knowledge inheritance and update of fault treatment. Structured semantic network is used to record key information and disposal operations of transformer faults, enrich machine learning samples and realize the update of knowledge information data. The KG provides a structured knowledge presentation through large semantic content, and staff can query historical failure cases at any time for historical review and experience summary.

3.5 KG-Based Fault Treatment Process

According to the constructed KG framework and relevant technologies, a knowledge-driven fault treatment for traction transformer is shown in Fig. 3, which consists of four vital knowledge graph/base, including entity knowledge map, concept knowledge map, fault treatment knowledge map, and fault case knowledge base. The existed relation database related to traction transformer is transformed into graph database to construct the entity map and the entities, relations and properties are automatically updated based on online monitoring data. The concept map is constructed by automatically abstracting from entity map and manual verification method to form domain ontology, which can be applied in abstract concept expression of transformer accidents. As for unstructured data, such as failure analysis report, professional standard, fault handing manual etc., the critical knowledge is extracted by natural language processing technology. Thus, combined the ontologies in concept map, the fault disposal/maintenance plan, scheduling rules, operation and maintenance principles, cause analysis, disposal points and other information are excavated and transformed into structured knowledge. Logical operation and rule base are established, and then fault treatment map is formed, which are also stored in fault case map. In addition, automatic risk analysis, failure cause and fault weak spot are developed by machine learning to update the entity or component status reasoning map.

When a fault occurs, the knowledge inference engine will query the concepts and entities closely related to the fault information by analyzing the similarities of the cases. After obtaining the relevant knowledge, fault information analysis, fault judgment analysis and fault disposal modules are used to judge the fault types and give disposal methods. Moreover, the whole process is a human control process, which can enable the safety performance of the machine decision-making. At the end of the fault treatment process, the machine can automatically extract the structured knowledge related to the happened faults to update case map for case recording, reviewing and reasoning.

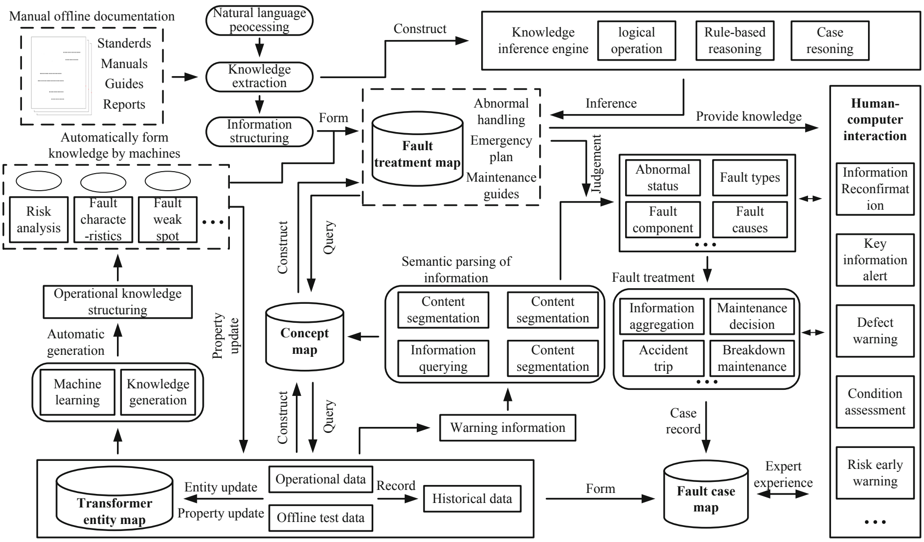

Fig. 3. Flow chart of fault treatment of traction transformer based on knowledge graph.

4 Conclusion

As for the actual specific businesses and scenarios of fault treatment and maintenance for traction transformer, this paper proposes a feasible and practical idea to integrate the traction transformer big data with robust semantic analysis, making a new attempt towards IO&M of traction transformer. After introducing the KG and motivations of KG implemented in O&M, a framework of KG-based IO&M of traction transformer is devised and the relevant critical components are presented in detail. In particular, the core functionality of condition assessment and maintenance decision-making are discussed. The proposed IO&M platform based on KG not only provides a panoramic perception for traction transformer, but also offers a feasible way for data management, condition assessment, identifying initial failure, decision recommendation and railway asset management, which can significantly save maintenance time and cost. In the future, the relative works need to be investigated in-depth, such as, the combination of "physical mechanism-based+knowledge-based" method, automatic knowledge extraction technology, interpretability of AI, domain KG construction, etc.

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