Fuzzy Ontology Reasoning for Power Transformer Fault Diagnosis

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***Abstract*—This paper presents a novel fuzzy ontology reasoner for power transformer fault diagnosis under a multi-agent framework. The developed ontology provides a comprehensive knowledge base as part of a multi-agent system to enable imprecision reasoning. It is the first time that a fuzzy ontology model is developed for accurate power transformer fault diagnosis. It aims to develop an improved ontology model for transformer fault diagnosis by applying the fuzzy ontology. The proposed technique deals with the imprecision situation using the fuzzy ontology, in order to build an ontology-based knowledge representation for accurate power transformer fault diagnosis. The proposed system is tested with actual transformer online data to demonstrate the functionality of the developed fuzzy ontology, which can identify the faults that are unidentifiable using a basic ontology model, and this can significantly improve the overall accuracy for transformer fault diagnosis under a multi-agent framework.**

***Index Terms*—Fault diagnosis, ontology, fuzzy sets, multi-agent systems, power transformer.**

I. INTRODUCTION

Power transformer is considered as one of the most important equipment in electric power systems, which converts voltage to higher or lower levels. All industries require a safe and reliable supply of power all the time and any failure in power transformers may cause losses to the industry supplied by these transformers. Therefore, its operation reliability is very important, which can be improved with online transformer condition monitoring and fault diagnosis using a dedicated knowledge-based system.

Agent and Multi-Agent System (MAS) are useful techniques that have been applied in a variety of industrial applications [1,2]. Particularly in power engineering, the agent technology has been employed for condition monitoring, controlling, automation, etc [3,4]. Meanwhile, a knowledge-based system is capable of utilizing computer programming to simulate the human intelligence in a limited way. The integration of MAS with a knowledge base can provide a robust decision making system for various practical applications, such as on-line fault diagnosis. However, the functionality of MAS applied in electric power systems is often limited due to its inability in dealing with the situations involving some uncertainty/imprecision.

There are various techniques in the field of MAS and knowledge bases, which have been applied for monitoring and diagnosis of power transformers, but their structure is too complicated and there still exists limitation of such techniques. For example, a basic ontology embedded in MAS was employed for power system automation in [5]. This system can take users' commands from a user interface console to perform certain actions. Real-time statuses of equipment can be collected by an ontology agent. The system was designed to apply the basic ontology for the purpose of knowledge representation only, which was not directly used for power transformer fault diagnosis. Ontology-based fault diagnosis was applied for power transformers in [6,7]. The technique proposed in [6] was able to derive subclasses or individuals as defined in the stage of building ontology. However, this technique did not involve the use of agents. The developed ontologies in [6,7] did not consider any situations involving some degrees of uncertainty/imprecision. However in real world uncertainty or imprecision is a common problem for fault diagnosis.

This paper proposes a fuzzy ontology reasoning approach for the first time to intelligent transformer fault diagnosis under a multi-agent framework. Firstly, basic ontology-based reasoning is introduced for power transformer fault diagnosis, and then improved further by developing a fuzzy ontology. The proposed system uses MAS to collect online data from power transformers distributed in different substations using relevant agents. The basic ontology and the fuzzy ontology provide a comprehensive knowledge base for fault diagnosis using online data sampled from on-site power transformers. The proposed basic ontology reasoner is able to deduce undefined knowledge from explicitly defined knowledge. Furthermore, the improved fuzzy ontology is capable of tackling the imprecision of fault diagnosis boundaries, which leads to significant improvement of fault diagnosis accuracies compared with that derived from basic ontology reasoning. The proposed system is easily upgradable online for potential practical applications, and thus is able to adopt new features to improve the fault diagnosis accuracy for power transformers.

II. MAIN TECHNIQUE USED IN THE PROPOSED APPROACH

A. Power Transformer Fault Diagnosis

Various diagnosis methods, e.g., chemical, electrical, thermal, have been applied on-line and/or off-line to detect faults for oil-immersed transformers. Dissolved Gas Analysis (DGA) is one of the most effective tools to diagnose conditions of oil-immersed power transformers. Oil samples are taken from a transformer and analyzed for fault diagnosis. Hydrocarbon fragments and hydrogen are formed as a result of the decomposition of mineral oil

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hydrocarbon molecules under electrical and thermal stresses in operations. Gases, such as acetylene (C_2H_2), methane (CH_4), hydrogen (H_2), ethylene (C_2H_4), ethane (C_2H_6), carbon monoxide (CO), etc., may be formed by combination of hydrocarbon fragments. DGA fault diagnosis is based on mapping gas ratios (such as 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) to certain fault types and different classification methods can be applied for fault detection. Duval Triangle, Doernenburg, IEC ratio, Roger's ratios etc. are currently utilized to diagnose transformer faults [8]. For instance, the Roger's ratio method for fault classification uses three gas ratios, i.e., R_1, R_2 and R_5, as given in Table I. Fault types can be identified by matching gas ratio ranges to particular fault types as listed in Table I. However, if a gas ratio does not match any fault type defined by the Roger's method, it is treated as "*Undefined fault*", and an expert needs to apply other relevant techniques to diagnose such a case.

TABLE I. DIAGNOSIS RULES OF THE IEC RATIO METHOD

Case	Fault Type	R_2	R_1	R_5
0	No Fault (NF)	R_2<0.1	0.1≤R_1≤1	R_5≤1
1	Low Energy Partial Discharge (LEPD)	0.1≤R_2 ≤3	R_1<0.1	R_5≤1
2	High Energy Partial Discharge (HEPD)	0.1≤R_2 ≤3	R_1<0.1	R_5≤1
3	Low Energy Discharge (LED), Sparking, Arcing	0.1≤R_2	0.1≤R_1≤1	1≤R_5
4	High Energy Discharge (HED), Arcing	0.1≤R_2 ≤3	0.1≤R_1≤1	3<R_5
5	Thermal Fault (TF)<150 ºC	R_2<0.1	0.1≤R_1≤1	1≤R_5≤ 3
6	Thermal Fault 150−300 ºC	R_2<0.1	1≤R_1	R_5≤1
7	Thermal Fault 300−700 ºC	R_2<0.1	1≤R_1	1≤R_5≤ 3
8	Thermal Fault>700 ºC	R_2<0.1	1≤R_1	3≤R_5

B. Multi-Agent System

An agent is a computer system situated in some environment, which is able to take information from this environment and perform autonomous actions according to its design objectives [9]. An agent-based system can be applied in power systems for the purpose of monitoring and controlling its components, e.g., power transformer, due to such properties of agent as being autonomous, reactiveness, pro-activeness, etc.

The Gaia methodology [10], as a formally presented methodology for designing MAS, is anticipated to facilitate an analyst to gradually shift from an initial ambiguous state to a more concise and methodical design, which can be implemented directly. Therefore, the agent system developed in this research has been designed based on the Gaia methodology for monitoring and diagnosis of power transformer, which can clarify, simplify and standardize a design process. As shown in Fig. 1, the developed multi-agent system comprises different types of agents, such as database, reporter, controller, user interface, collector and ontology agents. Under the developed agent framework, real-time data are sampled from a power transformer and stored into a database to be available to users on request. Generally in practice, a knowledge-based system or rule-based reasoning enables diagnosis and automation actions.

As known, it is important to share and reuse knowledge-based systems in relevant domains. The knowledge-based system presented in [11] has a significant disadvantage as that both domain knowledge and rules are located in its knowledge base. As a result, a success in one domain could hardly be replicated to another one due to a high degree of interconnections between domain knowledge and rules. Furthermore, a knowledge-based system with the use of rule-based reasoning cannot be easily improved, as it is impossible to know all the conditions for comprehensive rule-based reasoning.

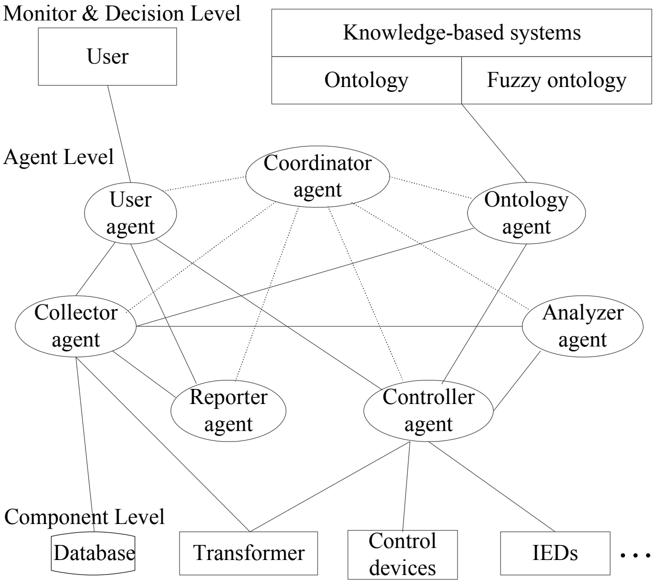

Figure 1. The hierarchy of the developed multi-agent framework

C. Description Logic (DL)

Knowledge can be represented in the form of logic. Choosing a formal knowledge representation, such as DL [12], is a key issue of building a knowledge base. Many types of DL (such as *ALC*, *SHIQ*, *ALCNIO*, *SHOIN*, etc.) can describe operations with different attributes. A huge number of shared properties and logic-based knowledge representation formalisms can be used in DL to form its precise definition. In DL important notations of a domain are described by concepts and rules. Concepts (or classes) and rules (or properties) in DL are the building constructors, such as conjunction, disjunction, negation, etc., which can be selected depending on DL types.

The syntax language for describing concepts supported by the Ontology Web Language (OWL) [13] is defined as follows: concept names (C_0, C_1, ...), property names (P_0, P_1, ...), concept constructor " $\cup$ " called unionOf, disjunction or *or*, concept constructor " $\cap$ " called intersectionOf, conjunction or and, concept constructor " $\exists$ " called existential restriction constructor, " $\forall$ " called value restriction constructor and so on. For instance, the concept of fault diagnosis for power transformer is defined as: "*A transformer has a thermal fault in its component, and the symptoms are either temperature or gas*". The DL description of this concept can be defined in (1).

$$\begin{aligned} &TransformerComponent \cap \exists Component.Thermal\_Fault \\ &\cap \forall has\_symptom.(Temperature \cup Gases). \end{aligned} \tag{1}$$

A DL structure consists of two parts, terminological box (TBox) and assertion box (ABox), representing a reasoner system. TBox contains intentional knowledge (schema of complex description), whereas ABox contains extensional knowledge (data of complex description). Various reasoners can be employed, such as Racer, FaCT, FaCT++ and Pellet;

and they differ in the types of algorithms used and the way they are implemented in reasoning tasks [12]. DL has been employed in many practical applications, such as software information and documentation, databases, query answering, ontology languages, etc. OWL is one of the most important applications of DL, using various tools and reasoning techniques.

D. Ontology

In the computer science domain, ontology is defined as: "A formal, explicit specification of a shared conceptualization" [14]. Ontology describes concepts and their relation in particular domains. Many programming languages have been developed for building an ontology. OWL and OWL2 are the standard ontology languages recommended by W3C [14]. The key feature of OWL is that it can be used not only to present information, but also to process it and to extract new information. Therefore, OWL has been applied in a wide range of applications, such as knowledge sharing and representation, question answering and automatic diagnosis, information system, ontology-based reasoning, etc [15–17]. OWL-DL is one category of OWL, which corresponds to DL and supports the maximum expressiveness without losing computational completeness. In ontology implementation, Protégé [18] is one of popular tools to support OWL, which is based on a graphical editor. The Protégé ontology editor also supports *SHIQ*(*D*) and *SROIQ*(*D*) [18].

Hierarchy classes in ontology are formed by superclasses and subclasses. Different types of properties, such as inverse, functional, transitive, symmetric, etc., help to restrict classes when building an ontology model. Inference problems could be performed by using various reasoning algorithms. A reasoner allows the inference to be made, based on the construction of compositional concepts and roles. For instance, concept *D* is subsumed by concept *C*, if all instances of *D* are also instances of *C*.

III. ONTOLOGIES FOR TRANSFORMER FAULT DIAGNOSIS

Seven essential steps have been recommended for the designing of hierarchy classes, properties, individuals, etc., to build an ontology model [14]. Based upon these recommendations, a basic ontology for power transformer fault diagnosis has been developed by the authors as reported in [19]. In this research an ontology agent has been developed to wrap the proposed basic ontology for enabling interactions between the developed basic ontology and the MAS system. Moreover, a fuzzy ontology is developed at the second stage of this work to deal with imprecision for improving the accuracy of fault diagnosis. Figure 2 shows the diagram of interactions between the developed ontology and the MAS system.

A. Basic Ontology for Power Transformer Fault Diagnosis

A fault diagnosis system embedded with ontology-based reasoning can provide a comprehensive knowledge base, which can be shared by other applications. For this purpose, an online fault diagnosis system adopting basic ontology reasoning has been developed firstly. A fault may appear in a power transformer during its daily operations, however, more likely, any type of faults could change the working status of a transformer, which is reflected in some symptoms related to a fault. In other words, any type of faults has some relevant symptoms. Knowing symptoms enables the identification of relevant fault types. For instance, a cooling system (fan) of a power transformer is normally used to dissipate heat to its external surrounding. A fault may affect the working status of a cooling system, which may lead to malfunction of its correct performance (e.g., fans stop working). This results in abnormal oil temperature rise, which is defined as a symptom. Thus, a temperature rise may indicate a problem of a cooling system, and later cause arcing faults. In practice, due to the complexity of transformer fault mechanisms, there exist various types of symptoms and faults [8].

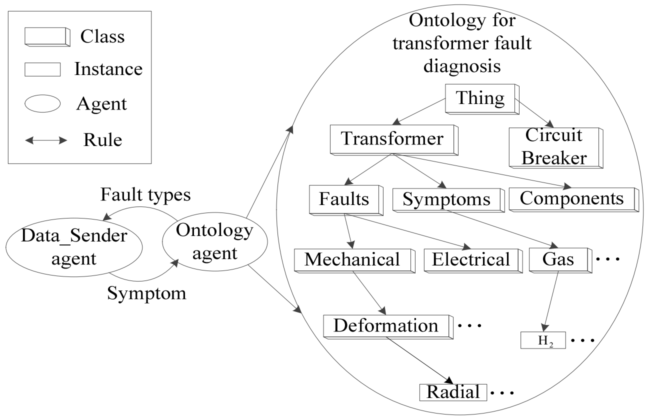

Figure 2. Interactions between the developed ontology under a MAS framework

To build an appropriate ontology for power transformer fault diagnosis, three different categories are defined, i.e., fault, symptom and component. The fault category contains various fault types, defined by some types of properties according to the symptom category. For instance, fault *A* has symptom *B*, thus fault *A* can be diagnosed by observing symptom *B*. The component category is also linked via some properties to the fault category, which reflects the relationship between faults and components. The three categories and their relations are employed as the basic concepts of ontology reasoning for transformer fault diagnosis. The basic elements of the developed ontology are illustrated in Fig. 3. The components of the developed basic ontology for power transformer fault diagnosis are defined as below, including classes, properties and related key features.

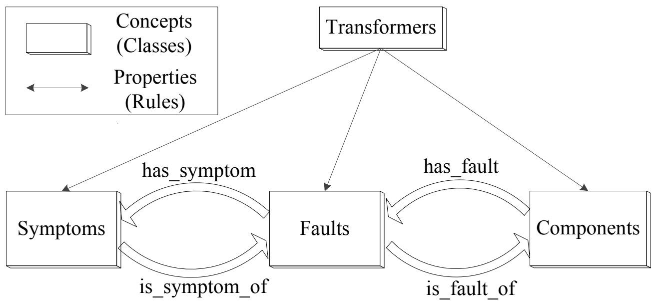

Figure 3. Main classes and properties of the developed basic ontology for power transformer fault diagnosis

The developed basic ontology for transformer fault diagnosis consists of three main classes: *Components*, *Symptoms* and *Faults*, and consequently each of them is defined as a subclass of class *Transformer*, as described in the following three axioms: *Symptoms* ⊆ *Transformers*, *Faults* ⊆ *Transformers* and *Components* ⊆ *Transformers*, which are expressed using OWL in Fig. 4.

```
<owl:Class rdf:about="#Transformer">
  </owl:Class>
    <owl:Class rdf:about="#Symptoms">
<rdfs:subClassOf rdf:resource="#Transformer"/>
  </owl:Class>
     <owl:Class rdf:about="#Faults">
<rdfs:subClassOf rdf:resource="#Transformer"/>
  </owl:Class>
    <owl:Class rdf:about="#Components">
<rdfs:subClassOf rdf:resource="#Transformer"/>
</owl:Class>
```

Figure 4. Class definition using OWL

Faults in a power transformer are normally classified into five types: *Electrical*, *Thermal*, *Mechanical*, *Degradation* and *Ageing*. These five types are defined as the subclasses of class Faults, described as the following: *Electrical_Faults* ⊆ *Faults*, *Thermal_Faults* ⊆ *Faults*, *Ageing_Fault* ⊆ *Faults*, *Degradation_Fault* ⊆ *Faults* and *Mechanical_Faults* ⊆ *Faults*. Each type of power transformer faults can be further subdivided into different types of related faults, as listed below in the case of the *Degradation* type of fault: *Degradation_Of_Insulation* ⊆ *Degradation_Faults*, *Degradation_Of_Iron* ⊆ *Degradation_Faults*, and *Paper_Degradation* ⊆ *Degradation_Of_Insulation*.

For illustration purposes, the Roger's ratio method described in Table I, as an example of a widely used DGA diagnosis technique, is represented as a class called "*Rogers_Method_Faults*" with eight types of faults, defined as subclasses. It is worth to mentioning that an ontology model can be extended using different methods of fault diagnosis.

Class *Symptoms* consists of various symptom types, which may appear in a power transformer. The subclasses of class *Symptoms* include acidity, temperature, electrical and physical symptoms. Class *Symptoms* contains a subclass *Gas_Ratios*, with five types of gas ratios *Ratio*1 (R_1) to *Ratio*5 (R_5) as listed in Section II, and three of them are used in the Roger's ratio method. Similarly, the class *Components* includes subclasses, such as *Winding*, *Cooling System*, *Taps*, *Oil*, etc.

Properties reflect the binary relations between classes or individuals. There are two main types of properties, i.e., object properties and datatype properties. They provide different attributes to classes. Two categories of properties, *has_category* and *is_category_of* with the inverse characteristics to each other, are normally defined. The inverse property represents that, if a property links individual x to individual y, then the inverse property links individual y to individual x. In this study, *has_category* property is the inverse of *is_category_of* property.

OWL is usually employed to define sub-properties of each property. In this work, each property has three sub-properties. For instance, the property *has_category* has three sub-properties as *has_fault*, *has_symptom* and *has_component*, with different characteristics, such as functional, inverse, etc. An example for defining the functional property in ontology for transformer fault diagnosis is exemplified here. It is assumed that the functional property called i*s_symptom_of* has only one symptom. If *High_Temperature* is a symptom of *Overheating* and also *High_Temperature* is a symptom of *Thermal_Fault*, it can be inferred that *Thermal_Fault* and *Overheating* must be the same, because *is_symptom_of* is a functional property. Similarly, for the property *is_category_of*, three sub-properties are defined, including *is_fault_of*, *is_symptom_of* and *is_component_of*.

To apply these properties for the classes as defined in the previous sections, the following statements are used:
a) *Faults has_symptom* some *Symptoms*,
b) *Symptoms is_symptom*_of some *Faults*,
where *Faults* and *Symptoms* are classes. It means that all types of faults have some types of symptoms, defined in class *Symptoms*. The inverse statement indicates that symptoms correspond to some types of faults. The following examples of power transformer fault diagnosis are given to illustrate the above statement. For instance, a fault of partial discharge may lead to the presence of hydrogen in the oil symptom (identified from gas ratio values). The statements to describe this restriction are:
Example of a) *Partial_Discharge has_symptom Hydrogen*;
Example of b) *Hydrogen is_symptom*_of *Partial_Discharge*.

Furthermore, the components of power transformer can be identified by relevant fault types, with the help of the following statements:
c) *Components has_fault* some *Faults*;
d) *Faults is_fault_of* some *Components*.

A further example is shown below for fault diagnosis. Almost all types of transformers have a tank made of carbon steel. Acidity can be defined as the mass of potassium hydroxide in milligrams, which is required for neutralization of acid in one gram of transformer oil. Consequently, a high amount of acid in oil is represented as a high acid number. The acid number generally tends to increase with the ageing of power transformer due to oxidative processes in the acid and insulation formation. The acid attacks the metal inside of the tank and may lead to a tank corrosion fault. Therefore, the presence of corrosion faults can be illustrated using a statement as "*Tank has_fault* some *Corrosion*".

Therefore, a high acid number indicates the presence of *Corrosion* in *tank*. Figure 5 shows the developed basic ontology for power transformer fault diagnosis. The communication between the developed basic ontology and power transformer is handled by an agent in this research.

The Roger's ratio method for transformer fault diagnosis has been embedded in the design of the basic ontology. The developed ontology contains class *Faults* with eight subclasses, which represent the typical cases of fault types in the Roger's ratio method. Three datatype properties are applied for restricting fault classes. The datatype property *has_ratio* contains three sub-properties, i.e., *has_ratio_*R_1, *has_ratio_*R_2 and *has_ratio_*R_5, which are applied in this basic ontology. The first case, defined in the Roger's ratio method as illustrated in Table I, corresponds to *No_Fault*, which can be defined in Protégé with the following statements: *Faults* and (*has_ratio_*R_2 some *float*[<1.0]) and (*has_ratio_*R_1 some *float*[≥0.1, ≤1.0]) and (*has_ratio_*R_5 some *float*[≤1.0]), (*has_ratio_*R_2 some *float*[<1.0]), which means, if received gas ratios are within the defined boundaries, then there is no fault in a power transformer.

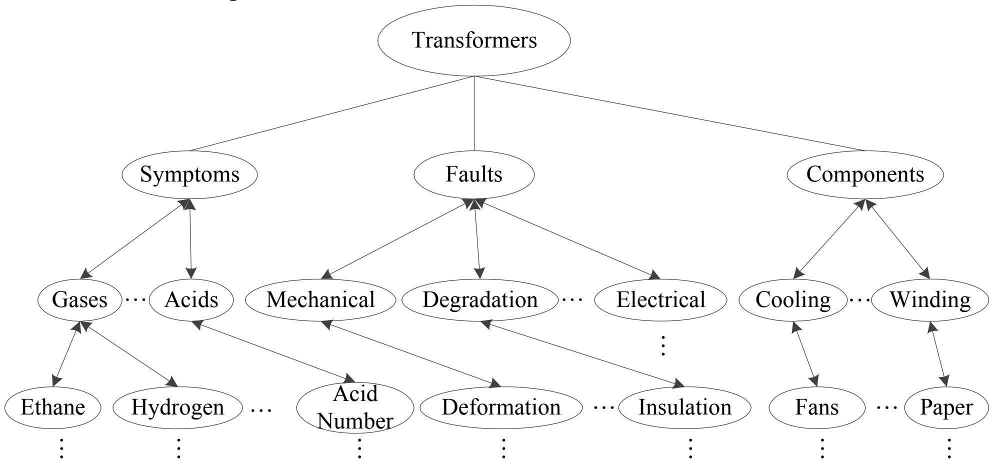

Figure 5. The developed basic ontology for power transformer fault diagnosis

Ontology can be formalized in a TBox definition with DL in *SHIQ* for the *No_Fault* statement [12] as described in (2),

$$\begin{aligned} &No\ Fault \equiv (\forall Faults.T) \cap (< 0.1\ has\_ratio\_R_2.T) \\ &\cap((\geq 0.1\ has\_ratio\_R_1.T) \cap (\leq 1.0\ has\_ratio\_R_1.T)) \\ &\cap (\leq 1.0\ has\_ratio\_R_5.T), \end{aligned} \tag{2}$$

which expresses *No_Fault* with three conditions of gas ratios. The other cases can be defined similarly in TBox.

One of the key features of applying ontology is to extract hidden information from explicit facts built in an ontology model. To consider this situation, an example based on the DL description is given in this paragraph. *Degradation* is a common type of faults in a power transformer due to transformer ageing. Moreover, degradation itself speeds up the ageing of the equipment. There are several factors other than equipment ageing that can also cause the degradation, such as water, temperature, byproducts, etc. A high temperature rise and the presence of water are the key factors (or symptoms) leading to degradation of transformer components, e.g., paper insulation. *Degradation* is an abbreviation for the concept description, which can be defined in TBOX as in (3),

$$\begin{aligned} &Degradation \equiv Faults \cap (\exists has\_symptom.Symptoms) \\ &\cap(\forall has\_symptom.(water \cup temperature)), \end{aligned} \tag{3}$$

which means that the degradation is a type of faults and has some symptoms, e.g., water or temperature. Such a case can be described in ABox stating these properties of an individual, which is listed in (4),

$$\begin{aligned} &Degradation(Paper\_Degradation), \\ &has\_fault(Paper, Degradation), \neg water(Paper). \end{aligned} \tag{4}$$

It means that the instance *Paper_Degradation* belongs to the concept *Degradation*; *Paper* has a fault *Degradation*, and there is no water in *Paper* (the paper is not wet). Users receive reasoning services from the specified DL, which can automatically deduce implicit knowledge from the explicitly represented knowledge, and it can yield a correct answer in finite time. For the case presented above, the instance algorithm determines instance relationships.

For the given ABox and the definition of *Degradation*, *Paper has_fault Degradation* because *Paper_Degradation* is an instance of *Degradation*, so all its symptoms are either *Water* or *Temperature*, and the insulation paper is not wet ($\neg Water(Paper)$), then concluding that the paper degradation is caused by temperature rise.

B. *Fuzzy Ontology for Transformer Fault Diagnosis*

Human reasoning is based on approximation and imprecision, which can be handled by fuzzy systems. The fuzzy set theory was proposed by Lotfi Zadeh for dealing with the approximate reasoning [20]. It has found various applications in such fields as artificial intelligence, control theory, etc. An element of the fuzzy set belongs to a set to some degree, defined as a membership function "$\mu_A(x)$", whereas in the classical set, the element either belongs to a set or not. In this research, crisp boundaries used in the case of the basic ontology are replaced with fuzzy boundaries by developing a fuzzy ontology. A fuzzy system has been applied in power systems for DGA fault diagnosis in [21]. The idea of expressing imprecise or vague objects is taken from the fuzzy logic and applied in semantic web ontologies, to represent the fuzzy ontology. The fuzzy ontology has been introduced by Straccia, which has been applied for non-crisp data within the ontology definition [22].

FuzzyDL has been proposed as an extension to classical DLs to enable tackling fuzzy/vague/imprecise concepts [23]. A fuzzyDL reasoner supports fuzzy logic reasoning, which is based on the fuzzy DL *SHIF*(*D*) with various data types. For instance, the concept query "(max−subs?*CD*)" determines the maximal degree of concept *C* subsuming concept *D*. The feature "Show Expressions" can be used to show values in an optimal solution.

Different components, such as fuzzy datatypes, modifier, concept and roles, are the essential elements for building a fuzzy ontology [24]. Trapezoidal, triangular, left-shoulder function (L-function), right-shoulder function (R-function) etc. are various functions used to specify a membership function in fuzzy modifiers, as shown in Fig. 6. Fuzzy modifiers have the capability of using some expressions, such as very, more or less, to express their membership function in fuzzy sets. Unlike the ontology described in [7], the fuzzy ontology is capable of dealing with the situations involving some uncertainty/imprecision. An example of representing Corrosion with some imprecision in terms of fuzzy ontology for power transformer fault diagnosis is given as: $Fault \cap \exists\ has\_symptom.High\_Acid\_Number$.

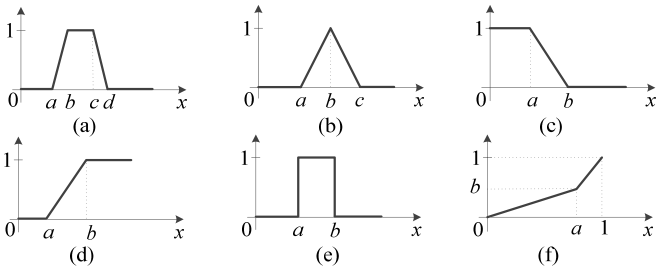

Figure 6. (a) Trapezoidal function, (b) Triangular function, (c) Left-shoulder function, (d) Right-shoulder function, (e) Crisp function, (f) Linear function.

The concept *High_Acid_Number* can be easily defined with a fuzzy concept "*Acid_Number*" and a fuzzy modifier "High". The fuzzy concept assertion "<*Acid_Number*: *High*≥0.9>" states that the acid number is high with at least a degree of 0.9. A fuzzy datatype "*High*" is annotated in Fig. 7.

```
<AnnotationAssertion>
  <AnnotationProperty IRI = #fuzzyLabel/>
  <IRI >#high </IRI >
  <Literal datatypeIRI = &rdf;PlainLiteral>
        <fuzzyOwl2 fuzzyType = "modifier">
              <Modifier type = "High" c="0.9" />
        </fuzzyOwl2 >
  </Literal >
</AnnotationAssertion >
```

Figure 7. Fragment of a fuzzy datatype annotation

Undefined fault cases usually appear when the value of gas ratios are close to crisp boundaries, given in the Roger's ratio method [25,26]. In order to overcome such a problem existing in basic ontology reasoning, the employment of non-crisp threshold based on fuzzy membership functions has been adopted in this study. The fuzzy ontology developed in this work defined ten datatypes with different functionalities and boundaries. Therefore, each of the ratios reported in the Roger's method can be presented as several ratios with fuzzy modifier characteristics. The summary of the ratios employed in this research is given in (5),

$$R_2 = \begin{Bmatrix} R21 \\ R22 \\ R23 \end{Bmatrix}, \quad R_1 = \begin{Bmatrix} R11 \\ R12 \\ R13 \end{Bmatrix}, \quad \text{and} \quad R_5 = \begin{Bmatrix} R51 \\ R52 \\ R53 \\ R54 \end{Bmatrix}, \tag{5}$$

where the values of membership functions for each gas ratio are illustrated in Fig. 8.

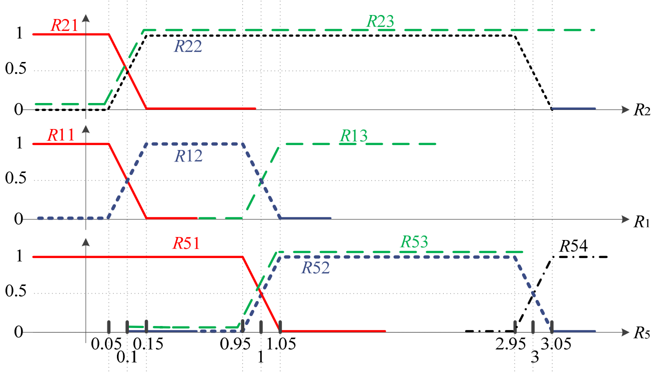

Figure 8. Fuzzy datatypes for three gas ratios of the Roger's method

For instance, the datatype *R*21 is defined as a left shoulder function with "*a*=0.05" and "*b*=0.15" (as in Fig. 6), instead of using crisp values of "*a*=*b*=0.1". This can be defined in fuzzy OWL2 [24] with the statements as listed in Fig. 9.

```
$<fuzzyOwl2 fuzzyType = "datatype">$
   $<Datatype type = "leftshoulder" a="0.05" b="0.15" />$
$</fuzzyOwl2>$
```

Figure 9. Fuzzy membership definition in fuzzy OWL2

A Protégé plug-in can be employed to facilitate the syntax of the fuzzy ontology annotation [24]. Similar to the basic ontology described in the previous section, the proposed fuzzy ontology for power transformer fault diagnosis contains various classes. The Roger's method can be revised using fuzzy membership functions, as shown in Table II. This can be illustrated for the first case of the Roger's method in the form of fuzzy ontology as listed in Table II.

TABLE II. REVISED ROGER'S METHOD FOR FAULT DIAGNOSIS USING FUZZY MEMBERSHIP FUNCTIONS

Case	Fault	R_2	R_1	R_5
0	No fault	*R*21	*R*12	*R*51
1	Low energy partial discharge	*R*22	*R*11	*R*51
2	High energy partial discharge	*R*22	*R*11	*R*51
3	Low energy discharge	*R*23	*R*12	*R*53
4	Sparking, arcing	*R*22	*R*12	*R*54
5	High energy discharges, arcing	*R*21	*R*12	*R*52
6	Thermal fault temperature<150 ºC	*R*21	*R*13	*R*51
7	TF temperature range 150 ºC-300 ºC	*R*21	*R*13	*R*52
8	TF temperature range 300 ºC-700 ºC	*R*21	*R*13	*R*54

The other cases of the Roger's ratio diagnosis method can be represented in a similar manner.

According to Table II, the case 0 represents *No_Fault*, if *R*21, *R*12 and *R*51 satisfy relevant boundary conditions as defined in Fig. 8. This can be described in Protégé with the following statement: *No_Faults EquivalentTo Faults* and (*has_ratio* some *R*21) and (*has_ratio* some *R*12) and (*has_ratio* some *R*51), whereas in the fuzzy DL form, this statement is defined in (6):

$$No\_Fault \equiv Faults \cap \left(\exists has\_ratio.R21\right) \cap \left(\exists has\_ratio.R12\right) \cap \left(\exists has\_ratio.R51\right). \tag{6}$$

The cases 1 and 2 of the Roger's method represent similar conditions for the *Partial_Discharge* fault (low and high energy); and they can be merged into one case. This case is formalized in TBox as represented in (7):

$$Partial\_Discharge \equiv Faults \cap \left(\exists has\_ratio.R22\right) \cap \left(\exists has\_ratio.R11\right) \cap \left(\exists has\_ratio.R51\right). \tag{7}$$

IV. Experimental Results And Discussion

In this section, experiment studies are carried out to evaluate the performance of the developed ontologies for fault diagnosis. For this purpose, real online DGA data and their actual faults are taken from [27-29] and investigated. The actual data contain one case of no fault, 2 cases of partial discharge, 14 cases of arcing, 25 cases of overheating and 28 cases of low energy discharge, giving a total of 70 DGA samples. In this research, a basic ontology agent and a fuzzy ontology agent have been developed and the same data are used to compare the performance of the two ontology models. These data are analyzed by an ontology agent that wraps the two ontology models for fault diagnosis.

For this purpose, the values of membership functions of the gas ratios are calculated and investigated. In the case that a membership function value is equivalent to one, the developed method performs similarly to the basic ontology as described in the previous section. For the membership function value below one, the diagnosis on fault types is made by considering whether the gas ratio combination belongs to one (or more) of defined classes. This can be illustrated with an example using actual gas ratios (as provided in Table III). A fault type for the set of gas ratio values (R_2=3.25, R_1=0.08, R_5=17.75) could not be correctly identified with the basic ontology, while the fuzzy ontology can solve this problem. With the help of fuzzy ontology, the following membership functions were obtained with $\mu(R_2=3.25)=\mu(R23)=1$, $\mu(R_1=0.08)=\mu(R11)=0.7$ and $\mu(R12) = 0.3$, $\mu(R_5=17.75)=\mu(R53)=1$ and $\mu(R54)=1$. Therefore, the conclusions on several combinations of the participating datatypes are made by ($R23 \cap R11 \cap R53$), ($R23 \cap R11 \cap R54$) and ($R23 \cap R12 \cap R54$). There are no matching conditions in Table II, whereas the case ($R23 \cap R12 \cap R53$) matches the third condition of Table II. Verifying the combination of membership functions with the table of defined classes (Table II), the fault type is identified as "Low Energy Discharge (LED), Sparking, Arcing" (case 3).

Table III illustrates the results obtained by the basic ontology and the fuzzy ontology for the first 20 of the actual data (the full set of analyzed data could not be provided due to the space limitation). The overall accuracy has been increased from 72.86% using the basic ontology to 95.71% by applying the fuzzy ontology. As shown in Table III, more faults can be correctly diagnosed with the fuzzy ontology compared with the basic ontology, including two cases of partial discharge and two cases of arcing that could not be diagnosed with the basic ontology.

The interaction between the developed agent and the developed ontology for transformer fault diagnosis enables an engineer to facilitate intended actions. The key advantage of the proposed system is its ability to update a knowledge-based system with more advanced ontology models for improving system reasoning performance, which can be achieved by designing dedicated ontology agents. This is the first time that the fuzzy ontology is applied for power transformer fault diagnosis under a multi-agent framework. In this study, an example fuzzy ontology system has been developed, which can be modified by using more comprehensive threshold boundaries of a fuzzy system for DGA fault diagnosis.

As a result, the ontology-based reasoning for power transformer fault diagnosis has been designed. The OWL-DL language has been applied to develop the ontology. Various classes and subclasses have been asserted and restricted by different types of properties. The developed ontology based on OWL-DL with DL reasoner had an ability to infer the hierarchy classes, subclasses, inconsistency, etc. The way developed ontology could extract implicit information from the explicit facts built in, was also reviewed in this work. An agent was designed to wrap the ontology for the purpose of interaction. In the study conducted, an ontology agent was able to receive the DGA samples and pass them to the ontology for fault diagnosis. In this case study the Roger's method was applied in form of OWL-DL ontology. Finally, the applied 70 DGA sample were investigated, and the accuracy of discussed fault diagnosis method was assessed. Following this, the present work describes the novel application of the fuzzy ontology in a power system, which was capable of dealing with the uncertainty. To investigate the improvement of the fuzzy ontology compared to the previously developed ontology, the fault diagnosis based on Roger's method was applied. The accuracy of developed fuzzy ontology was evaluated using the same DGA samples as previously; then the overall accuracy was assessed. It is shown that the use of fuzzy ontology can improve fault diagnosis accuracy considerably, as compared to the other types of knowledge-based systems discussed earlier.

TABLE III. THE ACTUAL DGA SAMPLES ANALYZED WITH THE BASIC ONTOLOGY AND FUZZY ONTOLOGY

N	R_2	R_1	R_5	Actual Fault	Basic Ontology	Fuzzy Ontology
1	1.16	0.46	5.2	Arcing	HED, Arcing	HED, Arcing
2	0.07	5.43	5.26	OH	TF> 700 ºC	TF> 700 ºC
3	1.65	0.17	3.13	Arcing	HED, Arcing	HED, Arcing
4	1.06	1.74	9.26	Arcing	Undefined Fault	Undefined Fault
5	0.04	3.86	6.94	OH	TF> 700 ºC	TF> 700 ºC
6	0.97	1.79	7.06	Arcing	Undefined Fault	Undefined Fault
7	0.01	40.9	5.07	OH	TF> 700 ºC	TF> 700 ºC
8	3.25	0.08	17.75	PD	Undefined Fault	LED, Sparking, Arcing
9	0.02	3.09	7.44	OH	TF> 700 ºC	TF> 700 ºC
10	0.01	1.42	10.02	OH	TF> 700 ºC	TF> 700 ºC
11	2.74	1.54	13.42	Arcing	Undefined Fault	Undefined Fault
12	0.01	2.69	8.62	OH	TF> 700 ºC	TF> 700 ºC
13	2.93	0.09	6.6	Arcing	Undefined Fault	LED, Sparking, Arcing
14	2.26	0.29	10.82	Arcing	LEPD, Arcing, Sparking	LED, Sparking, Arcing
15	3.42	0.08	5.6	PD	Undefined Fault	LEPD
16	0.02	2.39	7.16	OH	TF> 700 ºC	TF> 700 ºC
17	3.3	0.07	16.5	Arcing	Undefined Fault	LED, Sparking, Arcing
18	0.02	2.4	6.7	OH	TF> 700 ºC	TF> 700 ºC
19	0	4.85	1.85	OH	300 ºC< TF< 700 ºC	300 ºC< TF< 700 ºC
20	1.45	0.84	14	Arcing	LED, Sparking, Arcing	LED, Sparking, Arcing

In summary, a novel application of fuzzy ontology for power transformer fault diagnosis has been developed in this research and real DGA data are employed to verify the developed two ontology models embedded in a multi-agent system. Based on the results shown in real case studies, it can be deduced that the fuzzy ontology is a promising technique that can significantly improve the performance of multi-agent based fault diagnosis and thus enhance the operation reliability of oil-immersed power transformers.

V. Conclusion

This work aims to develop a new framework for intelligent power transformer fault diagnosis using a basic ontology and a fuzzy ontology embedded in a multi-agent system. The use of agent-based ontology reasoning for power transformer fault diagnosis can improve the fault diagnosis performance compared with conventional server client-based systems using the basic ontology model. The proposed novel approach has been successfully implemented in order to increase the overall fault diagnosis accuracy for oil-immersed power transformers. The developed ontology reasoner provides a powerful and web accessible knowledge base, which is interoperable and scalable. It is applicable to various types of power transformers and can be easily upgraded online using advanced fault diagnosis features for accurate fault diagnosis. The application of the proposed technique could potentially benefit the operation reliability of power systems, as it could result in reduction of the number of engineering experts for data analysis, lower maintenance expenses and extended lifetime of power transformers.

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