TRANSFORMER FAULT DIAGNOSIS BASED ON ONTOLOGY AND DISSOLVED GAS ANALYSIS

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ABSTRACT

This paper proposes an ontology model for accurate and efficient transformer fault diagnosis using an explicit, formal and machine-readable format. The model makes use of ontology to represent formally faults and their features such as causes, symptoms, effects, which form a transformer fault diagnosis knowledge base. Moreover, the model can be employed to exchange and reason information for transformer fault diagnosis. In this study, a dissolved gas analysis method is encoded into an ontology-based knowledge base, and real fault samples are used to verify the developed model. The experiment results demonstrate that the proposed model can accurately diagnose various faults.

INTRODUCTION

Power transformers are among the key equipment in power systems. Because power transformers are critical to the reliable operation of every power grid, it is essential that they function properly, which should be monitored closely and continuously to ensure their maximum operation uptime. In general, power system operators apply their knowledge, experience and expertise to deal with tasks on condition assessment, fault diagnosis and maintenance of transformers [1]. With the development of power system condition monitoring systems, the volume of data exceeds the data analysis ability of engineers with limited individual knowledge, as the data are in association with complex and comprehensive concepts and knowledge of power system operations [2]. Moreover, newly employed maintenance personnel are lack of fault diagnosis experience and it is often difficult for them to grasp such comprehensive diagnostic skills, which may lead to misinterpretation of fault phenomena. Therefore, developing an automated monitoring and fault diagnosis knowledge-based system for transformers is necessary to improve transformer availability and performance efficiency, and reduce influence of unexpected system failures.

At present, various researches on transformer fault diagnosis and knowledge representation has been carried out, *e.g.*, building fault diagnosis algorithms based on artificial neural networks or expert systems to improve fault diagnosis performance; employing a Pelri network model to describe fault knowledge for solving a universal representation problem for accurate fault diagnosis. But there exist certain weakness in the above methods. For instance, neural works and expert systems are comparatively weak in fault diagnosis knowledge mining and expansibility. The accuracy of the above diagnosis methods is highly dependent on diagnosis inputs or data distributions [3].

In this paper, the ontology technique is introduced for transformer fault knowledge representation. It is a structured knowledge representation method, which can describe knowledge clearly and accurately with a well-defined hierarchical structure of concepts [4]. It focuses on classification and constraints of allowable taxonomies and definitions. As a format provider for exchanging knowledge, the ontology technique promotes interoperability, knowledge reuse and information integration with automatic validation. Furthermore, one of the significant advantages of using ontology as a way in the representation of transformer fault diagnosis knowledge lies in the convenience for knowledge discovering and reasoning, so that it leads to obtaining new knowledge much easier [5]. Therefore, the ontology technique is a powerful tool to provide common semantic knowledge representation, knowledge sharing and reusing.

In order to develop a comprehensive ontology model for fault diagnosis of power transformers, it is necessary to analyze various types of fault information, different diagnostic schemes and relationships exhibited in power transformer operation data. This paper proposes a power transformer fault diagnosis system based upon ontology. This ontology provides a common semantic model for knowledge representation and information management. It can be used to integrate various information about transformer fault diagnosis, such as fault symptoms, fault types and fault causes, *etc*. The developed ontology model is represented by using OWL (Web Ontology Language) supported by W3C (World Wide Web Consortium) [6] in a visualized ontology editor software package, namely Protégé [7]. In order to infer automatically fault information, a reasoner can be adopted to extract hidden information from explicit knowledge, which gives corresponding diagnostic decisions. Finally, the IEC three ratio method [8] is

encoded into the proposed ontology model, and real sample data are employed to verify the effectiveness of the proposed method.

The rest of this paper is organized as follows: Section II describes the related background knowledge. Section III illustrates the modeling rules of ontology and presents the proposed ontology model. Section IV gives experiment configuration and the corresponding diagnosis results. Finally, a conclusion is given in Section V.

BACKGROUND AND RELATED WORKS

Dissolved gas analysis

Various diagnosis methods, *e.g.*, chemical, electrical, thermal, can be applied on-line and off-line to detect transformer faults. Dissolved Gas Analysis (DGA) is one of the most reliable techniques to detect incipient faults in oil-filled power transformers [7]. When there is a kind of faults, such as overheating or discharge inside a transformer, it may produce corresponding amount of characteristic gases in the transformer oil. These gases are detected at the part per million (ppm) level using gas chromatography. It is a technique of separation, identification and quantification of mixtures of gases. The commonly collected and analyzed gases are hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), ethane (C_2H_6), carbon monoxide (CO) and carbon dioxide (CO_2) [8]. Through the analysis of concentrations of dissolved gases, gassing rates and ratios of certain gases, DGA methods can determine the fault type of a transformer. Even under the normal transformer operational conditions, some of these gases may be formed inside.

Most of DGA interpretative methods employ an array of ratios of certain key combustible gases as fault type indicators [8]. These five ratios are listed as below.

$R_1 = CH_4/H_2$
$R_2 = C_2H_2/C_2H_4$
$R_3 = C_2H_2/CH_4$
$R_4 = C_2H_6/C_2H_2$
$R_5 = C_2H_4/C_2H_6$

Among various ratio methods, the IEC ratio method is widely used. It utilizes three ratios, *i.e.*, R_1, R_2, R_5. The coding rule and classification of faults by the IEC method are given in Tables 1 and 2 [8]. By applying IEC interpretation techniques on oil samples, fault types can be qualitatively and quantitatively determined, which are encoded into the proposed ontology model in this research.

Ontology

The notion of an ontology, rooted in Philosophy, was introduced into the field of computer science and artificial intelligence in recent years. Gruder originally defined an ontology as an explicit specification of a shared conceptualization [9]. An ontology determines formal specification of knowledge in a domain by defining the terms and relations among them. An ontology is composed of classes, properties and individuals. These elements are explained briefly as the following [1] [4].

Classes describes concepts in a domain. In the transformer fault diagnosis domain, examples of classes are “Components” or “Fault Types” and so on. Subclasses represent concepts that are more specific than superclasses (mother classes). When a superclass has a subclass, it means that they are linked by a subsumption relation, *i.e.*, “is a” relation, allowing a taxonomy to be defined. Based on class relations, a hierarchy of classes can be established from general classes to specific ones.

Table 1 Coding rule of the IEC ratio method

Ratios of gases	R_2	R_1	R_5
<0.1	0	1	0
0.1-1	1	0	0
1-3	1	2	1
>3	2	2	2

Table 2 Classification of faults by the IEC ratio method

Cases	Characteristic	R_2	R_1	R_5
F_0	No Fault	0	0	0
F_1	PD of low energy density	0	1	0
F_2	PD of high energy density	1	1	0
F_3	Discharge of low energy	1-2	0	1-2
F_4	Discharge of high energy	1	0	2
F_5	Overheating of low temperature<150℃	0	0	1
F_6	Overheating of low temperature 150-300℃	0	2	0
F_7	Overheating of medium temperature 300-700℃	0	2	1
F_8	Overheating of high temperature>700℃	0	2	2

Note: PD = Partial Discharge.

Properties are contained in a class definition, which describe relationships among classes. There are three types of properties: object properties, datatype properties and annotation properties. Object properties are binary relations between classes, which illustrate how a class is related to another class. For example, the class “Component” has a property called “occursIn”. The

property "occursIn" links the class "Component" with the class "Fault Type". Datatype properties describe the relations between individuals and data values. Annotation properties are used to describe classes, individuals and properties with meta data.

Individuals represent objects in a domain, which are the specific instances of a certain class.

Web Ontology Language

There exist different programming languages to describe formal ontology, such as Description Logics, Conceptual Graphs, First Order Logic [10]. OWL is chosen in this research, which is the standard language recommended by W3C. It is designed for applications that need to process the content of information instead of just presenting information to users. OWL possesses great machine interoperability of Web content than that supported by XML, RDF, and RDF Schema by providing additional vocabularies along with formal semantics [6]. OWL is intended to provide a language that can be used to describe concepts and relations between them, which are inherent in Web documents and applications. OWL allows only binary relationships between classes and it distinguishes object properties (linking objects to objects) and data properties (linking objects to data values of built-in OWL datatypes) [4].

Moreover, OWL provides efficient inference capabilities with embedded reasoners, which are used to perform consistency check [11]. Hence, it is necessary to guarantee that an ontology is built correctly in the sense that no syntactic error and inconsistency remain in the ontology. Also, explicit and manually constructed classes that belong to taxonomy constitute an asserted hierarchy. Based upon OWL reasoners, an inferred hierarchy is automatically computed allowing extracting hidden information from explicitly defined information. For example, if CO and CO_2 are discovered in transformer oil, an ontology can induce that it is potentially a solid insulation fault. Reasoners make it possible to use OWL for various applications, such as knowledge sharing and representing, information management and ontology-based reasoning.

Reasoner

A reasoner is a key component for working with OWL ontologies. Reasoners are used to infer information that is not explicitly contained within an ontology [12]. Reasoners also refer to classifiers, and generally provide four services, *i.e.*, consistency check, subsumption check, equivalence check and instantiation check. Protégé-OWL supports the use of reasoners implemented by the description logic implementation group. Various reasoners, such as RacerPro, FaCT++, HermiT, Pellet [12], can be used by installing the corresponding plugins in Protégé. The difference between reasoners are the types of algorithms used and the way they are implemented in reasoning tasks. In this paper, RacerPro is employed to deduce hidden information.

MAIN PROCEDURES FOR DEVELOPING ONTOLOGY-BASED DIAGNOSIS SYSTEM

In order to build a comprehensive and accurate ontology-based fault diagnosis knowledge system for transformers, firstly it is necessary to collect a large amount of information about transformer faults. In the case of fault diagnosis with manpower, domain experts handle faults via experience and knowledge directly, when faults are simple. However, when faults are complex, an expert needs to analyze and find fault causes according to complex fault characteristics. In this paper, fault knowledge is acquired by extracting relevant information from a variety of literatures and technical reports of power grid companies. These information is taken as a source of knowledge base. After such fault knowledge is obtained, they need to be organized and implemented in a formal programming language. In order to illustrate modeling rules, the modeling steps are illustrated as below [1] [11]:

A. Step 1 - Determine the domain and scope of the ontology

Before starting to develop an ontology, several basic principles are required:

(1) The domain the proposed ontology is power transformer fault diagnosis.
(2) Ontology functionalities include the representation of fault diagnosis knowledge, decisions of fault causes, fault types and corresponding maintenance recommendations.
(3) Ontology should provide answers of most common power transformer faults to equipment users and ontology developers.

B. Step 2 - Enumerate important terms in the ontology

Terms are the basic elements of an ontology. It is useful to write down a list of all terms, which are necessary to make statements or to explain to a user. A fault diagnosis process can be described as the following: when a certain component occurs in a fault, it shows some fault symptoms, and fault symptoms can be utilized to determine fault types. Then corresponding diagnosis methods can be employed to verify this decision and identify fault causes. Finally, according to the above information, the fault location, fault effect and specific maintenance suggestion can be provided. On the basis of the above analysis, seven important classes are defined, *i.e.*, "Component", "Fault Type", "Fault Symptom", "Fault Cause", "Diagnosis Method", "Fault Effect" and "Maintenance Suggestion", as shown in Figure 1.

C. Step 3 - Define properties of classes

Seven classes are defined in Step 2, which relate to each other through properties, especially object properties. According to the typical fault diagnosis process, twelve object properties are defined, and six of them are inverse to others, as depicted in Figure 2. The relations among

them are shown in Figure 3.

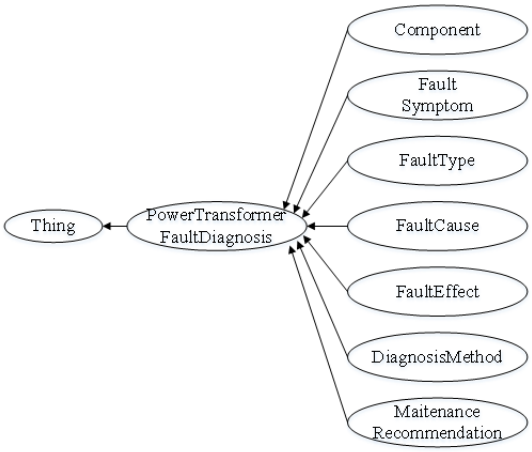

Figure 1 Basic classes in the ontology

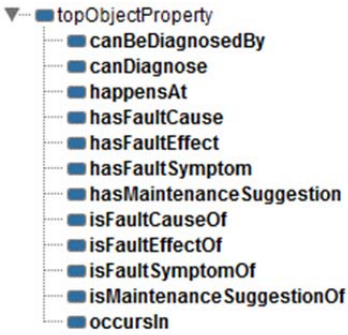

Figure 2 Basic object properties of ontology in Protégé

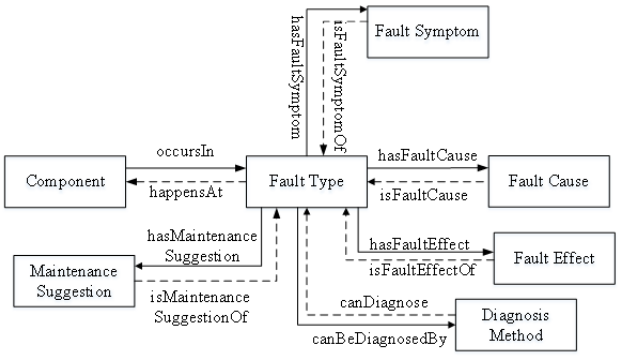

Figure 3 Relations among basic classes

D. Step 4 - Define subclasses and the class hierarchy

After defining the properties, subclasses and a class hierarchy should be defined to form a comprehensive fault diagnosis knowledge base. For example, the class "FaultType" contains subclasses of "WindingFault", "CoreFault", "CoolingSystemFault" and so on. The object properties can be used to describe the subclasses in detail, as shown in Figure 4.

The fault knowledge base is the foundation of fault information management and diagnosing fault types. The implementation of the proposed ontology is to encode the knowledge with OWL in Protégé. After the completion of ontology encoding, in order to guarantee the correctness of the ontology model, RacerPro installed in Protégé, is used to check semantic conflicts. And the coincidence of the related domain knowledge is normally checked manually.

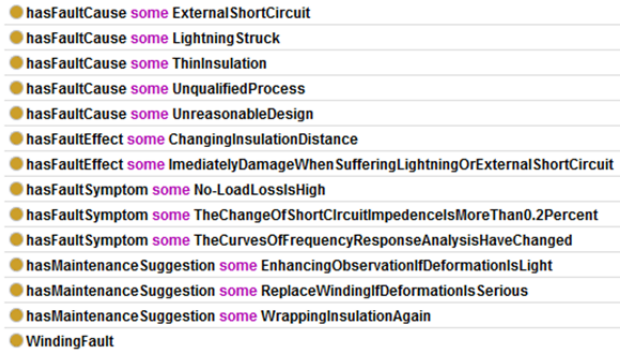

Figure 4 Definition of "Winding Fault" in Protégé

VERIFICATION OF THE DEVELOPED ONTOLGOY BASED TRANSFORMER FAULT DIAGNOSIS SYSTEM

In this section, in order to illustrate the validity of the proposed ontology model, the IEC three ratio method is defined in the ontology model. Then real transformer fault samples are mapped into the proposed ontology model (*i.e.*, creating instances). Finally, RacerPro is employed to automatically diagnose actual fault types.

Define classification and create instances

On the basis of Table 1 and Table 2, nine fault types are encoded into the proposed ontology model. For instance, three fault types, *i.e.*, fault types F_0, F_1 and F_2, are defined in the Protégé software with the following statements:

(1) No_Fault≡(hasRatio_R2 some double < 0.1) and (hasRatio_R1 some double >= 0.1, <= 1.0) and (hasRatio_R5 some double <= 1.0);

(2) PDofLowEnergyDensity ≡ (hasRatio_R2 some double < 0.1) and (hasRatio_R1 some double < 0.1) and (hasRatio_R5 some double <= 1.0);

(3) PDofHighEnergyDensity ≡ (hasRatio_R2 some double > 0.1, <= 3.0) and (hasRatio_R1 some double < 0.1) and (hasRatio_R5 some double <= 1.0).

In this research, 50 real transformer fault samples with onsite inspection results are collected from the historical database of several regional power supply companies and the relevant literatures in recent years [13] [14]. Then the 50 samples are mapped into instances through the ontology model for fault diagnosis, as shown in Figure 5.

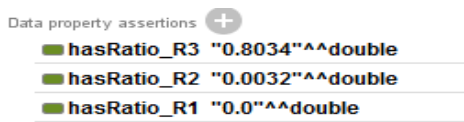

Figure 5 Create an instance in ontology

Verification results and discussion

After finishing the mapping of real fault samples, RacerPro is used to automatically infer fault causes, which are illustrated in Table 3. Because of the limited space, this table only lists 10 sets of data samples diagnosed with ontology-based reasoning. Among 50 samples, 45 samples can be diagnosed accurately, and the remaining 5 samples have no decisions, which are identified as "ND" using the Protégé software. When multiple faults occur in a transformer, gases from different faults are mixed up resulting confusing ratios, which are the possible causes of the unsuccessful diagnosis for the above 5 samples. Although only 50 samples are tested, from experiment results the accuracy of diagnosis is relatively high that indicates the developed ontology model is efficient for transformer fault diagnosis. And the results also show the proposed method is suitable for transformer knowledge representation. The proposed model can diagnose fault types automatically, which reduces the need for human intervention in handling complex data and individual knowledge. Moreover, the formal nature of ontology also enables the integration of data from heterogeneous sources, and it enhances the expandability of traditional expert systems for fault diagnosis, as well as the interoperability between heterogeneous systems.

Table 3 Real fault samples and diagnosis results

R_2	R_1	R_5	Actual Fault	Ontology Result
1.16	0.46	5.2	Arcing	F_3, F_4
3.3	0.07	16.5	Overheating	ND
1.65	0.17	3.13	Arcing	F_3, F_4
0.01	1.42	10.02	Overheating	F_8
0.04	3.86	6.94	Overheating	F_8
0.97	1.79	7.06	Arcing	ND
0.0	0.003	0.2976	PD	F_1
3.42	0.12	5.6	PD	F_3
1.45	0.84	14.0	Arcing	F_3, F_4
0.0	4.85	1.85	Overheating	F_7

Note: ND = Not Defined.

CONCLUSION

This paper has developed an ontology model for power transformer fault diagnosis. By using this model, detailed information about faults inside a transformer can be represented formally in a well-understood way. Protégé-OWL has been employed to build the ontology model. The proposed model has been verified by real case studies. The results demonstrate that the proposed ontology model can diagnose fault types accurately. Moreover, the ontology-based reasoning mechanism can also extract hidden information in knowledge, which can reduce workloads of power system operators, enhance the efficiency of fault diagnosis and reduce the maintenance cost considerably.

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