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A Knowledge Graph-Based Failure Information Fusion Method for Enhancing Reliability in Sustainable Systems

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Abstract: Failure Mode and Effects Analysis (FMEA) serves as a fundamental process in reliability analysis, providing critical insights into support system planning and equipment design optimization. However, traditional FMEA processes encounter several limitations, including restricted data availability, subjective expert assessments, and rigid structural requirements. The current evaluation approaches for expert opinions are constrained by small sample sizes, stringent requirements for structural consistency, and high demands for logical cohesion. To address these issues, this paper proposes a failure information fusion method utilizing a knowledge graph. By improving decision-making reliability and resource efficiency, the proposed method contributes to sustainable maintenance practices and operational sustainability. Furthermore, the method incorporates knowledge embedding technologies, facilitating reasoning through the transformation of graph structures into matrix representations. This process uncovers potential failure relationships and improves analytical depth. A case study involving an aircraft system is presented to demonstrate the method's effectiveness and versatility, showcasing its potential to enhance reliability and support system planning.

Keywords: failure analysis; knowledge graph; sustainable maintenance; reliability engineering; link prediction; supportability planning

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1. Introduction

Failure Mode and Effects Analysis (FMEA) is designed to enhance equipment reliability by identifying and addressing potential failure modes. By either improving equipment design to eliminate failures or implementing preventive maintenance strategies to mitigate risks, FMEA contributes significantly to efficient resource utilization and operational sustainability. FMEA achieves this by analyzing various potential failure modes, their causes, and impacts. As equipment systems become increasingly complex and operate in harsher environments, the diversity of potential failure modes has grown significantly. To effectively manage these challenges, it is crucial to identify as many potential failure modes as possible and thoroughly analyze relevant information before equipment deployment, thereby providing a solid basis for subsequent support program planning and preventive actions.

Currently, failure mode analysis during the development process still relies on the knowledge and experience of domain experts [1,2]. Analysis and assessment are typically conducted based on historical data, with strategies employed to integrate multiple expert opinions to establish failure mode priorities. Effectively integrating diverse expert opinions and data sources into a unified, structured framework for scientific and informed decision-making has become a critical challenge in achieving sustainable and reliable system development. This paper presents a knowledge graph-based failure information fusion method designed to address these challenges by employing advanced reasoning techniques to integrate expert insights and support comprehensive failure analysis. By enhancing the accuracy and efficiency of maintenance planning, the proposed method indirectly supports sustainable development goals by optimizing resource utilization and reducing system downtime.

Academia has developed several typical methods for information fusion, including Bayes [3–5], fuzzy rough set [6–8], and D-S evidence theory [9–11]. The Bayes algorithm can map information to the conditional probabilities of different nodes in a probabilistic network. Incorporating ideas from the physics of failure, Qiu synthesized the relationship between failure modes and failure mechanisms [12]. In industry, large amounts of data, such as records of operations and maintenance activities, have been accumulated to support a data-driven approach to FMEA [13]. Deng designed a physics-informed Bayes deep dual network to identify the most informative knowledge [14]. Nevertheless, the output of different information sources needs to be sampled statistically in probability mapping, demanding a large sample size. Under limited sample conditions, a metalearning network was specifically designed for intelligent failure identification, using metric-based information transfer to identify failures [15]. In contrast, fuzzy logic reasoning can be applied when there is insufficient data. During the equipment development phase, expert opinions are often uncertain or vague, making fuzzy inference systems useful for assessing the severity, occurrence, and detectability of failure modes to promote uncertain decision-making [16–18]. In addition, belief structures can capture the uncertainty and fuzziness of subjective evaluations [19,20]. Zhu [21] further considered the interdependence between expert preferences and psychological behaviors for comprehensive evaluations. Despite improvements combining various fuzzy set-based methods, limitations remain, such as the need for prior information, too many fuzzy rules, and ignoring randomness in risk assessment. Hierarchical analysis has been effectively explored in recent years as a systematic approach to multi-objective decision optimization for failure mode risk ranking. In the combined application of hierarchical analysis and fuzzy logic, fuzzy rough number extended multi-criteria group decision strategies have been developed [22,23], which have significant advantages in dealing with uncertainty and subjectivity in failure mode assessment. Fuzzy rough sets reduce attributes and elements by dividing equivalent sets, which inevitably requires the consistency and completeness of attributes in the domain. Therefore, fused information needs to have a unified and well-defined structure.

In addition to using the fuzzy approach to solve the problem of expert subjectivity in FMEA, the mathematical framework of Dempster–Shafer (D-S) evidence theory is often explored to deal with the epistemic uncertainty that affects the evaluation of risk parameters. The theory utilizes belief and likelihood functions to determine the authenticity of propositions, considering the weight of both risk factors and expert opinions [24,25]. However, it is prone to anomalous fusion faced with highly conflicting evidence, which requires means such as screening or preprocessing to ensure consistency of the evidence before it is fused. Indeed, in some real-world decision-making processes, experts may prefer to explore linguistic values rather than numerical values to assess failure modes. Linguistic assessment methods have been widely applied in FMEA in recent years, but they also suffer from ambiguity and uncertainty in the assessment of failure modes [26]. In response to the personalized characteristics presented by experts in the assessment information, Zhang [27] proposed an FMEA approach based on personalized individual semantics to improve the reliability and safety of the system in a linguistic decision-making environment. From another perspective, the impact of expert consensus decision making on the confidence level of FMEA is also important [28]. To address the inconsistence of expert cognitive ability, Feng proposed a new belief rule base model with multi-expert joint [29]. However, the presence of one failure mode may increase or decrease the possibility of others occurring. To address this issue, Wang improved the traditional FMEA method to account for not only the positive and negative effects of failure modes but also their attenuating effects on the overall system [30]. In addition, the correlation between failure modes and failure causes should not be ignored. To address this shortcoming, a new approach to FMECA can be supported using complex network theory [31]. Another framework was suggested to model and quantify common cause failures, focusing on component dependencies arising from shared causes [32]. Leveraging global context information, a knowledge graph for failure diagnosis was built using a novel relation-oriented model to provide information-rich fault-related knowledge [33]. Despite these advancements, making full use of failure information to analyze failure modes remains a challenge.

In actual analysis processes, it is difficult to define failure modes precisely or obtain a sufficient number of failure subsamples. This makes it challenging to integrate multi-source information using Bayes method or fuzzy rough sets. At the same time, the epistemic uncertainty of experts often leads to highly conflicting evidence, causing logical inconsistencies with the D-S synthesis method. Therefore, the purpose of this paper is to develop an information fusion architecture that addresses the current limitations of evaluation strategies. To address these limitations, this paper introduces a knowledge graph-based failure information fusion method that leverages advanced reasoning techniques to integrate expert insights and enable comprehensive failure analysis. By improving the accuracy and efficiency of maintenance planning, the proposed method enhances reliability while contributing indirectly to sustainability by optimizing resource utilization and minimizing system downtime. After presenting the related state of the art and current limitations, a new solution based on knowledge graph techniques will be elaborated, experimented, and evaluated. As an information management technique [34], knowledge graph can formally represent information of different property in a graph structure. The graph structure not only includes the semantic content of expert opinions but also allows connections between different pieces of information via node links. The global nature of the knowledge graph allows the combination of different expert knowledge and avoids the problem of insufficient data during the early stages of development. Moreover, the data extraction technique used in knowledge graph construction can abstract information from structured, semi-structured, and unstructured forms, overcoming the uniformity limitations of fuzzy methods. Furthermore, knowledge inference technique over the knowledge graph can exploit the topology of the graph to mine information, achieve organic fusion of failure information and dissolve the conflict of expert logical evidence. Therefore, this paper proposes a failure information fusion method based on knowledge graph technology, addressing the challenges of information fusion caused by subjective differences in expert assessments during the FMEA process. The main contributions of this paper are as follows:

(1) The proposed knowledge graph construction method connects information by integrating expert knowledge from multiple sources. Our approach relies on established analytical techniques such as FMEA, CMTA, and LORA to source knowledge. These techniques yield semi-structured data presented in tabular formats, facilitating clear identification of attributes and relationships necessary for constructing our knowledge graph. Thus, intelligent extraction of diverse information has been achieved, and various types of logistics support analysis reports have incorporated.

(2) A knowledge-driven fusion model for link prediction failure information is proposed. The model maximizes the value of expert knowledge from logistics support analysis, which helps avoid issues related to insufficient sample sizes.

(3) Knowledge reasoning technology can detect and resolve conflicts by using the structural features of the graph [35]. It allocates information weights to deduce failure information with the highest confidence, thus avoiding abnormal fusions caused by conflicting evidence. This method allows effective and selective refinement of different types of information.

In this section, we analyze the problems of existing failure information fusion methods and illustrate the advantages of using knowledge graph technology combined with knowledge reasoning methods.

The remainder of this paper is organized as follows: Section 2 explains the concept of knowledge graph and the related knowledge information of various supporting analysis techniques in detail. In Section 3, the domain ontology is created to form a scheme layer based on heterogeneous information networks. Meanwhile, entities and relationships are extracted from logistics support analysis knowledge information to construct the data layer. Section 4 introduces the TransD knowledge reasoning method based on graph content, including supporting analysis information, and the link prediction model used to implement the failure information fusion process. Section 5 presents a real case study involving an aircraft subsystem to demonstrate the visualization of knowledge graph results and obtain the failure information fusion analysis results with a high level of confidence. Section 6 provides the conclusion of the paper.

2. Preliminaries

We explore the knowledge inference process of knowledge graph for failure information fusion as a solution to the problems existing in the current analysis methods. In order to describe the relevant aspects of knowledge graph, this chapter details the sources of information for knowledge graph and its collection process.

During the failure analysis process, there are several supportability analysis techniques that can assist in exploring different aspects of the system. The content of each analysis technique is as follows:

- Failure mode and effect analysis (FMEA): A process used during the product design phase, where subsystems, parts, and components are analyzed one by one to identify potential failure modes, determine the causes of these failures, and assess their possible consequences.
- Damage mode and effect analysis (DMEA): An analysis of a wartime scenario in which weapons and equipment are subjected to a series of attacks and may be damaged, which is an extension of FMEA.
- Reliability centered maintenance analysis (RCMA): A process of determining the work requirements of equipment preventive maintenance and its maintenance level by using the method of logical decision.
- Corrective maintenance task analysis (CMTA): By determining the corrective maintenance work items of equipment, it provides a basis for evaluating and weighing whether the alternative support schemes meet the support requirements.
- Operational and maintenance task analysis (O&MTA): A method that breaks tasks down into individual operational steps for detailed analysis, in which process details of each supportability activities and resource requirements can be determined.
- Level of repair analysis (LORA): The process of performing a non-economic or economic analysis of products to determine a feasible level of repair or obsolescence.

FMEA of equipment support system is a necessary part of the development process. As the first step of the supportability analysis technology, it not only provides guidance for the subsequent maintenance and supportability project requirements, but also is further improved by the influence of the supportability analysis results. Therefore, the comprehensive supportability analysis technology constructs the knowledge graph of the supportability field to extract and fuse the failure-related information of the equipment in an omnidirectional way.

For knowledge graph of the supportability field, the main source of knowledge is the information extracted from each supportability analysis process. First, according to the technical process of supportability analysis in the development process, the information content obtained from each supportability analysis process is clarified. Then, the knowledge data that can be applied is organized and summarized. Finally, entities and relationships are identified to build semantic associations among the information, to build a knowledge graph of the supportability domain. The main knowledge sources of the supportability analysis process can be modularly subdivided into the six technology of supportability analysis.

Based on the structure diagram of equipment, the relationship between support information is established by mining knowledge from support analysis information of different agreement levels.

The knowledge extraction and model construction for the support domain knowledge graph are gradually expanded and improved throughout the support analysis process. The process is shown in Figure 1. Firstly, the basic framework of the atlas is established according to the agreed hierarchical Structure Block Diagram (SBD) divided by the equipment product tree, which can be divided into a series of levels, such as system, subsystem, ling replacement unit (LRU) and shop replacement unit (SRU). Secondly, the failure-related information of components is analyzed from the lowest agreement level upward, and the logical sequence of functions between each agreement level is clarified by combining the Functional Block Diagram (FBD) of each component. Then, the failure mode and damage mode are determined from the function, task and usage environment of the component, and the causes of the mode are analyzed from the own factors and external factors to evaluate the failure impact and damage impact. Thus, the FMEA report, DMEA report and their related failure damage information are output as a source of knowledge for the failure-related triple. Based on the output information of the two reports, the corrective and preventive maintenance work are determined, respectively. Among them, the corrective maintenance work is determined by CMTA to give the requirements, while the preventive maintenance work is performed by RCMA to make logic decision of important functional products. They can obtain the appropriate repair countermeasures as the source of knowledge of the repair-related triple. After the two repair jobs are aggregated, O&MTA is performed to refine and decompose the usage and maintenance supportability work item requirements. Therefore, A further division of the repair engagement level is carried out by LORA to output the supportability resource requirements for equipment maintenance work as the source of supportability-related triple knowledge. Finally, by gradually collecting report information aggregation along the supportability analysis process, a complete supportability domain knowledge graph is constructed.

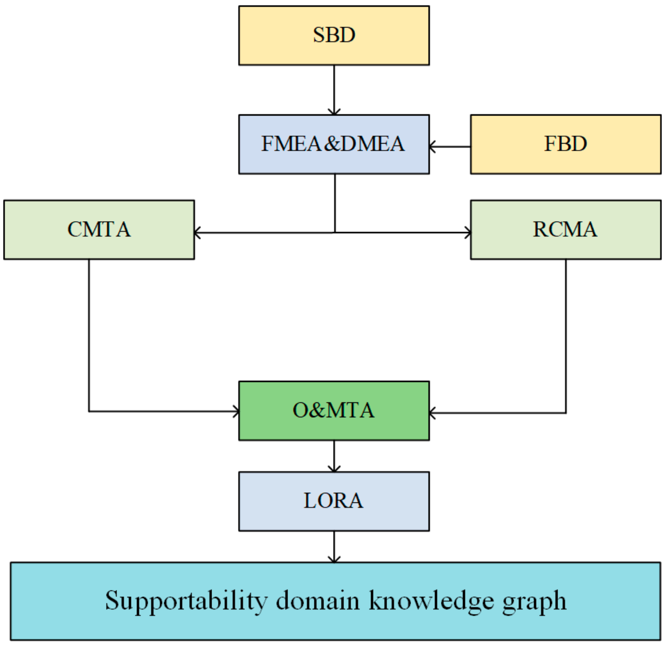

Figure 1. Process of knowledge information collection.

3. Construction of Knowledge Graph

A knowledge graph is composed of two main layers: the pattern layer and the data layer. This section describes the construction of the pattern layer of the knowledge graph in five steps, establishing its logical framework and foundational rules. Knowledge is then extracted using wrapper induction to complete the data layer.

The construction of schema layer requires normative constraints on the definition of knowledge data. Ontology is used as the schema layer of knowledge graph, and the knowledge system is constrained and defined through metadata, to achieve the purpose of knowing which data categories or special attributes are contained in this data type according to the ontology model. An ontology definition typically consists of five parts:

- Concept: Represents the essence of things, which is called class in ontology.

- Relationship: Shows how concepts are interconnected rather than existing in isolation.
- Attribute: Describes characteristics of a concept.
- Axioms: Represents the mapping relationships between concepts and inference rules.
- Instance: Represents specific pieces of information within the ontology.

The knowledge graph is represented by "entity, relation, entity" as the basic unit, and a relational graph is formed by a large number of such structures, so its storage format is also stored by relational triples. There are three common methods for storing graphs: one is the table-based storage method, another is RDF-based storage, and the third is graph database storage. As a high-performance graph engine, Neo4j has the advantage of visualizing triplet relations in the form of graphs, taking entity words as points and relations as edges, and using points and edges to construct knowledge graphs. After the construction of the mode layer and data layer, all the support information in the support analysis process is extracted by entities and relations. Thus, a perfect support domain knowledge graph can be gradually established, and the whole support system composition can be visually displayed, so as to facilitate the dynamic update of equipment support knowledge. The concept definition of ontology is the provision of category division of entities and the elaboration of essential connotation. The relation between entities of different categories is established through relation definition. There are certain regular link rules and mapping stipulated by axioms. There are certain regular link rules and mapping stipulated by axioms. Through the definition of these five parts, the ontology of knowledge graph of a certain domain (Algorithm 1) can be constructed.

Algorithm 1: ConstructOntology

```
Input: ResearchDomain, ConstructionTask
Output: Ontology

1: Initialize Ontology
2: Set ResearchDomain and ConstructionTask
3: IdentifyComponents(Ontology)
4: DefineConcepts(Ontology)
5: EstablishClassificationSystem(Ontology)
6: DefineAttributesAndRelationships(Ontology)
7: DefineConstraints(Ontology)
8: Finalize Ontology

Procedure IdentifyComponents(Ontology)
1: List all elements in ResearchDomain
2: Realize definition of ontology concept

Procedure DefineConcepts(Ontology)
1: Establish classification system for Ontology database
2: Divide into upper and lower-level structure

Procedure EstablishClassificationSystem(Ontology)
1: Based on defined concepts, establish hierarchical classification

Procedure DefineAttributesAndRelationships(Ontology)
1: For each concept, define attributes
2: For each concept, define relationships with other concepts

Procedure DefineConstraints(Ontology)
1: Define value constraints for attributes
2: Define relationship constraints between entity pairs
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The specific process is divided into the following basic steps:

1. Establish the research domain and construction task of ontology.
2. List the components of ontology, list the elements in the research field, and realize the definition of ontology concept.
3. Establish the classification system of ontology database and divide the upper and lower-level subdivision structure of ontology.
4. Define their respective attributes and corresponding relationships for ontology concepts.
5. Define the value constraints of attributes in the ontology and the relationship constraints between entity pairs.

3.1. Construction Task and Research Domain of Ontology

To build an ontology, the domain and scope of the study need to be firstly determined. Aiming at the knowledge graph of the supportability domain, the research scope can be divided into two domains of usage security and maintenance support from the perspective of supportability domain knowledge analysis. The purpose of the construction of the graph is to represent the knowledge structure among the supportability information related to the failure, so as to have an overall consideration of the failure mode and impact analysis.

3.2. Components of the Ontology

The knowledge source in the support field comes from the results of various support analysis reports, and the ontology components are derived from this information. By going through the entire support analysis workflow, these components have been summarized and extracted, as shown in Table 1.

Table 1. Elements of the work entity of support analysis.

Support Analysis Technology	Entity Elements
FMEA	Indenture level
	Function description
	Failure mode
	Failure reason
	Failure effect
	Compensation measures
	Detection method
DMEA	Damage mode
	Threat
	Damage effect
	Improvement measures
CMTA	Maintenance way
	Maintenance task
RCMA	Failure consequence
	Preventive maintenance task
	Maintenance level
LORA	Limited repair level
	Non-economic factor
	Replace level
	Repair level
	Scrap level
O&MTA	Operational support program
	Maintenance support program
	Required support resources
	Description of facility requirements
	Technical data description

3.3. Classification System of Ontology

The association between the entity elements of each type of safeguard analysis technology is divided, and the upper and lower levels of each technology are subdivided to establish the classification system of the ontology. Taking the safeguard object as the main body, it can be divided into five items of knowledge information. These items include function information, failure information, damage information, maintenance support information and operational support information. According to each content by can be further subdivided into related work information, as shown in Figure 2.

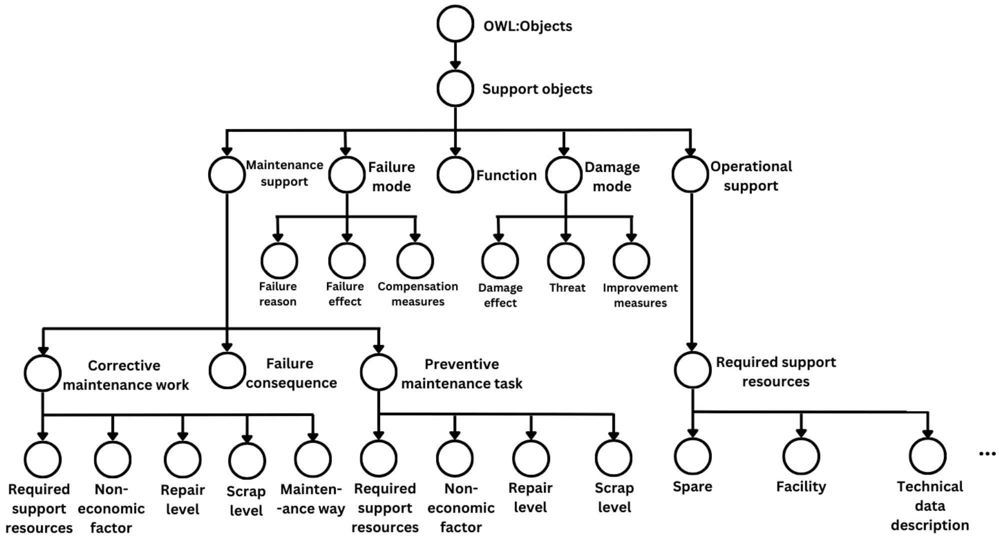

Figure 2. Knowledge classification system.

3.4. Entity Elements and Corresponding Relationships Definition

Some entity elements may have some attributes, which will also play a key role in the decision of resource protection. Therefore, it is necessary to define the attributes of entity elements as a supplementary part of the entity elements in the schema layer. By analyzing the contents of the report, the attributes contained in each entity element can be listed as shown in Table 2.

Table 2. Entity element attribute table.

Support Analysis Technology	Entity Elements	Property
FMEA	Failure mode	Frequency ratio
		Probability level
		Detection difficulty level
	Failure effect	Severity
DMEA	Damage mode	Damage rate
CMTA	Corrective maintenance task	Operating frequency
RCMA	Preventive maintenance task	Maintenance interval
		Operating frequency
O&MTA	Operational support program	Operating frequency
		Operation experience time
		Man-hour
	Maintenance support program	Operating frequency
		Operation experience time
		Man-hour
	Required support resources	Replacement rate

Based on the above classification system, the relationship between the entity elements of each type of supportability analysis technology can be defined, and the relationship between some entity elements of different supportability analysis technology can be analyzed.

3.5. Constraints of Triples Based on HIN

The association between the entity elements of each type of safeguard analysis technology is divided, and the upper and lower levels of each technology are subdivided to establish the classification system of the ontology. Taking the safeguard object as the main body, it can be divided into five items of knowledge information, which are function information, failure information, damage information, maintenance support information and using information. According to each content by can be further subdivided into related work information, as shown in Figure 2.

In this paper, the heterogeneous information network method (HIN) is adopted to build a mathematical model of knowledge graph [36]. This model can flexibly deal with complex multi-source heterogeneous data and retain more comprehensive semantic and structural information and defines the composition of relations between triples and the constraints of attributes and relations.

Definition 1. **(Information network)** *An information network is defined as a directed graph $G = (V,E)$ with an object type mapping function τ: $V \to A$ and a link type mapping function φ: $E \to R$, where each object $v \in V$ belongs to one particular object type $\tau(v) \in A$, each link $e \in E$ belongs to a particular relation $\varphi(e) \in R$, and if two links belong to the same relation type, the two links share the same starting object type as well as the ending object type.*

Definition 2. **(Network schema)** *The network schema, denoted as $TG = (A,R)$, is a meta template for a heterogeneous network $G = (V,E)$ with the object type mapping τ: $V \to A$ and the link mapping φ: $E \to R$, which is a directed graph defined over object types A, with edges as relations from R.*

G is a graph with $G = (V,E)$, where $V = \{v_1,\ldots,v_u\}$ is the set of nodes, and the set of edges $E = \{\varepsilon_1,\ldots,\varepsilon_e\}$ with Equation (1):

$$E = \left\{\varepsilon_k = \left(v_i, v_j\right) \in V^2, (i,j) \in [1;u]^2; i \neq j\right\} \tag{1}$$

Then, each node has a type τ which belongs to $T = \{\tau_1, \ldots, \tau_2\}$. The function f_v: $v \to \tau$ is used to return the type τ of node v. Each edge has a type μ belonging to the set $M = \{\mu_1,\ldots,\mu_m\}$. The function f_ε: $\varepsilon \to \mu$ returns the type μ of an edge ε.

This formalization can be used to define the nodes and edges characteristics with their types. These types can indeed be specified using a set of attributes from the whole $X = \{\chi_1,\ldots,\chi_x\}$. These attributes are properties or characteristics representing the nodes and edge types. These attributes can be customized for any type of nodes or edges depending on the information requirements to implement and exploit.

All attributes of a node type τ can be returned by the function in Equation (2):

$$f_T: \ T \ \to X_j \ with \ X_j \to X \tag{2}$$

Likewise, all attributes of an edge type μ can be returned by the function in Equation (3):

$$f_\mu: \ \mu \ \to X_j \ with \ X_j \to X \tag{3}$$

For two nodes v_p and v_n and an edge type μ_ℓ, the function g in Equation (4) returns a concrete edge ε_x if it exists and g in Equation (5) is the set $\{\varepsilon_1,\ldots,\varepsilon_a\}$ representing all real edges between two nodes v_p and v_n with $\{\varepsilon_1,\ldots,\varepsilon_a\} \subset E$ without constraint on edge type.

$$g: \ v_p * v_n * \mu_l \to \varepsilon_\chi \tag{4}$$

$$g : v_p * v_n \rightarrow \{\varepsilon_1, \ldots, \varepsilon_a\} \tag{5}$$

The value α of an attribute χ for a node v is returned by the function in Equation (6):

$$h_v : v * \chi \rightarrow \alpha \tag{6}$$

Likewise, the value β of an attribute of χ the edge ε is returned by the function in Equation (7):

$$h_\varepsilon : \varepsilon * \chi \rightarrow \beta \tag{7}$$

Finally, these values can be modified using the function ℓ in Equations (8) and (9):

$$\ell_v : \chi * \ v \ * \ a \ \rightarrow v \ for \ a \ node \ v \tag{8}$$

$$\ell_\varepsilon : \chi * \varepsilon * a \rightarrow \varepsilon \text{ for an edge } \varepsilon \tag{9}$$

The boundary definition of the entity nodes with their relationship is shown in Figure 3.

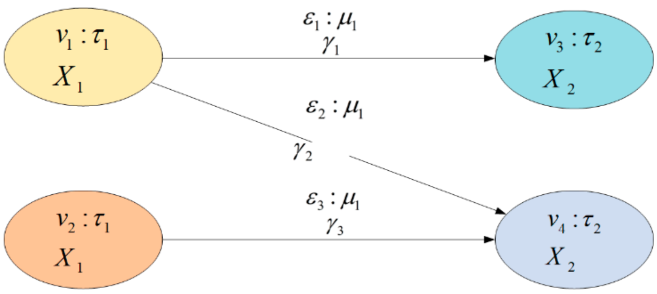

Figure 3. Triplet representation diagram.

3.6. Knowledge Extraction

Once the preliminary construction of the ontology base for equipment security resources is complete, the next step is to build the data layer of the knowledge graph. This involves applying relevant knowledge extraction techniques to the data sources, based on the concepts defined in the ontology base.

We propose to adopt the wrapper induction approach for entity extraction of the knowledge graph, then classify the logical associations between entity pairs according to the characteristics of knowledge information. By extracting semantic relationships, the triplets containing entity and relation are constructed.

(i) Entity extraction

Information extraction by wrapper induction is based on the sample instances marked by users, and the machine learning induction algorithm is applied to generate extraction rules based on separators. The delimiter is essentially the description of the context of the target semantic item, that is, the semantic item is defined according to the left and right boundaries of the semantic item. It is suitable for the feature format that clearly describes the structure of the required data block, such as table, list, Info box and other semi-structured data. For the information results obtained after the support analysis, they are mostly arranged in the form of summary tables. The entity elements of the ontology database are divided into categories, and each unit in the table is extracted as the entity data under the element category which can be utilized to achieve the goal of extracting entities from the support information.

(ii) Relation extraction

The specific implementation method is implemented to transform the table structure and data of relational database into RDF graphs. The summary table of all kinds of support analysis results is the main source of information. The header clearly shows the logical association between attribute categories of entity data and different cells, which can be extracted as the source of relation. According to the information contained in the support report, 43 kinds of triplets can be extracted to form triplets as shown in Table 3.

Table 3. The triple types of relation extraction.

Head Entity Label	Relation	Tail Entity Label
System	Contain	Subsystem
	Function	System function
Subsystem	Contain	LRU
	Function	Subsystem function
LRU	Contain	SRU
	Function	LRU function
	Exist	Damage mode
		Failure mode
	Have	Non-economic factor
	Need	Maintenance task
		Operational program
		Maintenance program
	Repair level	Maintenance level
	Replace level	
	Scrap level	
SRU	Exist	Damage mode
		Failure mode
	Function	SRU function
Subsystem function	Support	System function
LRU function		Subsystem function
SRU function		LRU function
Damage mode	Need	Improvement measures
		Maintenance task
	Lead	Higher level effect
		Local effect
		Final effect
	Because	Threat
Failure mode	Lead	Higher level effect
		Local effect
		Final effect
		Failure consequence
	Need	Detection method
		Compensation measures
		Maintenance task
	Because	Failure reason
Maintenance task	In	Maintenance way
	Repair level	Maintenance level
Maintenance support program	Support resources	Technical data description
		Description of facility requirements
Operational support program		Description of facility requirements
		Technical data description
Non-economic factor	Limit	Maintenance level

4. Failure Information Fusion Based on Links Prediction

In this section, the link prediction method is applied to ensure the inference process of resource knowledge graph. The node features in the graph can be mapped to the vector representation of low-dimensional space by the knowledge embedding method. The ranking score of link prediction is used as the evaluation criterion of information fusion to deduce the trusted knowledge triplet.

In accordance with existing knowledge, information mining identifies potential relationships between failure element nodes. The Trans series method, a representative technique for knowledge-embedded vector representation, expresses each relationship as a triple composed of a head entity vector h, a relationship vector r, and a tail entity vector t. The closer h + r is to t, the more accurately the vector representation captures each entity node, achieving the optimization target [37]. Based on the score function value, the rationality of triplet combination is ranked to judge whether the potential triplet is established.

Inspired by this idea, TransD improves the representation of entities and relations [38], which jointly constructs projection matrices for entities and relations, and each entity or relationship is represented by two vectors, one of which represents semantics, and the other one is used to construct mapping matrix. The mapping matrix is jointly determined by entities and relations. Perform the projection operation on the head and tail entity vectors. The corresponding score function is substituted to calculate the scores of different entities as the tail entity of the triplet. According to the scores, the rationality of triplet combination is sorted to judge whether the potential triplet is established. Continuous iterations are performed according to the loss function minimization principle to find the most reasonable vector representation of entities and relations. The candidate entities are substituted into the score function and ranked in order according to the score. The prediction link information at the top of the ranking is judged as the knowledge conclusion after failure information fusion.

5. Case Study

Using the report data from various documents throughout the support analysis process, a support domain knowledge graph was constructed for a specific type of aircraft. This graph consists of 2318 nodes and 7647 triplets. The complete knowledge graph is shown in Figure 4. Yellow nodes represent the SRU, purple nodes represent the LRU, pink nodes represent the failure mode, brown nodes represent the impact of the failure, green nodes represent the subsystem, and blue nodes represent the cause of the failure. The Failure information is integrated into the knowledge graph, which clearly show the connection and logic between them.

The mean reciprocal rank (MRR) and the scores of Hits@1, Hits@3 and Hits@10 were used as evaluation indicators in the experiment. In the experiment, the training dimension of the entity vector was selected as 50 dimensions, and the learning rate was 0.01. The gradient descent method was used for 3,000 iterations, and a test set of 500 randomly selected groups was used. The experimental evaluation results are presented in Table 4.

Combining the actual physical significance of supportability domain knowledge graph, the results show that once entity vector representation and relationship vector representation are given, we can reach the most adjacent tail entity node according to score function sorting. For example, the vector of head entity "LRU" and the vector of relationship "SRU" are presented, there is a probability of 0.401 that the predicted node is potential failure information to be discovered. Taking the LRU node named "anti-ice liquid device" as the head entity as an example, the first eight SRU nodes with "contain" relationship are predicted as shown in the Figure 5. Comparing the prediction results with label information, the 0.625% of predicted tail entity nodes are the components contained in actual device, and the remaining entity nodes can be connected by one or two links. It shows an indirect correlation between entities although there is no direct inclusion relationship in the knowledge graph.

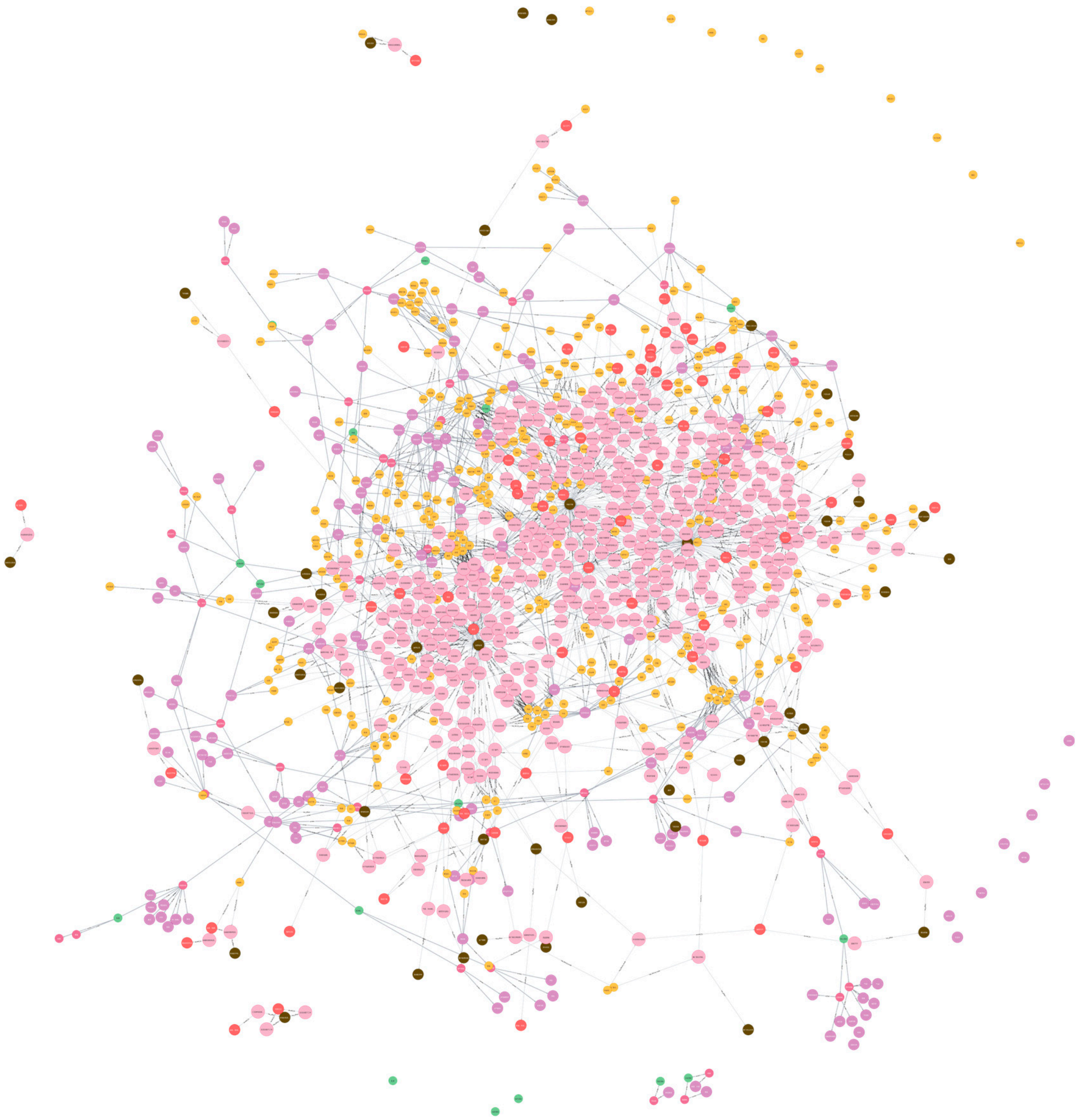

Figure 4. Full constructed knowledge graph representation.

Table 4. Link prediction evaluation indexes.

MRR	Hits@		
0.541	1	3	10
	0.410	0.608	0.813

In another case, the failure mode node "insensitive eccentricity adjusting mechanism" is considered as head entity node, the first six parts of tail entity nodes with the relationship of "because" are forecasted, as shown in Figure 6. The failure reason behind the second-ranked prediction is already present in the knowledge supportability domain graph. After expert analysis, the predicted cause—"improper installation"—along with a series of other causes, is identified as a potential contributor to the failure mode labeled as "insensitive eccentricity adjusting mechanism." These experimental results illustrate that the failure information deduced from the fusion of knowledge information offers greater credibility and interpretability.

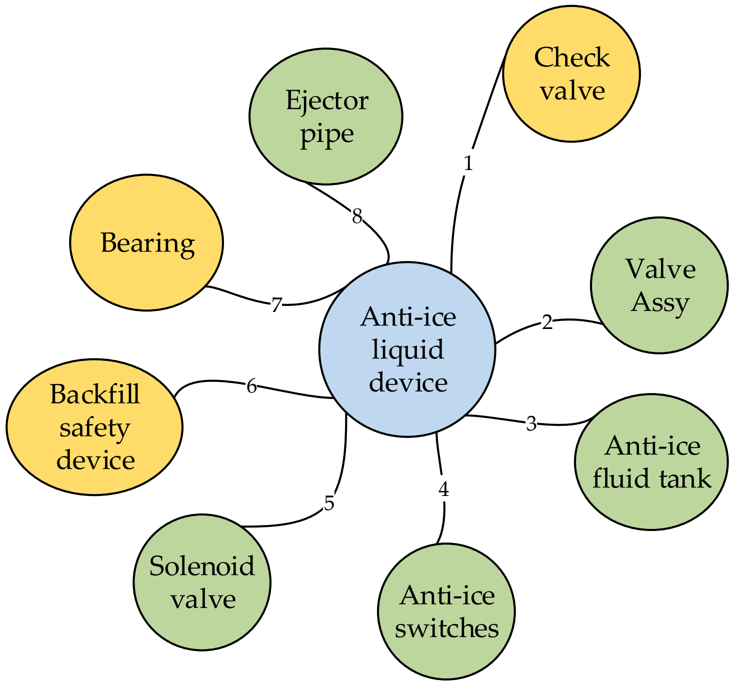

Figure 5. "Anti-ice fluid device—contain—" information prediction diagram.

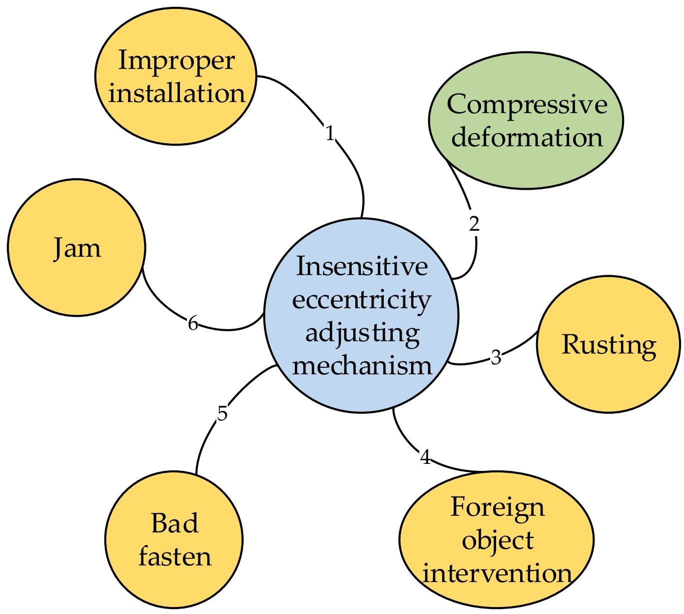

Figure 6. "Insensitive eccentricity adjusting mechanism—because—" information prediction diagram.

6. Conclusions

As equipment systems become more complex, their failure mechanisms and modes also become more diverse, making comprehensive failure analysis approaches, such as enhanced FMEA, increasingly necessary. In this context, knowledge graphs present a promising solution by integrating historical failure data with expert knowledge, providing a structured foundation for information fusion and supporting advanced knowledge reasoning. These capabilities enable informed decision-making and contribute to resource-efficient and sustainable maintenance practices.

This paper proposes a failure information fusion method based on knowledge graph technology, addressing limitations in existing methods, including constraints in sample size, data structure, and logical relationships. The proposed method constructs a knowledge graph specific to the supportability domain, based on diverse support analysis reports, which integrates comprehensive support-related information to facilitate failure inference and yield credible fusion results. By leveraging the knowledge graph, our method addresses the challenge of information fusion complicated by expert subjectivity in FMEA during the development phase. Furthermore, it utilizes historical data and information from similar products when sample sizes are limited, allowing for the quantification of subjective information weights within the graph structure. This mitigates the negative impact of conflicting knowledge on logical outcomes. Experimental results demonstrate that our method achieves high reliability in failure inference, effectively facilitating the fusion of failure information and the prediction of potential knowledge relationships.

Additionally, the proposed method offers an efficient approach for managing and utilizing extensive supportability and failure data. It enables direct expression, display, and linkage of substantial equipment information within an organizational structure, supporting applications such as information querying, link prediction, and decision-making in equipment support. This integration enhances the system's informatization level and facilitates timely access to accurate knowledge, empowering support personnel to implement efficient and sustainable maintenance strategies.

While the current knowledge graph provides a foundational framework for integrating expert knowledge within the support domain, we recognize limitations regarding the scale and diversity of entity-relationship representations. This initial implementation, though effective in demonstrating feasibility, represents a modest breakthrough rather than a fully comprehensive solution. Future research will focus on expanding the knowledge graph with additional entities and relationships, enhancing its complexity to support more sophisticated mining algorithms. Such an enriched structure will enable the graph to capture a wider array of failure patterns, ultimately supporting more robust decision-making processes. This planned expansion aligns with our long-term goal to develop a data-rich, comprehensive knowledge graph capable of accommodating advanced analytical techniques, offering deeper insights, and supporting the sustainable development of complex systems.

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