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Review

Knowledge graphs for operational decision-making in industrial maintenance: A systematic review

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ABSTRACT

Operational-level maintenance is essential to ensuring the normal functions of systems and equipment in the industry. The current practice for decision-making for operational maintenance is still expert-led and heavily relies on experts' implicit knowledge from their experience. This leads to the urgent need for better knowledge management, which can facilitate more efficient and effective operational maintenance. To fulfill this need, knowledge graphs (KGs) have been proposed by previous studies, due to their ability to digitize knowledge and their structural and semantic features to facilitate various decision-making approaches. Although multiple KG-based methods have been proposed and implemented, several questions about maintenance-related knowledge graphs remain unclear, including 1) What methods are employed to exploit the capabilities of KGs in maintenance decision-making, 2) In which scenarios KGs are applied, and how they are utilized, and 3) What are the challenges and opportunities of implementing KGs in practice. To address these questions, this study made a comprehensive systematic review. A total of 270 papers were retrieved from Scopus, and 76 papers were closely examined. The review finds that 1) KG-based querying, reasoning, and enhancement of other algorithms are common methods in decision-making problems; 2) most KGs are applied in fault diagnosis, but KGs also contribute to maintenance action identification and organization; and 3) most applications of KGs in industrial maintenance decision-making are limited to simple tasks and more exploration of efficiently using and sharing KGs is needed. This study summarizes the state-of-the-art works in knowledge graphs for operational maintenance, which can facilitate further research.

1. Introduction

Maintenance is of great significance throughout the entire life span of facilities in industrial contexts and consists of necessary activities in a specified operational condition (Pintelon & Gelders, 1992). Research trends have increasingly focused on digitizing maintenance processes and applying decision models to improve maintenance management with the development of Industry 4.0 (Bai et al., 2020). Decision models are applied at strategic, tactical, and operational decision levels. While strategic and tactical levels prioritize medium and long-term planning and optimizing, the operational level focuses on short-term day-to-day scheduling and maintenance action. Decision support systems at this level are usually scarce and task-specific (Van der Duyn Schouten & Dekker, 2000).

Sufficient operational decision support in industrial maintenance is essential for all maintenance management. Operational maintenance is the last step to execute maintenance actions under the constraints of time, information, and resources. Decisions at the operational level have a direct influence on the efficiency and accuracy of maintenance. Unsupported decisions in operational engineering maintenance situations can be biased and cause safety issues, according to Green et al. (2022).

Support for operational decision-making in industrial maintenance normally requires knowledge from experts and conceptual models for collaboration among experts (Potes Ruiz et al., 2013). Multiple expert systems have been proposed and tailored by domain experts, targeting maintenance tasks such as failure diagnosis on electrical power generation assets (Alvares & Gudwin, 2019), and predictive maintenance of mining excavators (Kumar & Srivastava, 2012). In these cases, decision support tools for operational maintenance are specifically designed, which are subjective, incompatible to other tasks and take a lot of efforts. The knowledge created in this way is not efficiently managed or reused.

More effective knowledge management can be achieved through learning from historical data and digitizing human expert experiences. Knowledge graphs (KGs), with their ability to model relationships between data and integrate diverse data sources, offer a promising option for overcoming these limitations in knowledge management. There is a growing trend of utilizing KGs as an effective and structured data format

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Table 1
Search sentences and returned results.

Decision-making aspects	Search sentence
Fault diagnosis	TITLE-ABS-KEY (“knowledge graph” AND maintenance AND (fault OR failure OR defect OR cause)) AND PUBYEAR > 2015 AND PUBYEAR < 2025 (LIMIT-TO (LANGUAGE , “English”)) AND (LIMIT-TO (SUBJAREA , “COMP”) OR LIMIT-TO (SUBJAREA , “ENGI”))
Action identification	TITLE-ABS-KEY (“knowledge graph” AND maintenance AND (solution OR treatment OR answer OR action)) AND PUBYEAR > 2015 AND PUBYEAR < 2025 AND (LIMIT-TO (LANGUAGE , “English”)) AND (LIMIT-TO (SUBJAREA , “COMP”) OR LIMIT-TO (SUBJAREA , “ENGI”))
Maintenance organization	TITLE-ABS-KEY (“knowledge graph” AND maintenance AND (schedule OR allocation OR plan OR group OR optimize)) AND PUBYEAR > 2015 AND PUBYEAR < 2025 AND (LIMIT-TO (SUBJAREA , “COMP”) OR LIMIT-TO (SUBJAREA , “ENGI”)) AND (LIMIT-TO (LANGUAGE , “English”))

in knowledge management after the concept of KGs was widely advocated by Google (Google, 2012). Although an official definition of KGs is absent, the data structure of a KG can be simply described in terms of nodes, edges (relations linking nodes), and their associated properties. The conceptual boundaries between ontologies and KGs are also unclear (Ehrlinger & Wöß, 2016). In many cases, KGs are regarded as extensions to ontologies, with the ability to additionally generate new knowledge by using reasoning engines (Ehrlinger & Wöß, 2016). Generally, an ontology emphasizes the structured representation of relationships among data types, whereas knowledge graphs focus on relationships between specific instances of data. While both can support complex application scenarios, knowledge graphs are more commonly associated with graph-based algorithms.

KGs have been applied in industrial maintenance fields, and several papers have offered reviews on this topic. The most relevant review in this domain is conducted by Xia et al. (2022), which focuses on graph-based approaches in different stages of cognitive predictive maintenance. However, Xia et al. (2022) only offers limited discussion on KGs for maintenance decision-making while attempting to cover all kinds of graph-based methods not just KGs. Li et al. (2021) investigated the adaptation of KGs in industrial maintenance services and acknowledges their contribution. However, this paper also puts emphasis more on how KGs can help with industrial pain points (e.g., comprehensive solution searching), rather than a specific discussion around applications of KGs in industrial maintenance. Other review papers relating to KGs in maintenance have a focus on specific domains such as fault diagnosis in power systems (Chen et al., 2022; Liu et al., 2023) and aircraft (Tang et al., 2023b). To the best of our knowledge, this paper is the first to aim at surveying KGs in the context of industrial operational maintenance decision-making.

The main research question of this paper is as follows: *How can KGs enhance operational maintenance decision-making in industrial contexts?*

This question is split up into the following specific questions:

- What methods are employed to exploit the capabilities of KGs in maintenance decision-making? (RQ1)
- In which scenarios are KGs applied, and how are they utilized? (RQ2)
- What are the challenges and opportunities of implementing KGs in practice? (RQ3)

The rest of this paper is organized as follows: Section 2 describes the review methodology, defines the research scope and analyzes research trends in this field. Section 3 answers RQ1 by summarizing and criticizing various knowledge graph-based methods for maintenance decision-making. Section 4 answers RQ2 by reviewing what maintenance scenarios KGs are applied in. Section 5 further outlines the current challenges to answer RQ3. Finally, Section 6 discusses future directions, and Section 7 concludes the paper.

2. Review method

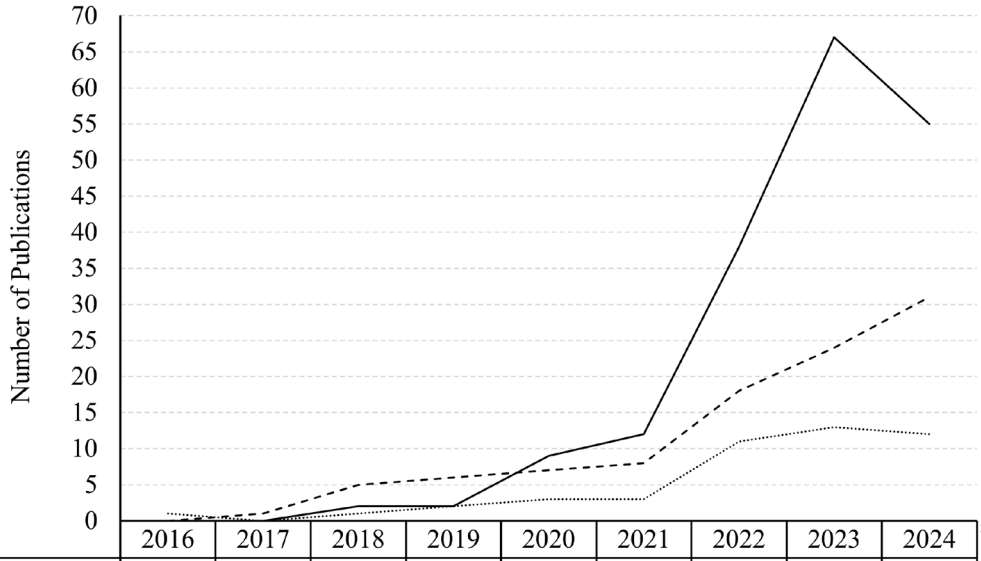
This paper reviews articles in the scope of KGs for operational decision-making in industrial maintenance. Operational level maintenance in the industry prioritizes daily scheduling and maintenance actions as stated in Section 1. These two maintenance decisions are influenced partly by strategic and tactical decision-making and partly by reactive maintenance. In industrial maintenance, operational decision-making (Dhanisetty et al., 2018) for reactive maintenance should cover three scenarios: (1) fault diagnosis, (2) maintenance action identification, and (3) maintenance organization. Fault diagnosis aims to identify failure mode, find fault causes, and locate faults (Pinto & Gonçalves, 2022). Industrial maintenance action identification is the selection of feasible actions for a repairable system when encountering or foreseeing potential faults. Maintenance organization at the operational level is to decide the final maintenance plan including scheduling and resource allocation when provided with feasible actions. KG-related methods applied in these decision-making scenarios should be differentiated from other graph-based methods that focus more on using the graph structure but ignore knowledge management.

This research consists of a comprehensive review of the current literature in this field. Separate search sentences were designed for the three different decision-making scenarios to avoid irrelevant results from vague search keywords. These sentences and their results are listed in Table 1. The literature search was conducted within Scopus; all three searches were limited to Computer Science and Engineering subject areas to exclude unrelated fields such as medicine and healthcare.

After the first round of screening, 270 items from Scopus were found (accessed on March 4th 2025). The results are presented in Fig. 1, which show that KG application in maintenance has emerged recently and requires further exploration and contributions. A rising trend in publication numbers of all three scenarios is clear in Fig. 1. Publications related to maintenance organization are relatively scarce. Research on KG in fault diagnosis is more prevalent than the other two scenarios, aligning with the overall research focus on failure analysis in the maintenance field, not limited to KG applications. In addition, the rapid growth in research on KGs may suggest that scholars have recognized KGs as a promising method for addressing challenges in this field. A further examination of the title and abstract was conducted to exclude certain papers out of scope (e.g., papers proposing methods only for knowledge graph construction) and review papers. 149 items were confirmed as relevant after the second round of screening. Finally, a total of 76 items with good quality were selected for in-depth analysis in this review paper after a full text review. It is interesting to note that some returned papers are overlapping across these three decision-making scenarios. The distribution detail of papers after the third screening is shown in Fig. 2.

3. Knowledge graph-based methods for maintenance

A KG is a presentation of information with both structural features and semantic features. Structural features often refer to nodes and edges that can be used for data querying and information retrieval. Semantic features are developed on top of the domain ontology when a KG is described as entities and relations that follow semantic rules. A brief illustration of structural and semantic features is shown in Fig. 3. Regarding structural features, traditional features such as the node degree (i.e., the number of edges adjacent to a node) and adjacency matrices (i.e., a square matrix $\mathbf{A}$, where A_{ij} equal to 1 indicates an edge linking nodes n_i and n_j) do not consider node types (Biggs, 1993). Hence, the variation of node types does not lead to differences in structural features



	2016	2017	2018	2019	2020	2021	2022	2023	2024
Fault diagnosis	0	0	2	2	9	12	38	67	55
Action identification	0	1	5	6	7	8	18	24	31
Maintenance organization	1	0	1	2	3	3	11	13	12

Fig. 1. Publication numbers for KGs in operational maintenance decision-making between 2016 and 2024.

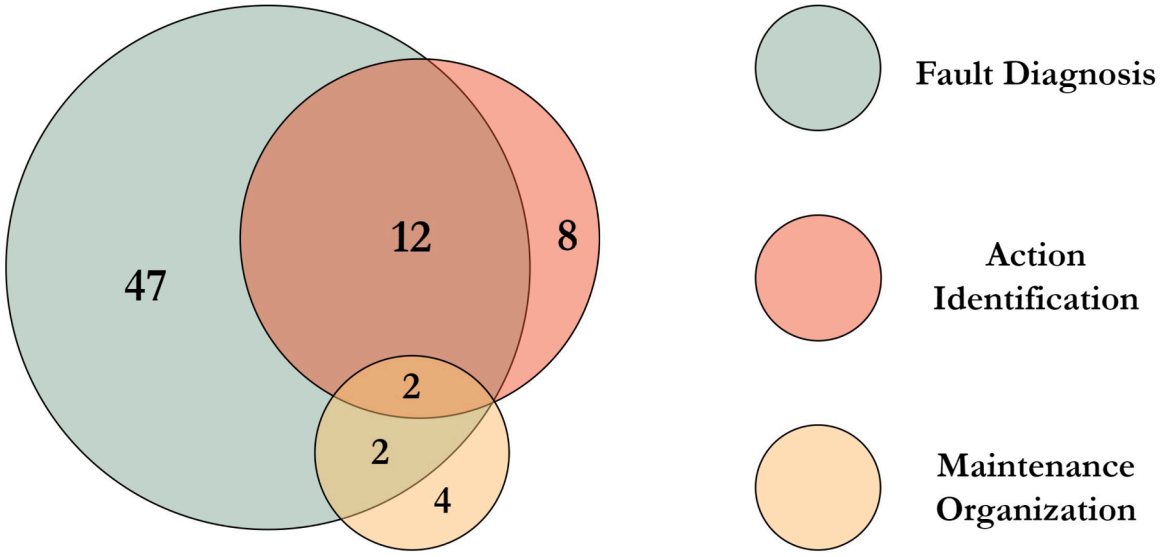


Fig. 2. Distribution of knowledge graph-related papers across maintenance decision-making domain.

as in Fig. 3(a). As for semantic features, it is the hierarchy and defined logic relationships among node types that signify differences as shown in Fig. 3(b).

Knowledge graph-based methods are adopted in the maintenance domain built on top of KGs. Methods in maintenance decision-making applications can be summarized into three categories based on how KG features are utilized: KG querying, KG reasoning, and KG-enhanced algorithms. The first two are knowledge-driven, developed on KGs structural and semantic features, while the last category mainly provides extra features for other decision-making frameworks, such as Bayesian network-based ones.

While this review focuses on maintenance applications, these categories align well-established research areas in the broader computer science (CS) literature. Extensive methods have been developed for KG querying, reasoning, and KG supported systems, many of which have been adapted to maintenance scenarios. An overview of typical approaches and representative methods from the CS perspective is summarized in Table 2. Many of these approaches have been extended or adapted for use in maintenance scenarios, as detailed in the following sections.

3.1. Knowledge graph querying

Knowledge graph querying is a method to retrieve information in a complete KG. It is conducted by finding answers to queries from the KG. To utilize KGs in a specific domain such as industrial maintenance, the majority of research first constructs a KG from domain knowledge and then queries the required information from it for maintenance. In this regard, a KG provides a similar role as a graph database.

KGs normally integrate various maintenance information and can answer maintenance decision-making questions directly with queries and querying methods. In this case, the main research focuses of KG

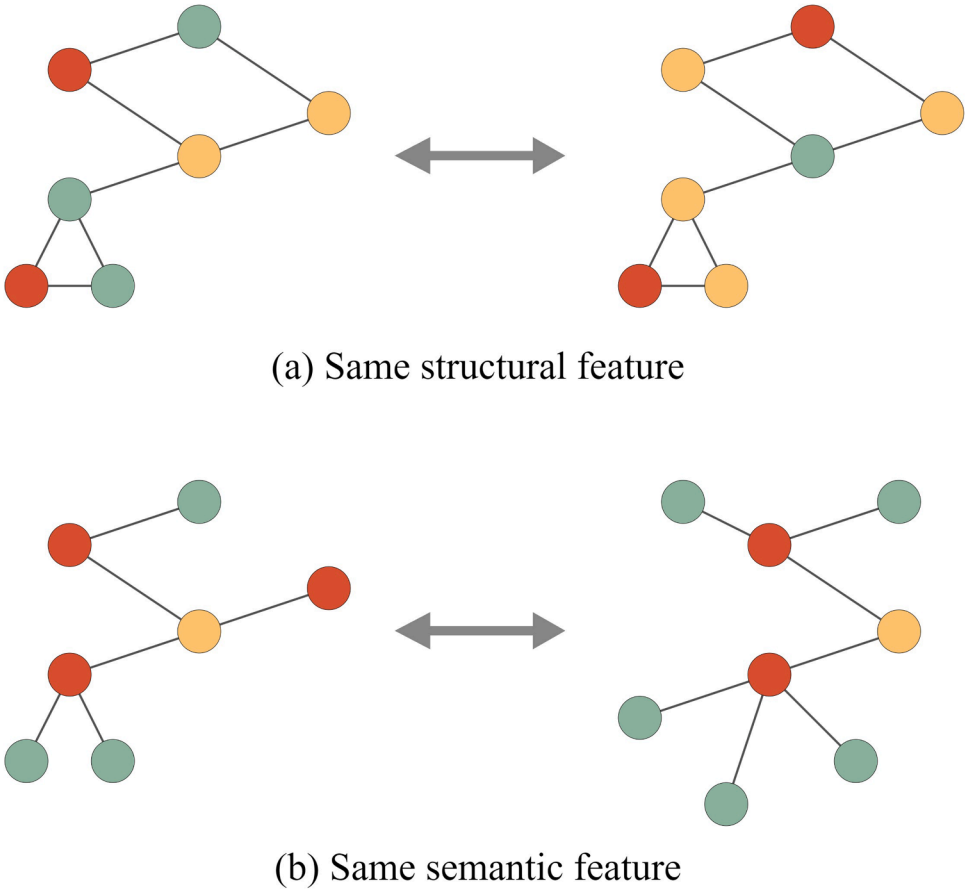


Fig. 3. Knowledge graph structural feature and semantic feature demonstration. (a) shows two graphs with identical topological patterns and sharing same structural features even if types differ. (b) shows identical semantic relations between different types of nodes within the two graphs, sharing same semantic features.

Table 2
Typical approaches and representative methods of KG techniques in computer science.

Category	Approaches	Methods	Key Ideas
KG querying	Query language	SPARQL, Cypher	Formal languages for retrieving structured data from graph database.
	Path query	Breadth/Depth First Search	Traverse the graph to locate target nodes or paths following different search order.
	Pattern matching	Similarity search (Zheng et al., 2016)	Quantify similarity between the KG and the query, then compare to identify desired targets.
KG reasoning	Knowledge graph embedding (KGE)	DistMult (Yang et al., 2015), TransR (Zhang et al., 2023a), Query2box (Ren et al., 2020)	Map entities and relation into vector space and carry out reasoning through vector operations.
	Graph Neural Networks (GNNs)	GAT (Veličković et al., 2018), Graphormer (Ying et al., 2021)	Treat KGs as raw graphs and perform multi-layer message passing to capture complex patterns for reasoning.
KG-enhanced systems	KG-enhanced question answering	GraphRAG (Edge et al., 2024), K-BERT (Liu et al., 2019)	Use knowledge graphs as external, structured knowledge sources to enhance language models with factual accuracy and logical support.
	Recommendation systems (Guo et al., 2020)	Entity2Rec (Palumbo et al., 2017), KTUP (Cao et al., 2019)	Use KG relationships to enhance user-item representations for better recommendations.

querying are processing unstructured queries and retrieving information by query methods. A flowchart describing the workflow for KG querying is shown in Fig. 4.

Unstructured queries generated from maintenance are mostly in natural language, which require Natural Language Processing (NLP) for translation to structured queries. Named Entity Recognition (NER) is used to identify valid information from plain texts (unstructured) and align it to nodes and edges in KGs (structured). Query classification is another way to match unstructured queries to machine-readable queries. This takes unstructured queries as the input and classifies them into specifically structured query categories. A complete enumeration of all target structured queries is required to achieve query classification. It is frequently used together with template modeling (a method that uses predefined query patterns to generalize query structures) to add flexibility by handling of variations in unstructured queries.

Given a structured query, the answer can also be retrieved through a search method such as Breadth First Search (BFS), or a specific query language such as Cypher (i.e., the query language used in Neo4j, a commercial graph database platform). An example Cypher query sentence in maintenance fault diagnosis can be written as:

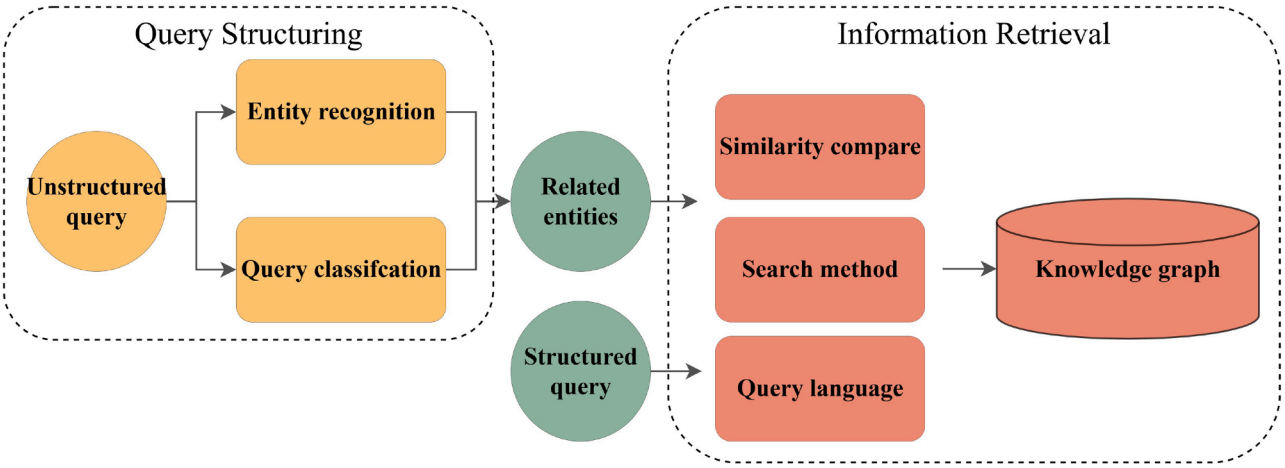


Fig. 4. Knowledge graph querying flow chart.

MATCH (defect: Defect {defectId: 'D837X'}) -[:is_A]-> (defectType: DefectType) -[:has_CAUSE]-> (cause: Cause) RETURN defect, defectType, cause

This query returns the record of a defect with ID 'D837X', and its defect type and possible cause based on predefined is_A and has_CAUSE relationship in the KG. In a KG, answers can be returned by such queries to support maintenance decision-making.

Similarity comparisons are used when querying information alone is not enough to direct to the answer. The basic principle behind similarity comparison in KGs is similar to Case Based Reasoning (CBR), which aims to find the most similar previous record to guide a new current problem (Kolodner, 1992). While CBR is designed to use specific case-derived features in one certain domain as indexes for case retrieval, KG similarity is calculated based on node embedding or subgraphs. An illustration is shown in Fig. 5. Generating embeddings (i.e., vectors or matrices that represent values or objects) and calculating similarity distances from them take advantage of both KG's structural and semantic features as most embedding models take both into consideration. It is more efficient to use such methods to derive features in KGs for similarity comparison, compared to CBR.

3.2. Knowledge graph reasoning

KG reasoning is the process of getting answers from an incomplete KG where answers can be accessed indirectly by inferring unknown entities or relations. In an ideal situation, a complete KG should be built and updated before application. However, incomplete KGs are implemented in most cases (Hogan et al., 2022). Two types of reasoning can be conducted within incomplete KGs to retrieve potential answers to queries according to the number of reasoning steps: one-hop reasoning and multi-hop reasoning. Rule-based methods, which infer missing entities and relations in KGs, rely on logical patterns. For example, inferring that two people are siblings if they share a parent is based on such rules. Embedding-based methods are more flexible and data-driven, and are commonly used in both one-hop and multi-hop reasoning. A flowchart illustrating KG reasoning process is shown in Fig. 6. From an incomplete KG, parts of known elements are first identified, and then reasoning methods are applied to infer complete KG triples.

One-hop reasoning is essentially a technology used in KG completion to predict links. A KG can be represented by triples (h, r, t), where h and t are head and tail entities of the link, respectively, and r is the relation between these two entities. One-hop reasoning can be framed as predicting the existence of a link (h, r, t) in the KG, where it is used to find the missing t in an incomplete link $(h, r, ?)$. A typical algorithm to achieve one-hop reasoning is TransE (Bordes et al., 2013). TransE first translates triple (h, r, t) into a d-dimensional embedding space as

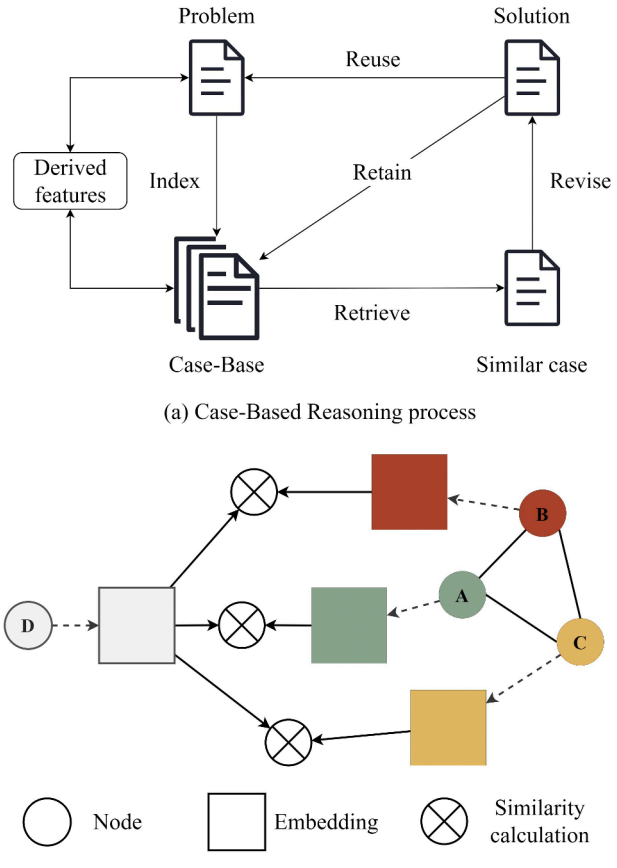


Fig. 5. Case-Based Reasoning and knowledge graph querying based on similarity.

$\mathbf{h}, \mathbf{r}, \mathbf{t} \in \mathbb{R}^d$ and then a score function $f_r(h, t) = - \parallel \mathbf{h} + \mathbf{r} - \mathbf{t} \parallel$ is used to judge the existence of the link.

Multi-hop reasoning involves more complex queries that require information from more than one triple in the KG. Unlike one-hop queries, which typically involve only one triple, multi-hop reasoning may combine multiple triples either along a path (i.e., path query when a deep root cause needs to be analyzed) or through a set of conditions that are not necessarily sequential (i.e., conjunctive query when a fault results from multiple causes), as shown in Fig. 7(b). In this case, more

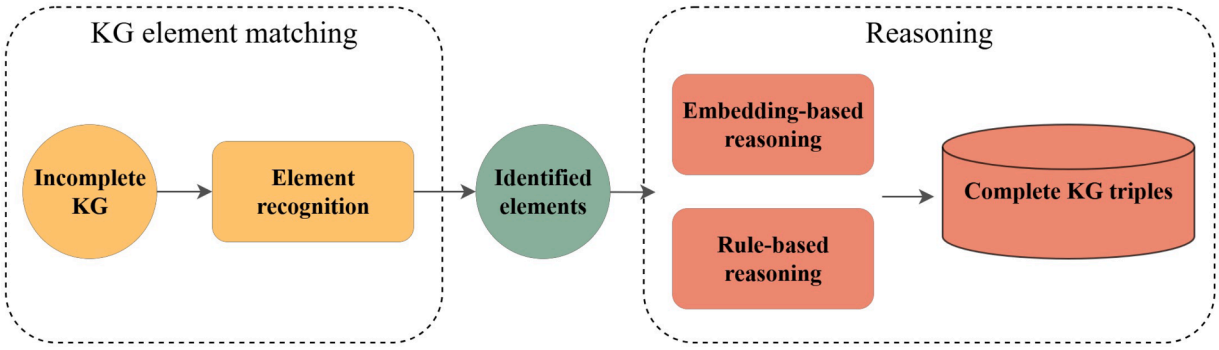


Fig. 6. Knowledge graph reasoning flow chart.

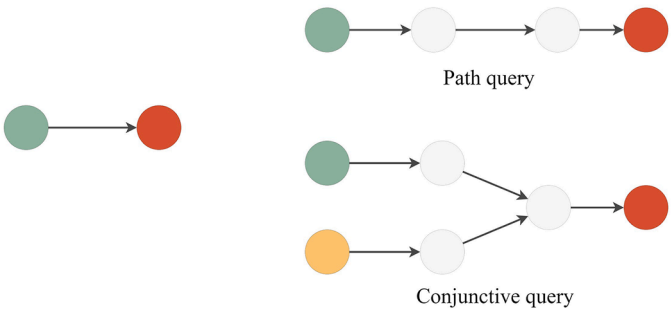


Fig. 7. Comparison of one-hop (a) and multi-hop (b) reasoning in knowledge graphs. Multi-hop reasoning includes path queries (sequential triples) and conjunctive queries (multiple paths jointly inferring one target).

complex architectures are nominally designed to extract node relations (Mao et al., 2024) and realize multi-step predictions.

For both types of reasoning, embedding methods should integrate structural and semantic features to generate more holistic embeddings; a notable example is the Graph Neural Networks (GNNs) (Xu et al., 2019). These embeddings can be used in combination with other techniques, such as attention mechanisms (Hou et al., 2023), to achieve an improved performance. Examples of one-hop and multi-hop queries for reasoning are shown in Fig. 7.

3.3. Knowledge graph enhanced algorithms

A KG can contribute to other algorithms with both structural features and semantic features to improve their performance. A typical way of combining traditional maintenance decision-making methods is to leverage KGs for Bayesian Network (BN). A BN is a probabilistic graphical model that deals with uncertainty problems and is commonly applied to maintenance fault diagnosis (Cai et al., 2017). The well-organized structure of KGs can facilitate the set-up of BNs. KGs can also provide BNs with extra features for probabilistic analysis, such as the weight of edges and embeddings aggregated from neighbors. A visual example of how KGs can support BNs is presented in Fig. 8.

KGs can enhance NLP-based decision-making frameworks with their semantic reliability. Question and Answering (QA) systems are utilized in decision-making to retrieve information and generate solutions with the development of NLP techniques. There is a research focus on integrating KGs to compensate for QA system weaknesses in structural reasoning (Kassner & Schütze, 2020). KGs can be employed either in combination with large language models (LLMs) (Yasunaga et al., 2022) to generate better answers or to guide prompt engineering by improving the quality of questions and fine-tuning LLMs (Pan et al., 2024).

Other algorithms can also benefit from KG features in the form of embeddings. Most of the embeddings encode both semantic and structural features of KGs while emphasizing on different aspects. An exception is random walk based ones (e.g., DeepWalk Perozzi et al., 2014, Node2Vec Grover & Leskovec, 2016), which involve randomly navigating through a graph based solely on its structure. Many algorithms integrate KG embeddings in their learning process and achieve improved performance. These algorithms are discussed in detail in the following sections together with their application.

4. Knowledge graph application scenarios

KGs applied to scenarios involving operational maintenance decision-making are discussed in this section. The three scenarios of decision-making mentioned in Section 2 are separately introduced and critically reviewed.

4.1. Knowledge graphs for fault diagnosis

Fault diagnosis is a very important part of operational maintenance decision-making and has been a research focus for decades. Many model-based, knowledge-based, and data-driven methods have been developed and applied in this research field (Zhong et al., 2020). These methods take advantage of a KG to collect fault-related information, enrich analysis features such as fault patterns and failure dependencies, and reason new knowledge for diagnosis.

4.1.1. Knowledge graphs for fault information retrieval

KGs can be used as querying tools in maintenance decision-making to retrieve relevant information and make use of acquired knowledge, as discussed in Section 3.1. This section analyzes the applications of KGs in gathering information for fault diagnosis. The summary is listed in Table 3.

Most applications of KGs in information retrieval are within the area of machinery maintenance. These methods exploit the structural features of KGs for assembling information which relates to fault diagnosis. The information includes basic information on equipment, historical fault records, fault causes, and fault locations. The retrieved information is either given to experts for further decision-making or used to support other traditional fault diagnosis algorithms, such as data-driven Bayesian networks (Zhang et al., 2023a). Information retrieved in maintenance can also contribute to the design stage by providing suggestions and feedback (Li et al., 2023b). These applications facilitate the diagnosis of faults within complex machinery systems. However, overall performance improvement is not mentioned since KGs in these applications only replace other querying tools and are not directly involved in fault diagnosis.

The basic information retrieval in KGs is through search methods and rule-based querying. The combination of a basic search algorithm and a result enhancement algorithm is a common choice when information

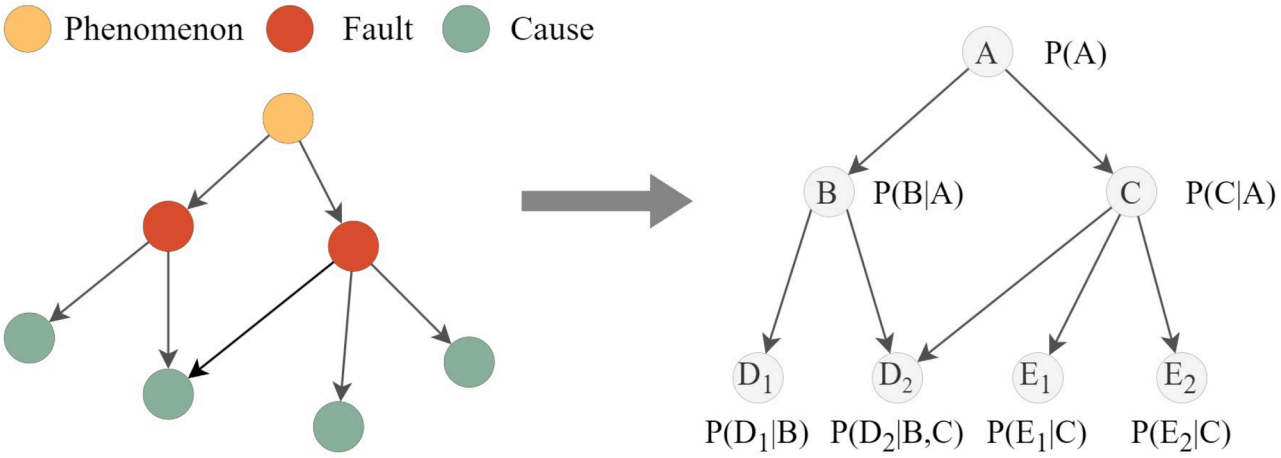


Fig. 8. A visual example of the relation between knowledge graphs and Bayesian networks.

Table 3
Knowledge graph for fault information retrieval.

Ref	Objectives	Methods	Semantic	Structural	Area
(Meng et al., 2024; Tang et al., 2023b)	Fault-related question answering	Question classification; Template-based querying	✓	✓	Aircraft
(Yun et al., 2019)	Fault diagnosis information search	Named Entity Recognition; Breadth First Search; Priority list	×	✓	Electric system
(Lim et al., 2023)	Fault location	Louvain algorithm (Lu et al., 2015); PageRank (Gleich, 2014)	×	✓	Factory equipment
(Wang et al., 2023)	Retrieve and visualize information of predicted possible faults to decision-maker	Rule-based querying; Bayesian formula	✓	✓	Industrial robots
(Yang et al., 2020)	Fault information retrieval to support diagnosis	Rule-based querying; Bayesian Network	✓	✓	Steam Turbine
(Xu et al., 2023)	Fault information retrieval to support diagnosis	Rule-based querying; Fuzzy Bayesian Network	✓	✓	Aero engines
(Gao et al., 2024; Lv et al., 2020)	Fault location from given attributes	Rule-based querying	✓	✓	Motor
(Liu et al., 2021)	Fault information storage and retrieval	Rule-based querying	✓	✓	Computer Numerical Control machine
(Zuo et al., 2023)	Fault location	Breadth First Search	×	✓	Network equipment
(Zheng et al., 2023)	Fault record storage and retrieval	Rule-based querying	✓	✓	Relay protection system
(Yi et al., 2023)	Fault event with highest probability retrieval	Naive Bayes model; Rule-based querying	✓	✓	Spacecraft system
(Teng et al., 2023)	Fault cause and solution retrieval	Rule-based querying	✓	✓	Low-earth orbit satellite
(Ragala et al., 2022)	Fault information storage and retrieval	Rule-based querying	✓	✓	Railway rolling stock
(Tang et al., 2023a)	Similar fault information retrieval	Case-Based Reasoning; Similarity calculation	✓	✓	Automobile engine
(Qiu et al., 2020)	Fault root cause search	Edge weighting; Breadth First Search	×	✓	Microservice system
(Ma et al., 2023)	Fault-related question answering	BERT; Similarity calculation	✓	✓	Nuclear power system
(Guo et al., 2023)	Fault-related question answering	Named Entity Recognition; Rule-based querying	✓	✓	Industrial robots
(Zhang et al., 2023a)	Match and retrieve fault information for further diagnosis	Similarity calculation	✓	✓	Product-service system
(Li et al., 2023c)	Fault information storage and retrieval	Similarity calculation	✓	✓	Factory equipment
(Li et al., 2023b)	Frequent faults warning and action recommendation for design stage	Conditional weight search; Similarity calculation	✓	✓	Tunnel boring machine
(Liang et al., 2022; Qu et al., 2023)	Fault retrieval and search result recommendation	Recommendation system	✓	✓	Power system
(Wang & Huang, 2023)	Fault retrieval and search result recommendation	Recommendation system	✓	✓	Automotive parts

Table 4
Features provided by knowledge graph and improvements.

Ref	Features	Semantic	Structural	To Methods	Objectives
(Kang et al., 2020)	Embedding	✓	✓	LSTM	Provide extra features to support LSTM for failure possibility prediction
(Xia et al., 2023b)	Hyperbolic embedding	✓	✓	Bayesian Network	Calculate probability from the embedding to enable BN for fault location
(Zhou et al., 2024)	CompGCN (Vashishth et al., 2020) embedding	✓	✓	Prompt engineering	Provide KG-guided prompts for LLM fault related question answering
(Zhou et al., 2022)	CompGCN (Vashishth et al., 2020) embedding	✓	✓	ALBERT (Lan et al., 2020)	Provide embedding for LLM fault related question answering
(Ren et al., 2021)	Adjacent matrix	×	✓	Principal Component Analysis (PCA)	Provide structural feature to detect and locate defect
(Xiao et al., 2022)	Edge correlation	×	✓	Weighted Random Forest (WRF)	Provide correlation stored in KG edges to help WRF for fault classification
(Chhetri et al., 2022)	Separate triples	×	✓	RGCN (Schlichtkrull et al., 2018)	Turn fault prediction task into KG node classification
(Li et al., 2023a)	Attention-based embedding	✓	✓	Neural networks	Integrate and provide multimodal features for binary failure classification

searches are carried out in the KG. Breadth First Search (BFS) is a simple and popular search method to apply in KGs (Qiu et al., 2020; Yun et al., 2019; Zuo et al., 2023). BFS guarantees a comprehensive search for all information stored in the KG although a KG is not necessarily a tree structure where BFS suits best. Additional measurements such as priority list (Yun et al., 2019) and edge weighting (Qiu et al., 2020) are used together with BFS to extract the most relevant and significant information and avoid redundant returns. Lim et al. (2023) applied the Louvain algorithm (Lu et al., 2015) for search and PageRank (Gleich, 2014) for results weighting to locate key components influenced by a defect. In these cases, a KG only acts as a well-structured database when structural features are involved while semantic features are not.

Rule-based querying can provide specific information for fault diagnosis in a more flexible way. It makes use of KG semantic features. A subgraph containing information on defect causes, element relations, etc. is returned when a specific query is applied. The subgraph can be further explained and visualized to assist expert decision-making (Wang et al., 2023). Rule-based querying can also help to form question-answering systems by combining NLP methods such as question classification (Meng et al., 2024; Tang et al., 2023b) and NER (Guo et al., 2023; Yun et al., 2019). Utilizing KG querying facilitates and enhances probabilistic methods such as Bayesian-based algorithms by providing necessary fault information. Rule-based querying supports both fault information retrieval before diagnosis (Xu et al., 2023; Yang et al., 2020) and fault location (Wang et al., 2023; Yi et al., 2023) after fault analysis. However, rule-base querying relies on expert-defined rules, which are reliable and easy to use but difficult to adapt to new requirements (Yun et al., 2019) and inefficient.

Similarity-based information retrieval is another method that provides a form of explainability by retrieving related past cases, making the results intuitive and interpretable through reference to known examples. Structural similarity and semantic similarity can be calculated separately for different search purposes (Li et al., 2023b; Tang et al., 2023a). They can also be considered a complete unit that forms embeddings, which are holistic representations in vector space. Various embedding generation methods are used for similarity comparisons, such as BERT (Ma et al., 2023) for contextual text embeddings, TransE and TransR (Zhang et al., 2023a) for graph entity and relation embeddings, and Graph Attention Mechanism (Li et al., 2023c) for relational embeddings. Similarity-based information retrieval is robust in tackling unforeseen problems and flexible in updating KGs because it does not rely on exact matches and rigid structures. However, insufficient data can cause the method to be underperformed.

A special application of KGs in fault information retrieval is through a recommendation system (Liang et al., 2022; Qu et al., 2023; Wang & Huang, 2023). KGs provide embeddings to the recommendation model to solve the cold-start problem (which occurs when data is not yet sufficient) and enhance its overall performance. However, utilizing a recommendation system to retrieve fault information is merely offering a more user-friendly interaction method. The purpose of a recommendation system is to improve search results according to user-item interaction (such as when users click on a link); no fault diagnosis is conducted. Hence, individual subjective differences exist to affect the objectivity required for fault diagnosis.

4.1.2. *Knowledge graph-enhanced fault diagnosis methods*

KGs can provide fault diagnosis methods with structural and semantic features beyond fault related information. Table 4 presents a summary of features offered by KGs and the methods that benefited from them.

The summary shows that most features are represented as embeddings from different models. Zhou et al. (2024) and Zhou et al. (2022) both employed CompGCN (Vashishth et al., 2020) to generate knowledge-aware embeddings to support LLMs. The difference between these two applications is that (Zhou et al., 2024) uses CompGCN to encode query-related entities and their neighbors as knowledge-aware embeddings to guide a prompt, while Zhou et al. (2022) directly feeds CompGCN embeddings into ALBERT (Lan et al., 2020) and scores the final answer. Xia et al. (2023b) adopted a Multi-Field Hyperbolic embedding method to specifically support the Bayesian Network. The hyperbolic embedding outperforms traditional embeddings by its ability to present logical gates, which is vital for further utilizing Bayesian methods. Similarly, Li et al. (2023a) designed a graph attention mechanism for a smart grid system with a large number of nodes. This method enhanced the ability to capture the correlation between nodes when generating embeddings. These works highlight the crucial role of embedding models in impacting the quality of KG features and the performance of the subsequent algorithms.

KGs can also provide structural augmentation by providing embeddings to large networks. Ren et al. (2021) took advantage of KG's structural connection to assist its main fault diagnosis method. This approach is built on top of a multilevel KG and makes use of the KG adjacent matrix to assist fault detection and location, together with Principal Component Analysis (PCA). Xiao et al. (2022) used the fault-feature correlation in KG's edge to assist the decision tree node split, therefore achieving fault classification. Inspired by node classification methods, Chhetri et al. (2022) turned fault prediction into a node classification task. A binary node status is predicted (e.g., failed or working) by inputting KG triples directly into RGCN (Schlichtkrull et al., 2018). All these methods benefit from the organization of graph structure, but the KG is not fully exploited as its semantic meanings and reasoning capacities are not used.

Table 5
Knowledge graph reasoning in fault diagnosis.

Ref	Categories	Methods	Semantic	Structural	Objectives
(Hou et al., 2023)	One-hop reasoning targeting r	GNNs for embedding; CNNs for feature extraction; Attention mechanisms to score possibility	✓	✓	Complete knowledge graph and facilitate fault knowledge retrieval
(Xia et al., 2023a)	One-hop reasoning targeting r	Compressed RGCN (Schlichtkrull et al., 2018) as encoder; GAT (Veličković et al., 2018) and residual block for refinement; DistMult (Yang et al., 2015) to predict the existence of triples	✓	✓	Reason fault cause and solution by predicting whether related edge exists
(Tian et al., 2023)	One-hop reasoning targeting r	Decision tree for feature embedding; Distance-based loss function for binary prediction	×	✓	Fault prediction by judging whether a node is linked to a known failure node by relation of similar rather than non-similar
(Cai et al., 2023)	One-hop reasoning targeting t	TransR (Lin et al., 2015)	✓	✓	Complete fault knowledge graph
(Mao et al., 2024)	Multi-hop reasoning targeting path query	Improved GraphSAGE (Hamilton et al., 2017) for embedding; Multi-layer Knowledge Aggregation Network (KAN)	✓	✓	Fault root cause reasoning
(Zhao et al., 2022)	Multi-hop reasoning targeting path and conjunctive query	BERT for hop classification and subgraph retrieval; Sentence-BERT (Reimers & Gurevych, 2019) for answering	✓	✓	Fault knowledge retrieval

4.1.3. Knowledge graph reasoning for fault diagnosis

KGs can be directly used for fault diagnosis by reasoning new knowledge. As discussed in Section 3.2, there are mainly two types of reasoning: one-hop reasoning and multi-hop reasoning. The purpose of one-hop reasoning is to predict the existence of link (h, r, t). Multi-hop reasoning is categorized by query types (i.e., path and conjunctive). Table 5 summarizes their applications in fault diagnosis with their method details and objectives.

KG reasoning has been enhanced by machine learning algorithms (e.g., TransE Bordes et al., 2013, TransR Lin et al., 2015 and DistMult Yang et al., 2015) and graph-based deep learning algorithms (e.g., RGCN Schlichtkrull et al., 2018, GAT Veličković et al., 2018 and GraphSAGE Hamilton et al., 2017), but for domain-specific adaptation, refinement is still needed.

KG reasoning can be used for straightforward tasks when combined with machine learning algorithms. For example, Cai et al. (2023) applied TransR to help enrich a fault KG and add missing edges. Preliminary fault diagnosis can also be achieved. For example, Tian et al. (2023) employed decision trees to gain feature embeddings and used these to predict relations between normal failure nodes. However, this framework is incapable of other complicated fault diagnoses, as this was a binary task with only two relation types (i.e., similar and non-similar).

The integration of deep learning algorithms allows for the implementation of more complex and universal tasks. Hou et al. (2023), Xia et al. (2023a) both designed a framework to integrate one-hop reasoning to achieve fault knowledge retrieval and fault diagnosis by relation prediction. Attention mechanisms were also applied in each method to deal with the independent weights of the nodes. The effectiveness of attention mechanisms was proved by Xia et al. (2023a) in the experiments. These approaches provide a feasible solution to utilize KGs for fault diagnosis. However, the performance of these one-hop reasoning methods is not comparable to traditional diagnosis methods, since they only applied deep learning techniques in a general way and did little maintenance-oriented adjustment. Future work is required to improve their accuracy and support their domain-specific adaptation.

In the case of multi-hop reasoning, Mao et al. (2024) improved GraphSAGE with multiple knowledge aggregation networks to achieve fault root cause reasoning. This method has a special focus on fault diagnosis-related features, such as the sensitivity of causes and sampling differences among diagnosis tasks while achieving good performance. The purpose of this work was to generate new knowledge about fault root causes based on existing KGs rather than case-based analysis, making it more of a knowledge management method than a fault diagnosis approach.

4.2. Maintenance action identification

Many decisions are involved in maintenance action identification. The first step is to validate the feasibility of certain actions, i.e., whether these actions are suitable to solve the fault, and obtain a set of feasible maintenance actions. Then, selective maintenance (Rice et al., 1998) is undertaken to further select a subset under multiple resource constraints, such as time, cost, space, etc. As the status of the system ranges from perfectly functioning to completely failing, imperfect maintenance for the intermediate status is considered. Imperfect maintenance has various options (e.g., minimal repair, corrective repair, and preventive repair) and is impacting the maintenance decision-making on policies (Richard Cassady et al., 2001). Finally, these actions are evaluated for long-term decision-making, considering the impact on system performance over time.

Typical methods applied in maintenance action identification are data-driven or knowledge-driven. For data-driven methods, elaborated mathematical programming models (Liu & Huang, 2010) are used, as well as machine learning algorithms (e.g., Markov decision process Ahadi & Sullivan, 2020) and deep learning methods (e.g., reinforcement learning Xu et al., 2022). Knowledge-driven methods, such as Expert Systems (Shen & Grivas, 1993), are designed on the basis of digitizing knowledge.

KGs can also be applied to action identification. Although KGs seem not to be utilized for long- and medium-term effectiveness evaluation and policy selection (imperfect maintenance), KGs are capable of identifying operational maintenance action. A summary of KGs applications in action identification is listed in Table 6.

All reviewed papers demonstrate a means of providing suggestions on feasible actions for corresponding faults. Many studies (Chatterjee & Dethlefs, 2022; Li et al., 2023c; Lu et al., 2023; Xiong et al., 2024) retrieve related actions stored in KGs. Xia et al. (2023a) and Farah et al. (2020) use one-hop reasoning when the KG is incomplete and actions cannot be reached directly. Xiong et al. (2024) utilizes GraphSAGE to get defect and action node embeddings and verifies the existence of their link to find a feasible maintenance action. However, none of these papers consider resource constraints and fail the task of selective maintenance. Chatterjee and Dethlefs (2022) focuses on standard question answering, such as identifying typical actions for repairing specific defects, without incorporating any constraint-related factors. Li et al. (2023c), Lu et al. (2023), and Farah et al. (2020) rely on similarity comparison from existing KG elements, while no constraints are considered in their KGs. Xia et al. (2023a) and Xiong et al. (2024) apply GNN-based methods (e.g., ACRGCN and GraphSAGE) to reason maintenance

Table 6
Knowledge graph in action identification.

Ref	Methods	Feasibility	Adaptivity	Constrained
Chatterjee and Dethlefs (2022)	LLM; Template-based querying	✓	×	×
Li et al. (2023c)	Similarity calculation	✓	✓	×
Lu et al. (2023)	Similarity calculation	✓	✓	×
Xia et al. (2023a)	ACRGCN	✓	×	×
Farah et al. (2020)	Similarity calculation; ComplEX (Trouillon et al., 2016) for reasoning	✓	✓	×
Xiong et al. (2024)	GraphSAGE	✓	×	×

Table 7
Knowledge graph in maintenance organization.

Ref	Objectives	KG function	Direct contribution	Principle methods
Ansari et al. (2023)	Maintenance scheduling under human resource constraint	Information retrieval	×	Linear programming; Genetic algorithm
Louadah et al. (2024)	Maintenance scheduling under resource constraint	Information retrieval	×	Mixed Integer Programming (MIP)
Papadakis et al. (2023)	Maintenance scheduling under priority order and resource constraints	Offer maintenance task options for scheduling	✓	Rule-based querying
Lim et al. (2023)	Maintenance scheduling with key tasks identification and simulation	Integrating information and reasoning key tasks	✓	Design structure matrix; Louvain algorithm; PageRank; Cognitive Digital Twin

actions, yet they also overlook how constraints can influence action selection.

Despite these limitations, some works (Farah et al., 2020; Li et al., 2023c; Lu et al., 2023) present good adaptivity when confronting unseen problems. This capacity is fulfilled by similarity calculations, which are discussed in Section 4.1.1. This method aims to imitate the intelligence experts possess when addressing unknown faults by fully using historical records as domain knowledge. Others (Chatterjee & Dethlefs, 2022; Xia et al., 2023a; Xiong et al., 2024) cannot handle unseen problems because the premise of their methods is that both defect and action nodes must exist in the KG.

Although KGs demonstrate the potential to offer a solution for the identification of maintenance actions, the overall application is limited to the selection of actions at the initial stage without considering any constraints. Research on utilizing reasoning ability of KGs focuses on KG completion rather than optimizing action identification. Further research is needed to explore KG's potential in this area. Furthermore, the current performance highly relies on the quality of KG and there is no unified standard or metric for evaluating results.

4.3. Maintenance organization

From the perspective of long-term optimization, maintenance organization takes system degradation and uncertainty into account (Zhang et al., 2023b). For operational organization, the two main focuses are a) real-time maintenance task scheduling and b) resource allocation.

Decision-making methods used in maintenance organization overlap with data-driven methods for action identification (see Section 4.2) to some extent, since they are similarly applied under resource constraints. KGs can support decision-making in manufacturing (Rožanec et al., 2022) by providing the description of complex interrelationships and maintenance knowledge to planners. KGs are also compatible with advanced decision-making techniques. For example, Zheng et al. (2021) integrated KGs into reinforcement learning and achieved solution optimization with prior rules offered by KGs. However, few papers (listed in Table 7) utilized KGs in operational maintenance organization with good quality.

The simplest utilization of KGs for maintenance organization is to retrieve related information (e.g., available resources) for other traditional methods (Ansari et al., 2023; Louadah et al., 2024). KGs in this case do not directly contribute to maintenance organization but provide essential information for other optimization algorithms. Task allocation and shift planning can be conducted by linear programming and genetic algorithms (Ansari et al., 2023). Resource constrained short-term scheduling optimization can be achieved by Mixed Integer Programming (MIP) (Louadah et al., 2024). In contrast, KGs in Papadakis et al. (2023) were utilized as the principal element for maintenance organization. Although (Papadakis et al., 2023) similarly employed KGs as a querying tool to obtain tasks for scheduling, this work regulated the returned results by encoding scheduling priority and resource constraints into rules. In this way, rule-based reasoning in KGs directly contributed to automated scheduling. Lim et al. (2023) designed a more efficient combination of KGs and design structure matrix (DSM). This method used DSM to analyze complex dependencies in the system and enables KGs to identify key maintenance tasks. Maintenance disruption is minimized taking advantage of KG's structural efficiency. The final evaluation and simulation of this work were conducted in a digital twin.

The papers in Table 7 demonstrate the positive applications of KGs in operational maintenance organization, but the overall exploration is still in its very early stage.

5. Major gaps

5.1. Limited applications in maintenance action identification and organization

KGs play an important role in the decision-making of operational maintenance. The various KG applications in fault diagnosis have proved the feasibility to serve different purposes. KGs have been applied for facilitating information usage, improving diagnosis performance and adapting to unforeseen problems. They proved noteworthy benefits in employing KGs to provide intelligent choices, though only a few papers focused on maintenance action identification and organization.

However, the application of KGs is unbalanced and mainly focuses on the fault diagnosis scenario. The total amount of papers about KGs in action identification and maintenance organization is small. Moreover, the applications are commonly overlapping cross scenarios as visualized in Fig. 2, which makes the papers focusing solely on these two scenarios even fewer. This indicates that the application of KGs in operational maintenance decision-making is still in a very early stage.

5.2. Limited utilization of KGs beyond information retrieval

A KG can be used for complex tasks. Several papers managed to design algorithms on top of KGs for maintenance decision-making and realize fault diagnosis (e.g., Mao et al., 2024; Xia et al., 2023a), action identification (e.g., Farah et al., 2020) and organization (e.g., Lim et al., 2023). KGs are enhanced for different purposes. A common method is to add weights to nodes and edges of KGs with priority, frequency, probability, etc. to customize the search. NLP methods may be applied before the construction of a KG to standardize the input, or after the construction of a KG to improve readability. In case of a more complex situation, e.g., incomplete KGs or unforeseen problems, one-hop and multi-hop reasoning and similarity-based comparison are conducted.

However, in maintenance decision-making, most KGs are utilized for knowledge storage and information retrieval, which is the most basic function that a KG provides. Despite the efforts of using KGs' structural features for better information location and semantic features for semantic-aware search, KGs essentially act as graph databases, and the potential of KGs has not been fully exploited. One reason is that most KGs are built to manage general domain knowledge rather than capture specific, instance-level cases, which restricts their applicability in real-world reasoning tasks. Additionally, KGs can produce meaningful reasoning results if they are comprehensively constructed from high-quality data. However, obtaining such data is challenging, and data cleaning during KG construction remains a significant obstacle. Finally, traditional KG reasoning methods rarely incorporate numerical values, making it difficult for them to handle constraints or scheduling-related issues in operational maintenance tasks.

5.3. Isolated development and restricted data sharing

The development of KGs is isolated, although KGs are easy to construct and share. Most of the papers constructed their own domain-specific KGs from scratch. Many of them built their KGs using NLP algorithms on their private documents and historical records. The original data and KGs are not shared as an open source database due to commercial or safety reasons. This leads to duplication of construction work and difficulty in method validation. These methods can be trained and tested on open-source databases in commonsense areas, like Freebase and Wikipedia. However, they do not have a convincing performance on domain-specific tasks since these databases focus on different kinds of information and have little overlap with domain knowledge. Also, the lack of a common open-source KG in the industrial maintenance domain results in inconsistent standards and impedes knowledge reuse. It is also difficult to benchmark the algorithm without an open database.

6. Future directions

6.1. Domain-specific knowledge graph completion

The quality of KGs has an essential impact on the performance of decision-making methods, regardless of the different kinds of functions KGs are offering. Incomplete KGs can fail to return desired results for information retrieval. For example, missing links between fault symptoms and failure types may cause false negatives in fault diagnosis, where actual faults go undetected due to the absence of critical relations. KG reasoning methods have been developed to deal with this problem, but the accuracy is largely subject to the completeness level of KGs, since these methods are trained on the KG. Efforts should be made to overcome this problem, especially in domain-specific research areas where available data is limited.

KG completion can also generate new knowledge for better decision-making. One key purpose of utilizing KGs in maintenance is to digitize expert experiences as machine-readable knowledge. Similar to expert intuition playing a crucial role in forming implicit knowledge for decision-making, KG completion is effective in identifying potential relationships among triples and along paths, uncovering implicit connections that are important in decision-making. By filling in missing links or suggesting likely associations based on observed patterns, KG completion can reduce the impact of false negatives and improve the robustness of downstream reasoning.

6.2. Cross domain knowledge reuse

The availability of industrial maintenance knowledge is limited since maintenance data is always considered sensitive and cannot be shared. As discussed in Section 5.3, this results in the isolated development of domain-specific KGs. Hence, knowledge reuse across different domains can benefit KG-based methods.

Transfer learning can leverage knowledge from tasks to improve performance in other related tasks. Although data from different sections of industrial maintenance cannot be used directly, the decision-making processes are similar. Applying transfer learning in combination with KGs can contribute to the problem of data scarcity and sensitivity since no original data is needed. It can also improve the performance of decision-making methods by integrating knowledge from other domains.

Knowledge graph standardization is another measurement to facilitate knowledge reuse. Many works define their own maintenance knowledge schema and build KGs on top of it. Differences between the KG schema will impede knowledge reuse. Hence, the establishment of a standard domain knowledge schema to guide KG construction is necessary. The domain ontology could be a suitable option.

6.3. Knowledge graph integration with advanced algorithms

The potential of KGs can be further exploited by integrating them with other advanced algorithms and making use of KG structural and semantic features. The prosperous development of graph-based machine learning algorithms and deep learning frameworks in computer science can boost the application of KGs. Some successful examples are provided in this review paper, such as Mao et al. (2024), Zhou et al. (2024). Although necessary adaptation of KGs in practical application is needed and its exploration is at an early stage, it is a promising research direction in maintenance decision-making.

To fully exploit the potential of KGs in maintenance decision-making, a comprehensive framework could be developed that integrates KGs with learning and optimization components. The first step is to construct a knowledge graph that includes all necessary elements required by operational maintenance–not in terms of domain breadth, but in terms of functional completeness. For instance, even if current systems cannot yet handle constraints effectively, those constraints should still be explicitly modeled within the KG. Once constructed, the KG can learn from existing maintenance cases through reasoning mechanisms, where advanced GNNs and reasoning algorithms can be integrated here. Information retrieval can then be used to extract relevant knowledge and information for specific maintenance situations. Finally, advanced algorithms such as reinforcement learning or optimization methods can be incorporated to handle numerical factors–such as scheduling and resource allocation–guided by the structured insights obtained from the KG reasoning process.

7. Conclusion

Industrial maintenance at the operational level is an important part of the operation and maintenance stage, and KGs are regarded as a solution to solve the challenges of knowledge management and expert reliance faced by maintenance decision-making. To systematically summarize the different usage of KGs in this field, this paper divided operational maintenance decision-making into three scenarios and surveyed various KG-based methods in each separate scenario to discuss their

applications and limitations. The main contributions of this paper are highlighted as follows:

This paper answers RQ1 by outlining three major types of KG-based methods in maintenance decision-making: KG querying, KG reasoning, and KG enhancement. The analysis of structural and semantic features of KGs provides a clearer understanding of how these methods support decision-making in maintenance. By clarifying how KG-based methods are utilized in maintenance, this work also encourages broader adoption and deeper investigation into their potential.

For RQ2, this paper identifies three key operational maintenance decision-making scenarios where KGs are applied: fault diagnosis, action identification and maintenance organization. This review critically examines the practical applications of KGs. Although a large number of studies employ KGs as querying tools for simple tasks like information retrieval, efforts have been made to fully leverage both semantic and structural features of KGs for advanced reasoning and automated decision-making in maintenance. By analyzing existing studies and integrating findings from different works, this review provides a structured understanding of how KGs are currently applied in maintenance decision-making and a clear assessment of the state of research in this area.

In response to RQ3, this paper highlights the major gaps and future directions to apply KGs in maintenance decision-making. This systematic review pinpointed three major gaps related to insufficient exploration of KGs and limited knowledge communication. Additionally, this review proposed three future research directions aimed at enhancing KG quality and improving usage efficiency in maintenance decision-making.

This study aims to contribute to a comprehensive understanding of the applications and limitations of KGs in operational maintenance decision-making and provides a foundational basis for researchers and industrial practitioners in developing KGs in maintenance.

CRediT authorship contribution statement

Rui Kang: Conceptualization, Methodology, Formal analysis, Investigation, Data Curation, Writing – Original Draft, Visualization. Writing – Review & Editing. **Junxiang Zhu:** Conceptualization, Methodology, Investigation, Writing – Review & Editing. **Stephen Green:** Conceptualization, Methodology, Writing – Review & Editing. **Ioannis Brilakis:** Writing – Reviewing and Editing, Supervision, Project administration, Funding acquisition.

Data availability

No data was used for the research described in the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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