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Abstract: In the operations management of hydropower stations, there is a problem that a large amount of multi-source heterogeneous structured and unstructured data are challenging to manage and reuse effectively. To improve knowledge organization and collective knowledge sharing, we introduce ontology-based knowledge modeling into the knowledge management and knowledge services of hydropower stations. Specifically, it defines an ontology-based knowledge representation model and constructs a detailed example of ontology knowledge representation and an ontology knowledge base, focusing on three key aspects of hydropower stations, i.e. operation and maintenance of equipment, fault warning and emergency planning. Furthermore, this paper proposes an ontology comprehensive similarity algorithm (OCSA), based on which an ontology-driven visualization application for hydropower knowledge retrieval, prediction and warning, and emergency drill is implemented. Through real-world case studies, the feasibility and effectiveness of the ontology-based knowledge base construction method and critical technology application for hydropower operation and maintenance are demonstrated, improving hydropower stations' knowledge management and application capability.

Keywords: hydropower station; ontology; knowledge base; ontology comprehensive similarity algorithm; knowledge management

1 Introduction

With the successful commissioning of giant cascade hydropower stations, e.g. the Three Gorges, Wu Dongde and Bai Hetan, hydropower is becoming increasingly important in China's "Double Carbon" strategy and renewable energy development (Fan et al. 2019; Zhang and Pang. 2015). The safe, stable, and efficient operation of power plants is the top priority of hydropower production. A large amount of multi-source heterogeneous knowledge and information in the form of structured or unstructured documents such as design and construction drawings, technical specifications, operation procedures, installation and maintenance manuals, and expert experience have been accumulated in the construction and operation of hydropower stations. However, issues such as scattered management, single service objectives and low automation (He and Qiang. 2012; Yang et al. 2021; Huang et al. 2019) greatly restrict the capability of knowledge management and knowledge services in the field of hydropower engineering, and adversely affect the safety and efficiency of hydropower stations. Therefore, there is an urgent need to construct a knowledge base for operation and maintenance of hydropower stations with the help of a new generation of knowledge modeling and knowledge representation technology to digitize and intellectualize any knowledge in the form of structured or unstructured documents, facilitating the decision-making process for hydropower operation and maintenance personnel with comprehensive business information.

Knowledge representation is an important basis for knowledge base construction. The traditional knowledge representation methods include predicate logic representation (Melekhin 2019), generative rule representation (Du et al. 2020), frame representation (Pluwak 2021), semantic network representation (Li 2013), script representation (Song 2020; Fu et al. 2019), process representation (Oikonomou 2022), object-oriented representation (Xing et al. 2003; Zhu 2020), etc. However, these methods are incompetent for constructing a new generation of knowledge base for operation and maintenance of hydropower stations due to lack of effective reasoning mechanism, or because it is not convenient to express deep knowledge and cannot guarantee the accuracy of knowledge expression and reasoning (Zhang 2012).

Ontology is a structured knowledge representation method, which can describe knowledge clearly and standardized, has an excellent conceptual hierarchy and logical solid reasoning ability (Pouya and Brenda. 2020; Hou et al. 2006; Philipp et al. 2019), and has become the underlying foundation and research hotspot of artificial intelligence knowledge engineering. The ontology can describe operation and maintenance knowledge of hydropower plants in a structured and standardized way, providing new ideas for the construction of the hydropower knowledge base such as operation and maintenance knowledge retrieval, fault monitoring, emergency plan formulation, and other typical knowledge management and knowledge service applications.

Ontology-based knowledge bases and knowledge retrieval as a fundamental application of ontology concepts have been widely studied in several fields at home and abroad. Huang(2017) studied ontology-based retrieval techniques for agricultural knowledge bases and used semantic reasoning algorithms to semantically retrieve agricultural knowledge bases, which provided accurate agricultural information to relevant practitioners. Li et al. (2011) studied an ontology-based semantic retrieval algorithm and verified that the proposed algorithm has a high rate of completeness and accuracy by example. El Souri et al.(2019) combined the manufacturing knowledge of enterprises with the design process to improve the product design knowledge base. Chhim et al.(2019) constructed an ontology-based knowledge reuse method for product design and manufacturing processes. Huang Y and Bian(2015) applied ontology-based knowledge retrieval to the field of tourism to develop a semantic web tourism information system to provide personalized recommendations for tourists. Hisham and Hoa.(2009) implemented semantic retrieval of biomedical concepts based on an ontology model of the biomedical domain. It can be seen that the most significant advantage of ontology retrieval is the ability to retrieve knowledge at the semantic level, thus improving the accuracy and comprehensibility of results.

Ontology-based fault diagnosis can accurately describe faults and symptoms from the knowledge level, so as to perform symptom analysis and fault warning based on operational information. Zhang et al.(2018) constructed an ontology-based knowledge base for water inrush warning to complete a unified formal description of knowledge in the field of water inrush, and realize intelligent analysis and early warning of water inrush in underground engineering. Based on ontology theory, Liu et al.(2020) constructed a knowledge base of gas accidents, which can effectively calculate the probability of dynamic gas accidents under Spatio-temporal constraints. Li (2019) proposed an ontology knowledge representation model applicable to the field of turbine-generator unit fault diagnosis. Peng et al.(2013) proposed an ontology-based complicated structure fault knowledge representation and mapping method for complex hydraulic system fault diagnosis problems. Dendani and Khadir.(2012) developed a turbine fault diagnosis technology based on domain ontology case reasoning, which realized documented knowledge representation and reasoning. Ontology fault diagnosis usually achieves the reasoning function with the help of inter-ontology conceptual relationships and attribute constraints. Accurate and influential constraint rules determine the quality of fault diagnosis warnings.

The emergency plan is a contingency action plan for emergency conditions in hydropower plants, which involves cross-domain, multi-source and heterogeneous knowledge. The formal construction of ontology-based emergency plans is conducive to conceptual unification, knowledge sharing, and decision intelligence during emergency handling (Sun et al. 2013). Jiao et al.(2021) constructed a geographic ontology model for an emergency response to biohazard events, and realized the intelligent generation of emergency response plans. Wang et al.(2020) proposed an emergency plan method based on deep ontology learning, constructed the knowledge base of emergency plans in the field of high-speed railway, and provided decision support for emergency disposal. Mehla and JAIN.(2020) proposed an ontology case hybrid model to provide support for large-scale disaster emergency response. Amailef and Lu.(2013) achieved rapid response in emergency systems by constructing ontology-based case reasoning models.

This paper introduces ontology as a concept into the knowledge representation for operation and maintenance of hydropower plants, studies the construction method of ontology-based knowledge base for operation and maintenance and proposes the knowledge reasoning algorithm based on OCSA, systematically constructs the ontology knowledge representation model and the critical technology of knowledge base application. Finally, the engineering application of ontology-driven hydropower operation and maintenance knowledge retrieval, fault warning and emergency plan drills is realized.

2 Ontology-based knowledge representation

2.1 Knowledge representation model

Hydropower station is a typically complex and large-scale system. The operation and maintenance of hydropower plants involve multi-disciplinary heterogeneous domain knowledge and abundant differentiated knowledge service scenarios of hydro-mechanics, therefore a unified standardized ontology representation model needs to be established. This paper introduces several generic ontology modeling meta-words, such as class, attribute, instance, relation, and axiom, to construct a formal definition model of knowledge representation based on ontology, as shown in Formula (1).

$$\text{Ontology} = < \text{C}, \text{R}, \text{A}^{c}, \text{A}^{R}, \text{H}, \text{X} > \tag{1}$$

Where **C** represents the set of classes and **R** represents the set of associative relations of classes, both of which are used to describe the concept names or concept relations of knowledge. For example, in the classification of hydropower units, "water turbine" represents the ontological composition meta-word "class" and can be further divided into "axial flow hydraulic turbine," "mixed flow hydraulic turbine," and "tubular hydraulic turbine" and other inherited subclasses. Table 1 shows the four fundamental relations in ontology construction:

Table 1 Basic relations in ontology

Relation	Description
part-of	Used to represent part-to-whole relationships between classes
kind-of	Used to represent inherited relationships between classes
instance-of	Used to represent the relationship between classes and instances
attribute-of	Used to represent the relationship between classes and attributes

$\mathbf{A^c}$ and $\mathbf{A^R}$ are the attribute sets of classes and relations respectively, which are used to describe the characteristics of classes and relations. They can be divided into object attributes and data attributes. For example, "water flow variation characteristics during operation" are object attributes of the water turbine, while simple numerical characteristics such as "runaway rotational speed" are data attributes.

H represents the set of instances and their attribute values, and the instances are the specific objects corresponding to the classes. "Xiangjiaba power station #1-#8 units" are 8 instances of the "mixed flow water turbine" class.

X stands for axiom, which refers to existing facts that can constrain classes or relations, and is the primary constraint of knowledge reasoning.

2.2 Knowledge modeling

The ontology model of equation (1) is used as the knowledge representation method for hydropower plants to model the knowledge of three typical business areas: operation and maintenance of equipment, fault warning and emergency planning. The OWL ontology description language with powerful semantic expression and reasoning capabilities is used for program implementation.

2.2.1 Operation and maintenance

(1) Knowledge for operation and maintenance of equipment

Taking the hydro-generating unit as an example, the core equipment of hydropower station can be divided into five basic categories: hydraulic turbine, generator, speed regulation system, excitation system and auxiliary system. The OWL language that defines the basic class "hydraulic turbine" is as follows:

```
< owl:Class rdf:ID= " #Hydraulic turbine " >
    < rdfs:label xml:lang = "zh" > Hydraulic turbine < /rdfs:label >
    < rdfs:comment >将水能转换成旋转的机械能< /rdfs:comment >
< /owl:Class >
```

(2) Relations among knowledge for operation and maintenance of equipment

① Kind of (Inheritance relation)

Inheritance relations (top-down relation) are represented by the tag “< owl: subClassOf >” in the OWL language. For example, the concepts "generator" and "synchronous generator" in OWL are represented as follows:

```
< owl:Class rdf:about = "#Generator " />
< owl:Class rdf:about = "#Synchronous generator " >
    < rdfs:subClassOf rdf:resource= "#generator " />
</owl:Class>
```

② Part of (Part-whole relation)

There is no label that directly represents the relation between the part and the whole between classes in the OWL language, so the “part of” attribute needs to be redefined as follows:

```
< owl:ObjectProperty rdf:about = "#partOf" />
    < rdfs:label xml:lang = "zh" >部分与整体</rdfs:label>
    < rdfs:comment>表示类间部分与整体关系</rdfs:comment>
</owl:ObjectProperty>
```

For example, "Hydraulic turbine shaft system is composed of spindle, operating tubing, water seal, water guide bearing and thrust bearing," which is represented by OWL as follows:

```
< owl:Class rdf:about = "#Water guide bearing " />
    </owl:Restriction>
        < owl:onProperty rdf:resource= " #partOf " />
        < owl:someValuesFrom rdf:resource = "#Shafting part " />
    </owl:Restriction>
</owl:Class>
```

③ Attribute of (Attribute relation)

Attribute relation between ontology concepts can be divided into data type and object type. The OWL language describes the relation between instances of classes, RDF Literals and XML Schema using data attributes. Object attributes describe the relation between instances of two classes. For example, the data attribute "rated output" of the hydraulic turbine is represented by OWL as follows:

```
< owl:Class rdf:about = "#Hydraulic turbine " />
< owl:DatatypeProperty rdf:about = "#Rated output " >
    < rdfs:domain rdf:resource = "#Hydraulic turbine " />
    < rdfs:range rdf:resource = "&xsd;double" />
</owl:DatatypeProperty>
```

The object attribute "used for: polar crane for stay ring" expressed in OWL as follows:

```
< owl:ObjectProperty rdf:about = "#Use to" >
    < rdfs:domain rdf:resource = "#polar crane " />
    < rdfs:range rdf:resource = "#Stay ring " />
</owl:ObjectProperty>
```

④ Instance of (Instance relation)

The relation between classes and instances is described through object attributes, data attributes or some mutual constraints between attributes. For example, "HLS152-LJ-790 turbine produced in September 2003 has a rated flow of 554.52m^3/s, a rated output of 714MWt, a rated speed of 107.1r/min, and several active guide blades of 24", which can be expressed in OWL as follows:

```
<owl:Class rdf:about = "#水轮机" >
    <型号 rdf:datatype="&xsd;date"> HLS152-LJ-790</型号 >
    <生产日期 rdf:datatype="&xsd;date">2003.09</生产日期>
    <额定流量 rdf:datatype="&xsd;double">554.52</额定流量>
    <额定出力 rdf:datatype="&xsd;double">714</额定出力>
    <额定转速 rdf:datatype ="&xsd;double">107.1</额定转速>
    <导叶数 rdf:datatype ="&xsd;int">24</导叶数>
</owl:Class>
```

The knowledge base of hydro-generator unit ontology is shown in Figure 1. The hierarchical diagram of the hydro-generator unit ontology model class is shown in Figure 2.

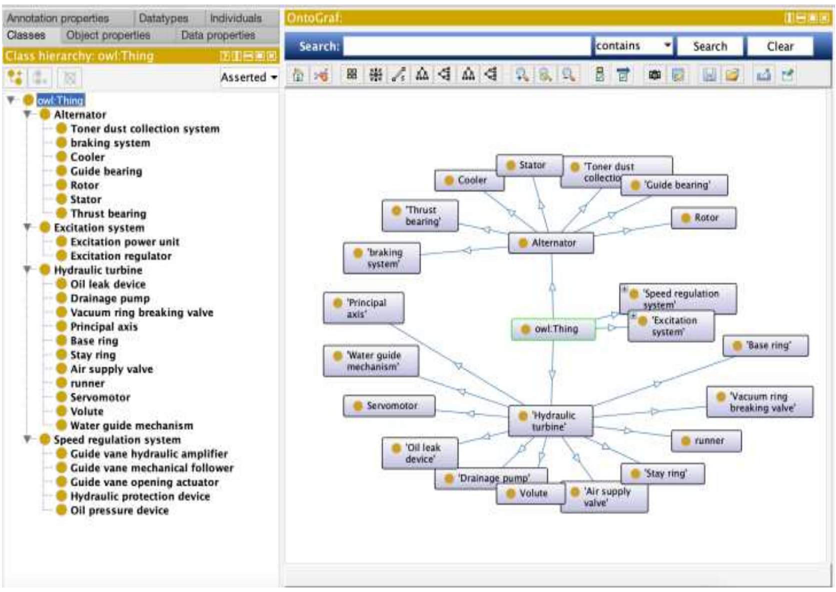


Fig. 1 Knowledge base of turbine unit ontology model

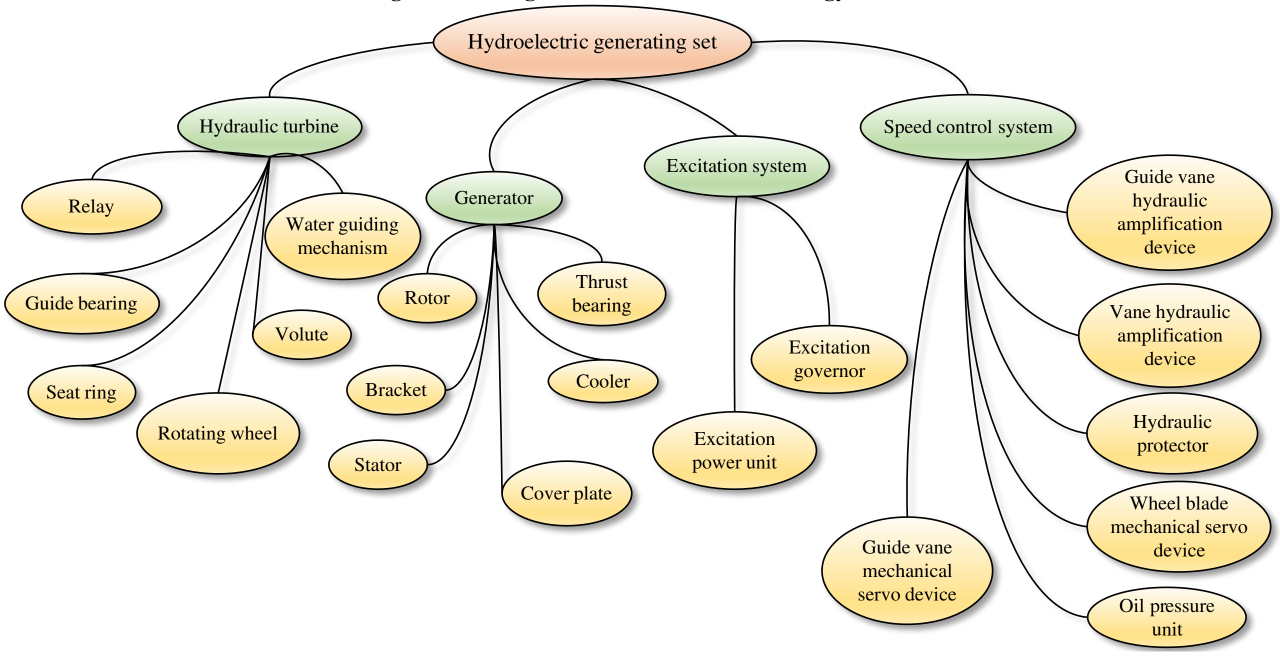


Fig. 2 Hierarchy diagram of turbine unit ontology model

2.2.2 Fault warning

(1) Knowledge of fault diagnosis

The critical part of fault diagnosis ontology knowledge modeling is to define the core ontologies in diagnosis object, diagnosis behavior, and diagnosis maintenance. By analyzing the common fault types and characteristics of hydro-generator sets, three core ontologies, namely equipment ontology, process ontology and diagnosis ontology, are defined to describe the concepts and interrelations of equipment entities, maintenance processes and diagnosis decisions.

①Device ontology: It mainly includes diagnosis equipment class, component information class, equipment operation status and fault characteristics class.

②Process ontology: The description is for the equipment status class and the equipment maintenance class. The equipment status class is divided into three subclasses: component status, operation characteristic status, and process step status; the equipment maintenance class is mainly divided into maintenance process, steps in the maintenance process, etc.

③Diagnosis ontology: It mainly contains fault class, fault characteristic class and fault symptom class. The mapping from fault characteristics to faults is obtained by pattern matching, and then the causes of faults are identified and repair strategies are proposed. Table 2 shows some classes of hydro-generator set faults.

Table 2 Fault diagnosis of water turbine generator set

Fault knowledge	Class Composition
Equipment entity	Stator, Rotor, Runner blade, Thrust bearing bush, Draft pipe,...
Fault types	Mass unbalance fault, Misalignment fault, Guide vane or blade opening uneven fault, Vibration caused by eccentric vortex in draft tube, Vibration caused by cavitation, Uneven magnetic pole fault in generator stator bore, Rotor winding interturn short circuit fault...
Fault characteristics	Axis orbit, Vibration changes with load, Vibration changes with unit overflow, Unit swing changes with overflow, Vibration changes with temperature, Vibration changes with speed, Amplitude changes with load...
Fault symptoms	(1/2-1/6) rotation frequency, 1x frequency, 2x frequency, 3x frequency, high frequency, (50HZ-100Hz) characteristic frequency...

The hierarchy of the hydro-generator unit fault diagnosis class and the core ontology class can be represented by OWL relational statements as follows:

```
< owl:Class rdf:ID = "# Fault" />
  <rdfs:subClassOf rdf:resource="&owl;Thing"/>
    </owl:Class>
    < owl:Class rdf:ID = "#Mass imbalance" />
      <rdfs:subClassOf rdf:resource=" Fault "/>
</owl:Class>
```

(2) Knowledge relations of fault diagnosis

The combination, inheritance, instance and attribute relations of fault diagnosis knowledge are still described by keywords “kind of,” “part of,” “attribute of” and “instance of” in OWL. For example, a loose stator combination seam fault is a sub-concept of the fault type (kind of); checking whether the unit is operating in a vibration zone is an integral part of the maintenance strategy (part of); a rotation frequency of twice the frequency is an attribute of a misalignment fault (attribute of); the case of upper frame vibration fault of the unit is an instance of mass imbalance fault (instance of).

(3) Knowledge attributes of fault diagnosis

The attributes of the hydro-generator unit fault diagnosis ontology are descriptions of the internal structure of the fault classes. Among them, object attributes represent inter-class relations. For example, the attribute "has character" describes the relation between the fault symptom and the fault characteristic class, whose value domain is the fault characteristic and the definition domain is the fault symptom. The data attribute represents the primary data type, for example, the data attribute "axis trajectory" of fault characteristic class is "string" type. Some object attributes of the fault diagnosis class of the hydro-generator unit are shown in Table 3.

Table 3 Some object attributes of fault diagnosis of hydro-generator set

Object attributes	Definition domain	Value domain	Instructions
Has component	Fault character	Fault component	Fault characteristics of equipment components
	Fault symptom	Fault component	Fault symptoms of equipment components
	Fault component state	Fault component	Components corresponding to equipment component status
Has character	Fault symptom	Fault character	Fault symptoms associated with fault characteristics
	Fault character state	Fault character	Connection between equipment operating characteristic state and fault characteristic
Has symptom	Fault	Fault symptom	Multiple symptoms of fault exist
Correspond	Fault symptom	Fault	A fault symptom corresponds to a fault

The partial attribute OWL of the fault diagnosis knowledge class is represented as follows:

```
<owl:ObjectProperty rdf:about="#hasCharacter">
    <owl:ObjectProperty rdf:about="#isCharacterOf"/>
    </owl:inverseOf>
    <rdfs:domain rdf:resource="#Fault_type"/>
    <rdfs:range rdf:resource="#Fault_character"/>
</owl:ObjectProperty>
```

(4) Axiomatic assertion.

It is used to describe constraints in the fault diagnosis ontology of hydro-generator unit. The axiom in OWL is expressed as follows:

```
<owl:Class rdf:about="#Rotor mass eccentricity">
    <owl:equivalent Class>
<owl:Class>
<owl:intersectionOf rdf:parse Type="Collection">
    <rdf:Description rdf:about="#Fault type"/>
    <owl:Restriction>
    <owl:onProperty rdf:resource="#2X"/>
    <owl:qualifiedCardinalityrdf:datatype="&xsd;nonNegativeInteger">2</owl:qualifie-d Cardinality>
    <owl:onDataRangerdf:resource="&xsd;integer"/>
    </owl:Restriction>
</owl:Class>
</owl:equivalent Class>
</owl:Class>
```

The knowledge base of the hydropower fault warning ontology is shown in Figure 3. The class-hierarchy diagram of the hydropower plant fault warning ontology model is shown in Figure 4.

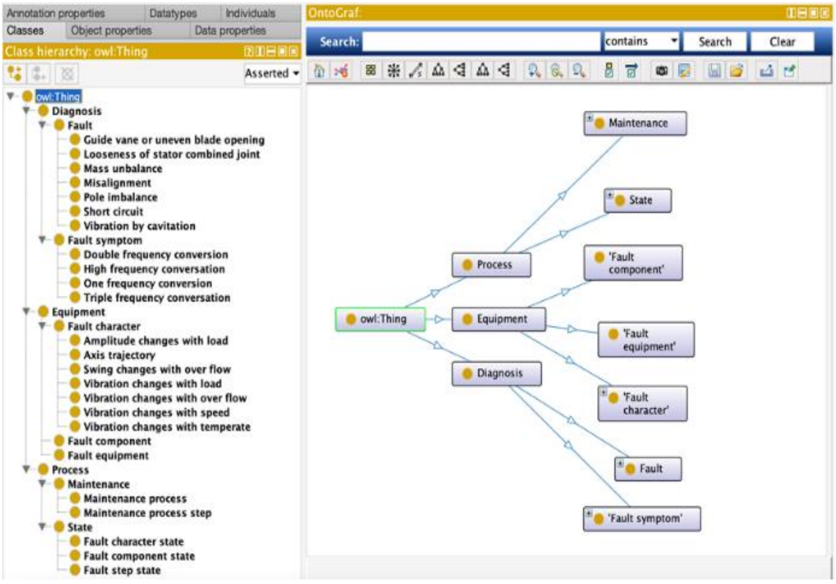


Fig. 3 Ontology knowledge base of hydropower station fault warning

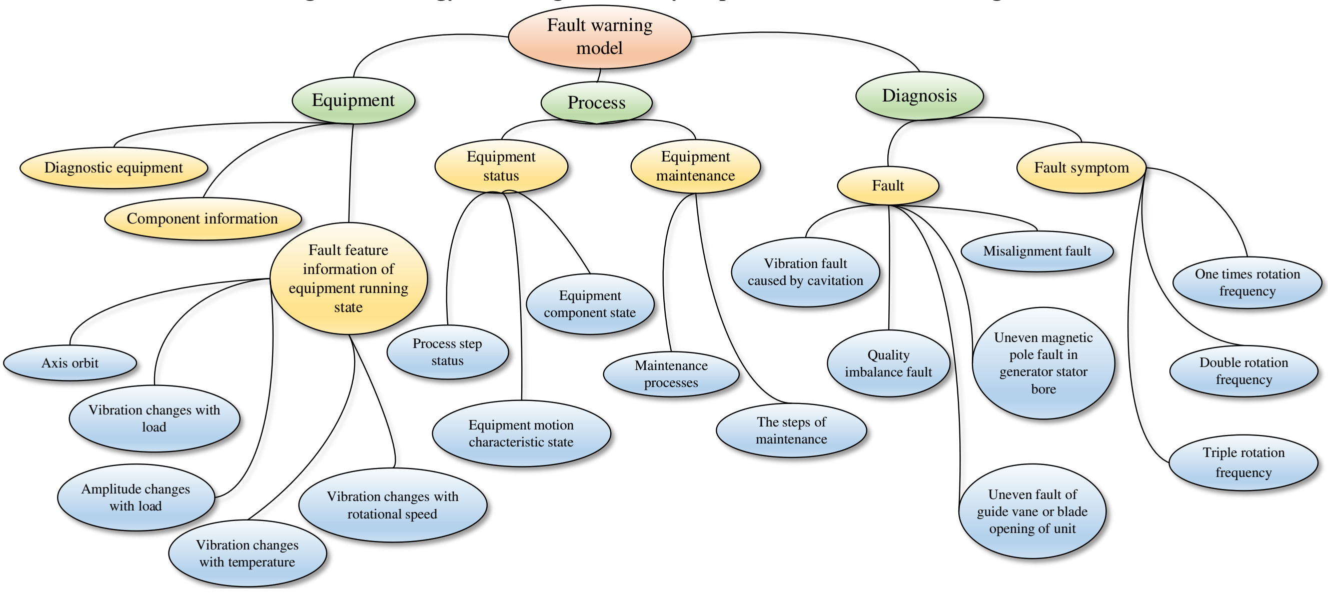


Fig. 4 Class hierarchy diagram of hydropower station fault warning ontology model

2.2.3 Emergency plan

(1) Knowledge of emergency plan

Taking into consideration the knowledge characteristics of hydropower plant emergency plans, the base class ontology is defined as 2 classes of object and process, and further expanded into 4 subclasses of emergency events, emergency characters, emergency resources and emergency actions.

The emergency events refer to the process of occurrence, development and change of things, which are subclasses of process. Events can be composed of multiple sub-events, typically including event type, event environment, event time, and event location, for example, plant flooding, generator on fire, SF_6 gas leakage from circuit breaker, oil leakage from governor, etc. The event environment includes precipitation level, snowfall level, temperature, wind, wind direction, etc. The event location includes main power house, switchyard, main control room, pump room, gate chamber, etc. Emergency characters refer to the relevant departments or personnel who specifically perform emergency actions, which are subclasses of the object; Emergency resources describe the equipment used by emergency personnel in the emergency process, including basic safety apparatus, warning and protective safety tools, etc. which are subclasses of object; Emergency actions refer to emergency actions specifically performed by emergency personnel, which are subclasses of process.

Based on the analysis of the contents of emergency plans for the hydropower station, the classes of emergency plans for hydropower operation and maintenance knowledge are defined according to the above basic classes, as shown in Table 4.

Table 4 Some categories of hydropower station emergency plan

Emergency ontology	Composition of classes
Emergency events	Types of events: Earthquake, Flood, Fire, Air leakage, Oil leakage...
	Event environment: Rain level, Snow level, Wind direction...
	Event time: Year, Month, Day, Hour, Minute, Second
	Location: Main power house, Pump room, Gate chamber...
Emergency resources	Basic safety tools, Auxiliary safety tools, Protection tools...
Emergency organization	Expert teams, Government departments, Work departments, Office departments, Command departments...
Emergency action	Firefighting operations, Gate closing operations, Rescue operations, Compartmentalization operations, Pump activation operations...

(2) Knowledge relation of emergency plan

The knowledge relation of hydropower station emergency plan mainly includes:

①Inheritance: It is used to indicate that a contingency plan class is a subset of another class. For example, a generator on fire is a type of fire emergency disaster.

②Combination: It is used to indicate the inclusion relation of the emergency planning class. For example, the incident handling process class consists of emergency events, emergency resources, emergency organization, and emergency action classes.

(3) Knowledge attribute of emergency plan

The data attributes of emergency plan knowledge define the basic data types of class instances, for example, NAME and ID describe the name and number of a certain emergency plan entity respectively, and their data types are ***string*** type and ***int*** type respectively. For example, the value domain of the attribute "has target" is the emergency object and the definition domain is the emergency action, which is used to describe the relation between the emergency object and the emergency action class; The value domain of the attribute "influence" is the emergency event and the definition domain is the emergency action, which is used to describe the emergency event contributing to the emergency action. Some of the OWL codes of the attributes of the contingency plan are given below:

```
<owl:ObjectProperty rdf:about="#Has target">
    <rdfs:domain rdf:resource="# Emergency action "/>
    <rdfs:range rdf:resource="# Emergency object "/>
</owl:ObjectProperty>
<owl:ObjectProperty rdf:about="#Influence">
    <rdfs:domain rdf:resource="# Emergency event "/>
    <rdfs:range rdf:resource="# Emergency action "/>
</owl:ObjectProperty>
```

The ontology knowledge base of hydropower station emergency plan constructed in this paper is shown in Figure 5, and the hierarchy of hydropower emergency plan ontology classes is shown in Figure 6.

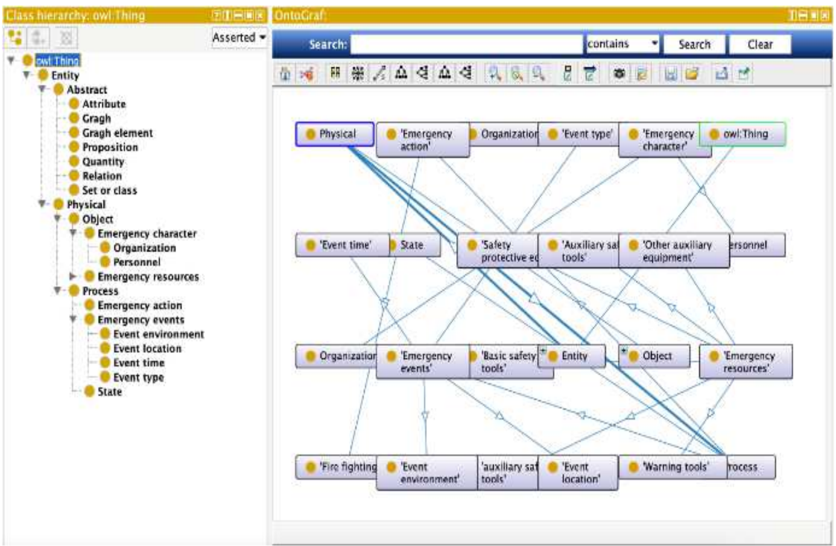


Fig. 5 Ontology knowledge base of hydropower station emergency plan

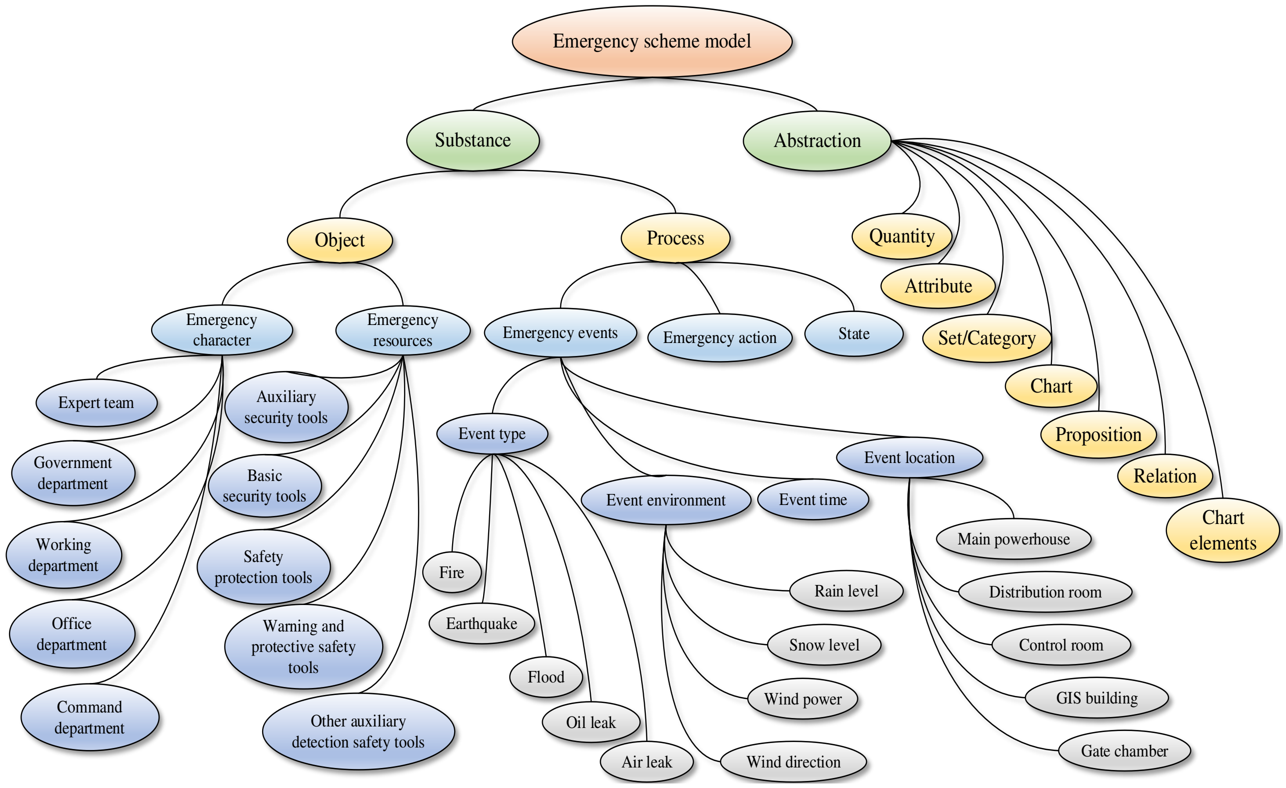


Fig. 6 Class diagram of ontology of emergency plan

3 The key technology of knowledge base for hydropower operation and maintenance based on OCSA

3.1 OCSA and knowledge retrieval

Knowledge matching is the basis of typical applications such as knowledge retrieval, fault warning and emergency planning for hydropower operation and maintenance. Considering the semantic similarity of three levels of ontology names, attributes and relation structures, an OCSA-based knowledge matching algorithm is proposed as the basis of the ontology-driven knowledge base application algorithm.

Similarity is a metric to describe the semantic matching degree among knowledge base ontologies, which are ontology name similarity, ontology attribute similarity and ontology structure similarity, and the weighted sum of the three is the comprehensive ontology similarity. Knowledge retrieval means matching queries and knowledge integration of the ontology knowledge base based on the comprehensive similarity of ontology and query requirements.

(1) Ontology name similarity calculation

Let the names of ontologies O_1 and O_2 be strings s_1 and s_2 respectively, and weight the calculation of string similarity $ProStr(s_1,s_2)$ and word sense similarity $ProWor(s_1,s_2)$ to obtain ontology name similarity $ProNam(O_1,O_2)$.

$ProStr(s_1,s_2)$ is calculated in Equation (2), where $len(Pubs_i)$ is the length of the ***i-th*** common substring, and

len(s₁) and ***len(s₂)*** are the lengths of s_1 and s_2.

$$ProStr(s_1, s_2) = \frac{2\sum_i \mathrm{len}(\mathrm{Pub}s_i)}{\mathrm{len}(s_1) + \mathrm{len}(s_2)} \tag{2}$$

The calculation of $ProWor(p_1,p_2)$ is shown in Equation (3). Where p、p_1、p_2 represent the word sense nodes of ***WordNet*** synonym set. p is the parent node of p_1, p_2, and words s_1, s_2 are located on nodes p_1, p_2 respectively.

$$ProWor(p_1, p_2) = \frac{2\log ratio(p)}{\log ratio(p_1) + \log ratio(p_2)} \tag{3}$$

WordNet is a standard synonym set where semantic relations connect words in the set. ***ratio(p)*** represents the number of words in node p and its sub-nodes/total number of ***WordNet*** words. $ProWor(s_1,s_2)$ is the maximum value of the similarity of synonym sets of words s_1 and s_2, i.e.

$$ProWor(s_1, s_2) = \max(ProWor(p_1, p_2)) \tag{4}$$

The obtained similarity calculation results $ProStr(s_1,s_2)$ and $ProWor(s_1,s_2)$ are weighted to get the ontology name comprehensive similarity $ProNam(O_1,O_2)$.

$$ProNam(O_1, O_2) = \alpha ProStr(s_1, s_2) + (1-\alpha) ProWor(s_1, s_2) \tag{5}$$

Where α is the weight value, indicates the degree of influence of string similarity on ontology name similarity.

The flow of ontology name similarity calculation is shown in Figure 7.

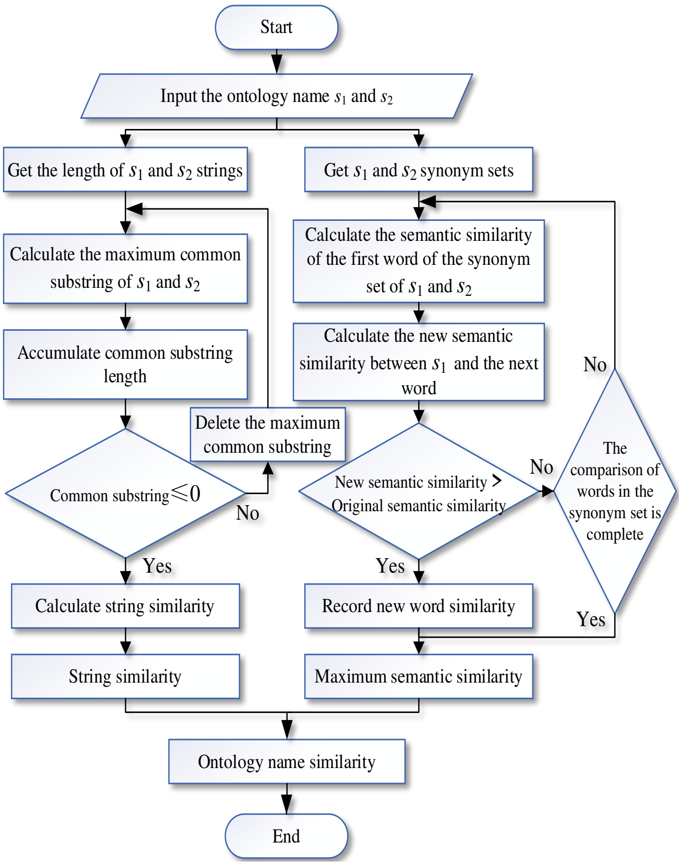


Fig. 7 Flow chart of ontology name similarity calculation

(2) Ontology attribute similarity calculation

Ontology attributes are divided into data attributes and object attributes. Similar to the ontology name similarity calculation method, the attribute similarity calculation taking into account data attributes and object attributes is shown in Equation (6). ***ProAttD(O₁,O₂)*** and ***ProAttO(O₁,O₂)*** represent data attribute similarity and object attribute similarity, respectively. γ is the weight value, which indicates the influence degree of attribute type on attributes. The specific calculation process is shown in Figure 8.

$$Pro\text{Att}(O_1,O_2)=\gamma Pro\text{AttD}(O_1,O_2)+(1-\gamma)Pro\text{AttO}(O_1,O_2) \tag{6}$$

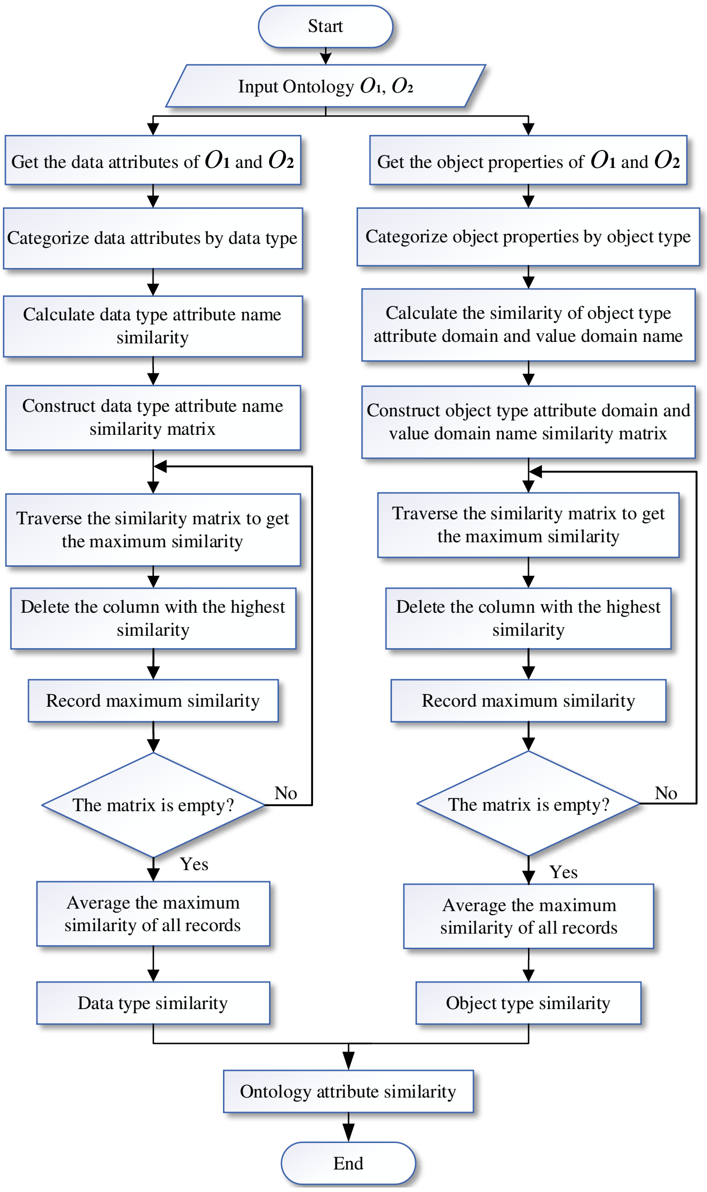


Fig. 8 Flow chart of ontology attribution similarity

(3) Ontology structure similarity calculation

The similarity of the ontology structure ***ProStru(O1,O2)*** is calculated as:

$$ProStru(O_1,O_2) = \alpha ProFat(O_1,O_2) + \beta ProBro\text{-}set(O_1,O_2) + \mu ProSon\text{-}set(O_1,O_2) \quad (7)$$

Where ***ProFat(O₁,O₂)*** represents the parent ontology similarity of ontology $\boldsymbol{O_1}$ and ontology $\boldsymbol{O_2}$; ***ProBro-set(O₁,O₂)*** represents the brother ontology similarity of ontology $\boldsymbol{O_1}$ and ontology $\boldsymbol{O_2}$; ***ProSon-set(O₁,O₂)*** represents the child ontology similarity of ontology $\boldsymbol{O_1}$ and ontology $\boldsymbol{O_2}$; $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\mu}$ are the weights. The specific calculation process is shown in Figure 9.

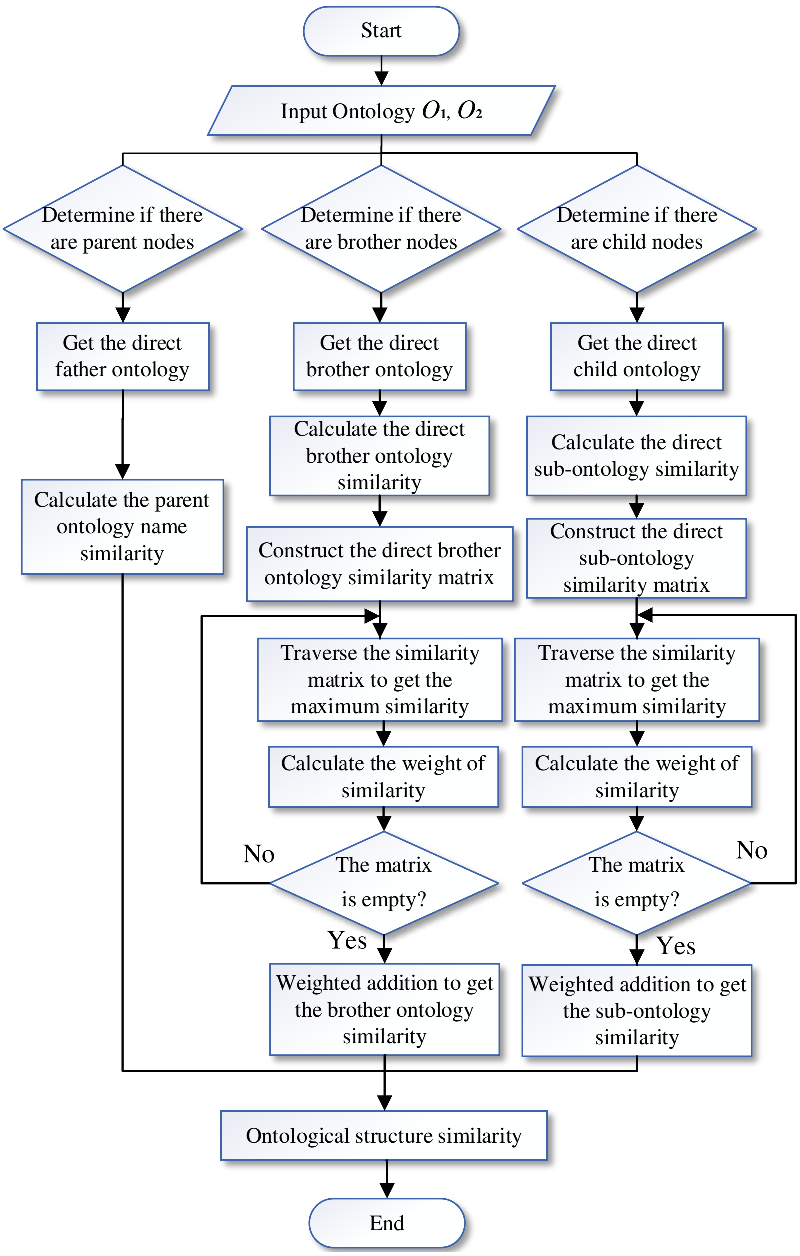


Fig. 9 Flow chart of ontology structure similarity calculation

(4) Ontology comprehensive similarity calculation

The similarity of ontology name, ontology attributes and ontology structure are weighted to obtain the combined ontology similarity ***Pro(O₁,O₂)***.

$$Pro(O_1,O_2)=\tau_1 ProNam(O_1,O_2)+\tau_2 ProAtt(O_1,O_2)+\tau_3 ProStru(O_1,O_2) \quad (8)$$

where, $\tau_1+\tau_2+\tau_3=1$, each weight value is determined according to its degree of influence on the similarity. In order to reduce the influence of artificially set weights on similarity, this paper uses the $\xi(z)$ function to calculate the weights, where z is the magnitude of the similarity value obtained from each of the above calculation processes, and the calculation formula is:

$$\xi(z)=\frac{1}{1+e^{-5(z-0.5)}} \tag{9}$$

3.2 Hydropower fault warning

The multi-layer mapping between ***Equipment*** **operating status-Symptom information** and ***Symptom-Fault*** is established based on the comprehensive similarity of the ontology, which enables early warning and forecasting of hydropower faults. Firstly, real-time operational status information is obtained, and then the equipment component status and equipment operational status are matched with the fault symptom in the fault diagnosis ontology knowledge base to determine the type of fault that may occur. There are complex ***Many-to-Many*** mapping affiliations between fault symptoms, fault types and fault phenomena. The influence of fault symptoms on fault types is calculated according to the constraints to determine the maximum possible fault. The OCSA flow chart for ***Status-Sign-Fault*** is shown in Figure 10.

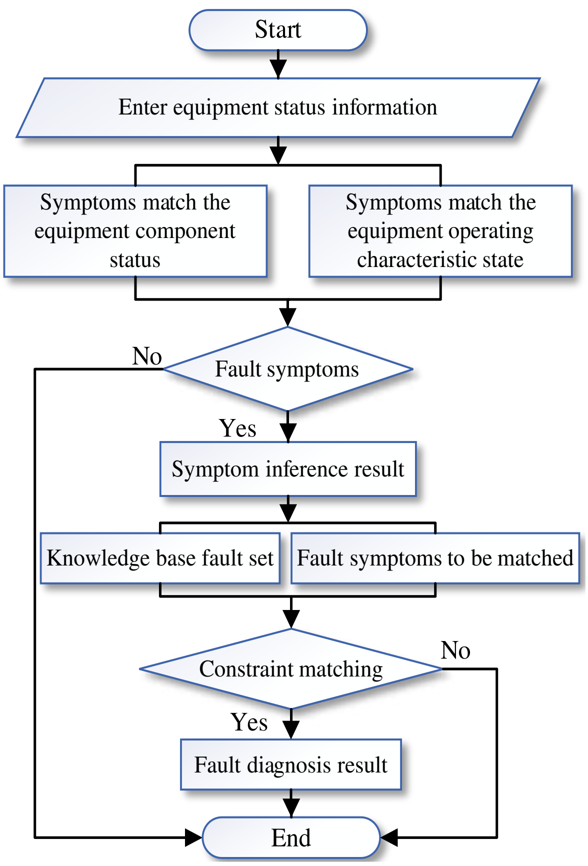


Fig. 10 Design flow chart of state symptom fault comprehensive similarity algorithm

3.3 Hydropower emergency plan drill

The basis for generating and rehearsing emergency plans for hydropower stations is the knowledge base of similar plans. According to the characteristics of the existing plans, the similarity between the target case and the ontology knowledge base plan is calculated, and the plan that is greater than the set threshold is selected as the similar plan.

The calculation of the conceptual similarity of the emergency plan is similar to the previous one, while the attribute similarity differs depending on its type. Take two common attributes, numeric and symbolic, as examples, their calculation methods are as follows.

(1) Numerical attribute similarity

$$Sim(p_i, q_i) = 1 - \frac{|p_i - q_i|}{\max_i - \min_i} \tag{10}$$

Where $\boldsymbol{Sim(p_i,q_i)}$ represents the numerical similarity of the ***i-th*** attribute in case ***P*** and ***Q***; $\boldsymbol{p_i}$ and $\boldsymbol{q_i}$ represent the value of the ***i-th*** attribute in case ***P*** and ***Q***; $\boldsymbol{max_i}$ and $\boldsymbol{min_i}$ represent the upper and lower limit of the value range of the ***i-th*** attribute in case ***P*** and ***Q***; numerical attributes are generally represented by the spatial distance between numbers.

(2) Symbolic attribute similarity

$$Sim(p_i, q_i) = \begin{cases} 0 & p_i = q_i \\ 1 & p_i \neq q_i \end{cases} \tag{11}$$

Where $\boldsymbol{Sim(p_i, q_i)}$ represents the symbolic similarity of cases ***P*** and ***Q*** at the ***i-th*** attribute. Symbolic attributes are generally represented by explicit characters or text, and it is only required to compare whether the symbolic attributes of target cases and historical cases are consistent.

(3) Similarity of attribute synthesis

$$Sim(p, q) = \sum_{i=1}^{n} \beta_i * Sim(p_i, q_i) \tag{12}$$

Where $\boldsymbol{Sim(p_i, q_i)}$ represents the partial case similarity between the target case and the historical case in the ***i-th*** attribute, $\boldsymbol{\beta_i}$ represents the weight of the ***i-th*** attribute in the same attribute, and ***n*** represents the number of case attributes.

The flow of the comprehensive similarity algorithm for emergency cases is shown in Figure 11.

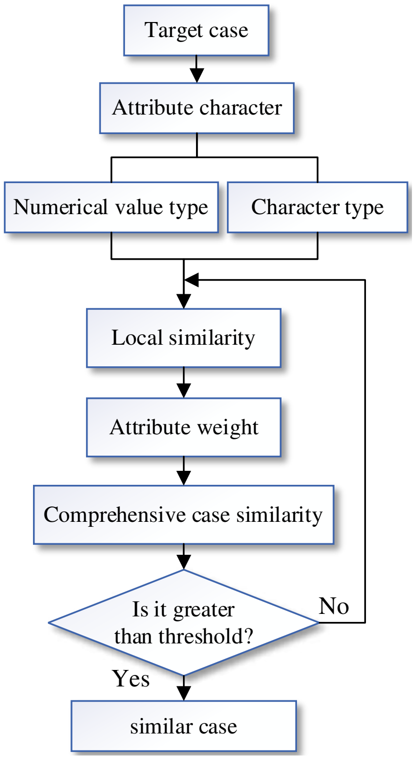


Fig. 11 Flow chart of emergency case comprehensive similarity algorithm

4 Case studies

4.1 Overall framework

This paper takes Xiangjiaba hydropower station as the research object. Based on the ontology knowledge representation model, a large number of structured or unstructured documents such as specification drawings, technical specifications, installation and maintenance manuals, and even expert experience accumulated in power plant operation and maintenance are modeled and visualized in multiple dimensions. Based on the OCSA to carry out compositive application research on ontology-based hydropower operation and maintenance knowledge retrieval, fault diagnosis and prediction, emergency plan rehearsal, etc. The ontology-based knowledge base for hydropower operation and maintenance and multi-dimensional knowledge visualization platform based on Unity3D engine are developed. The overall framework of the platform is shown in Figure 12.

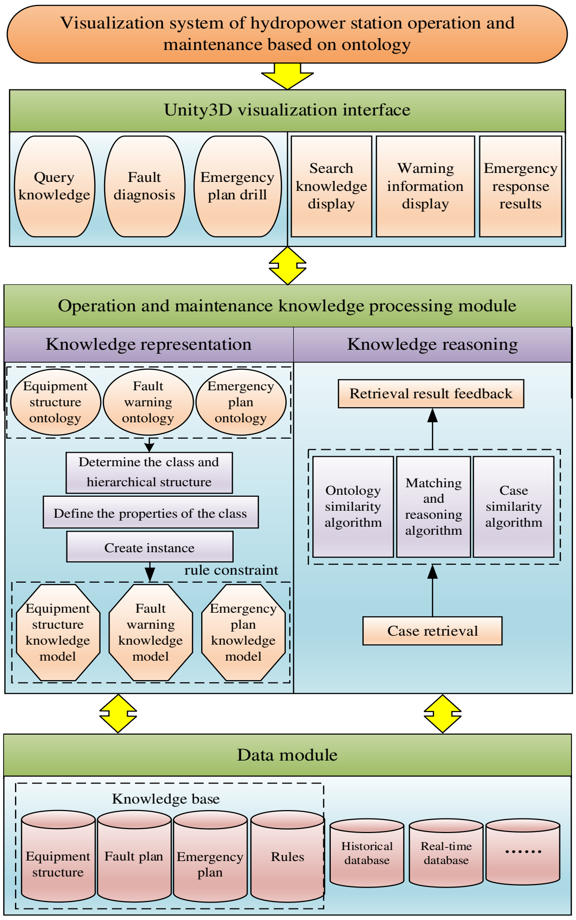
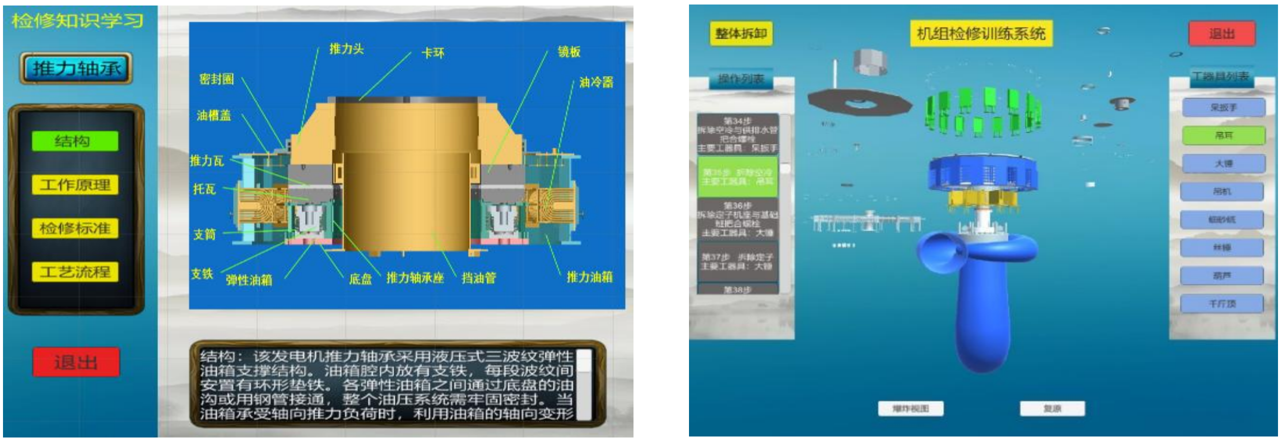


Fig. 12 Framework of hydropower knowledge base & visualization based on ontology

4.2 Function implementation

4.2.1 Operation and maintenance knowledge retrieval

Based on the ontology knowledge model of hydropower equipment structure, a multi-dimensional knowledge retrieval system for hydropower equipment operation and maintenance is constructed by using unity3D. Taking Xiangjiaba power station 800,000 kW giant hydro-generator unit as an example, 3DMax software is used for 3D modeling of physical structure, and ontology knowledge point matching between 3D model and knowledge base is completed based on OCSA. When the user selects a component of the turbine unit, a multi-dimensional visualization interface presents the knowledge of the equipment structure, working principle, operation and maintenance management. When the user clicks on the interactive overhaul function, the system will track the user's virtual overhaul operation steps in real-time and compare them with the unit overhaul process knowledge ontology, and if the operation is wrong, it will be prompted by text or voice for timely correction. The visualization interface of hydro-generator set overhaul knowledge retrieval and interactive operation is shown in Figure 13.



(a)Maintenance knowledge learning interface (b)Unit maintenance training system

Fig. 13 Interactive maintenance knowledge retrieval and visualization of hydro generator units

4.2.2 Fault diagnosis warning

The ontology-based fault warning for hydropower operation mainly includes remote real-time monitoring of equipment status data, historical status query, fault diagnosis and alarm. Using the fault warning ontology to dynamically analyze the common fault types and treatment methods of equipment, the fault phenomena and warning information can be visualized in the knowledge visualization platform, and the causes of faults and treatment measures can be explained.

Table 5 shows the preliminary diagnostic results obtained by using the real-time monitoring data of #2 as the experimental sample, with current, vibration frequency, lubricating oil temperature and oil pressure as the monitoring characteristics. The result shows that the current, vibration double frequency and lubricating oil temperature exceed the set upper limit as the fault symptoms "excessive current change," "excessive vibration double frequency amplitude," and "excessive oil temperature change. "After the fault symptoms are identified, it is further determined whether all fault symptoms match a particular fault. The results show that the three fault symptoms of "excessive current change," "excessive vibration double frequency amplitude," and "excessive oil temperature change" are all matched with the rotor misalignment fault. Therefore, the possibility of rotor misalignment failure in hydro-generators is the highest.

Table 5 Test data and fault diagnosis results

Characteristics	Symptom	Fault		
		Rotor unbalance	Rotor winding inter-turn fault	Rotor misalignment
Current	True	True	True	True
Frequency multiplication	True	False	False	True
Oil temperature	True	True	True	True

Oil pressure	False	-	-	-

FIG.14 shows the visualized effect diagram of the unit fault warning when the rotor is misaligned, which informs the operation and maintenance personnel of the fault information and corresponding solutions in a 3D visualized way.

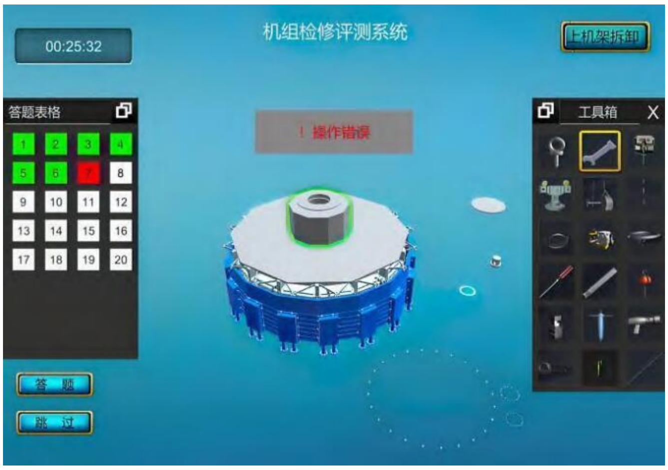


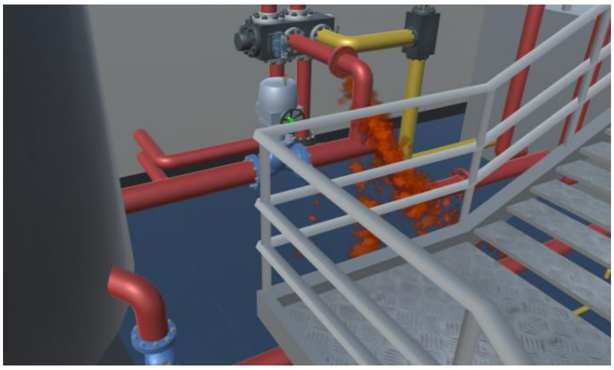
Fig. 14 Effect drawing of fault warning of hydro-generator unit

4.2.3 Emergency plan drill

The knowledge base for operation and maintenance and multi-dimensional visualization platform of Xiangjiaba hydropower station can realize 3D visualization of the emergency plan ontology and conduct 3D simulation of emergency drills. Through Unity3D engine's script mounting, sound loading, scene switching and other functions, the scenes and event information of the emergency plan, equipment parameters, animation simulation, emergency treatment process demonstration, video sound and professional knowledge are displayed to users. The system can reproduce the emergency accident working conditions with a vivid image of the whole process of emergency rehearsal interactive presentation to strengthen the operation and maintenance personnel to the emergency event of the field disposal ability.

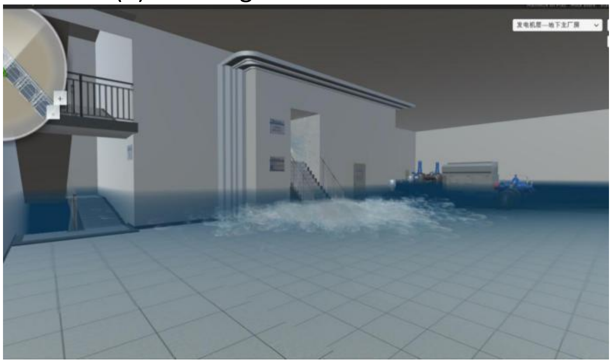
FIG.15 shows typical emergency scenarios of generator on fire, workshop flooding, oil leakage of the governor and SF6 gas leakage of the circuit breaker. When the user selects "Generator on fire emergency plan," the ontology service program of the emergency plan will start the corresponding emergency event, and the generator set in the visualized scene of the hydropower station will be on fire. The system will also send an alarm message.

(a)fire scenario



(b)oil leakage scenario

(c)air leakage scenario

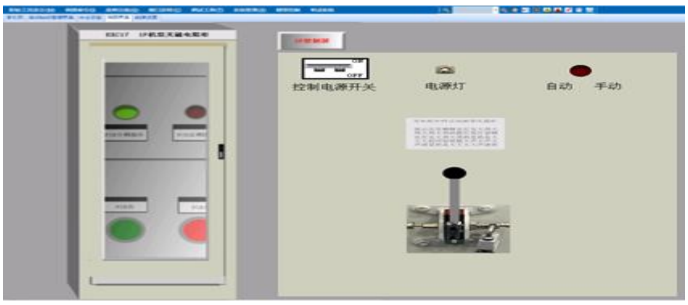


(d)water leakage scenario

Fig. 15 Typical emergency scenarios hydropower station

The emergency responses are generated through the knowledge reasoning of the emergency plan and returned to the user, who makes the emergency action. The instructions provided to the user according to the severity of the fire occurring are as follows: 1) the generator outlet circuit breaker is tripped; 2) the demagnetization switch trips the emergency demagnetization shutdown; 3) the generator outlet switch and voltage transformer are tripped; 4) the hydraulic turbine layer rain valve is opened to complete the generator on fire extinguishing treatment. The operation ends, and the fault disappears. The first viewpoint can be used in the system to complete the above instructions from the user role, as shown in Figure 16.

(a)Generator outlet switch cabinet switch operation



(b)Emergency shutdown operation

(c)Generator outlet switch and voltage transformer switching operation

Fig. 16 Emergency drill process

5 Conclusion and future work

There is a large amount of unstructured knowledge and information in the management of hydropower stations. Issues such as scattered management, maintenance difficulties, single service objectives, inefficient use and inappropriate operation, greatly restrict the knowledge management and knowledge services in hydropower station maintenance. Taking the operation and maintenance visualization project in Xiangjiaba hydropower plant as a case study, this paper introduces ontology-based knowledge modeling and knowledge representation methods into knowledge management and knowledge base construction of hydropower operation and maintenance, and proposes a series of ontology comprehensive similarity calculation methods as well as three critical technologies of ontology-driven hydropower knowledge retrieval, fault warning and emergency drill for three distinct application areas, and constructs an ontology-based knowledge application framework and knowledge base for hydropower operation and maintenance and a multidimensional knowledge visualization platform based on Unity3D engine. Finally, the implementation process of ontology-based knowledge retrieval, fault warning, and contingency planning exercises for hydropower plants is further demonstrated through case studies to verify the effectiveness of this method.

As the infrastructure of AI knowledge engineering and semantic web, ontologies and ontology-based knowledge modeling methods can be further applied to natural language processing-based knowledge representation methods such as knowledge graphs. The intelligent ontology knowledge base based on massive text is automatically constructed through artificial intelligence algorithms, providing new ideas for intelligent knowledge management and knowledge application of hydropower station operation and maintenance.

Declarations

Ethical Approval

Not applicable

Consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

Not applicable here.

Competing interests

The authors declare that they have no conflict of interest.

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Authors' contributions

BQZ was the main contributor to the conception and revision of the manuscript. SYL was the main contributor to editing the manuscript. HWZ provided technical guidance for the manuscript. XYD provided the hydropower station data for the manuscript. All authors read and approved the fnal manuscript.

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