Using Evidence Combination for Transformer Defect Diagnosis

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***Abstract*— This paper describes a number of methods of evidence combination, and their applicability to the domain of transformer defect diagnosis. It explains how evidence combination fits into an on-line and implemented agent-based condition monitoring system, and the benefits of giving selected agents reflective abilities. Reflection has not previously been deployed in an industrial setting, and theoretical work has been in domains other than power engineering. This paper presents the results of implementing five different methods of evidence combination, showing that reflective techniques give greater accuracy than non-reflective.**

I. Introduction

Condition monitoring is a key requirement for effective asset management. However, the volume of data generated can rapidly become overwhelming for engineers to deal with, and often requires expert analysis. An automated system for data capture and interpretation would greatly improve the usefulness of condition monitoring, ultimately increasing the reliability and longevity of plant.

This demands a flexible, reconfigurable system capable of integrating multiple data sources and interpretation techniques. Multi-agent systems (MAS) technology provides a structure for designing such a system, as different tasks can be encapsulated in separate agents. These agents can then use their social ability to co-ordinate their behaviour, and the system goal of data interpretation emerges rather than being explicitly stated. This allows new monitoring technologies to be seamlessly integrated into the community as they become available.

The COndition Monitoring Multi-Agent System (COMMAS)[1] was developed to exploit the benefits of MAS technology, by dividing the process of transformer defect diagnosis into tasks assigned to multiple agents. Transformers are key assets to utilities, making analysis of their health a pressing issue. Previous work has defined an architecture for condition monitoring[2] and the design and development of specific agents for defect diagnosis[3][4][5].

This paper will describe diagnostic steps taken by COMMAS, and the process of evidence combination previously employed by the system. We believed that the results of the evidence combination stage could be improved by implementing more sophisticated techniques; various schemes are described and tested on transformer defect data to validate this theory. Finally, conclusions are drawn about the most successful and flexible method of evidence combination for the application of condition monitoring.

II. Condition Monitoring Multi-Agent System

Partial discharge activity is caused by an electric field surrounding a conductor exceeding the dielectric strength of the conductor's insulation, resulting in an electrical discharge. Defects causing partial discharge can be introduced during manufacture or may be the result of degradation over time. Six classes of defect have been identified: bad contacts, floating components, suspended particles, protrusions, rolling particles, and surface discharges[6].

The purpose of COMMAS is to monitor sensors for data generated by partial discharge activity, then interpret the data to identify the defect type. The engineer is presented with defect diagnosis information, corroborated by data from multiple sensors and interpretation techniques. This process can be split into four stages:

- Data Monitoring: where data is collected from sensors and particular features extracted from it;
- Interpretation: where various intelligent system techniques try to classify the defect type, based on the feature vector;
- Corroboration: where a consensus is reached on the defect class, based on all available information; and,
- Information: where information from the diagnosis process is provided to engineers.

Each of these stages is performed by one or more agents, as shown in Figure 1. The three interpretation agents currently used by COMMAS (C5.0 Rule Induction, K-Means Clustering, and a Back-Propagation Neural Network) are detailed in [1] and [4], which document the design, training, and testing of these agents. The purpose of the Substation Manager Agent is discussed at length in [7], and details of the Engineering Assistant Agent can be found in [8].

The Transformer Diagnosis Agent must determine the most likely defect, based on the diagnoses from the three interpretation agents and defect positioning information from the Δt Calculation Agent. A weighted average scheme has been previously reported[1], where each agent provides its assessment of the probability of the defect belonging to each of the six classes. The conclusion of the Diagnosis Agent is then the defect class with the highest average probability.

However, years of research have shown that interpretation techniques will tend to classify particular defect types with more accuracy than other types, and each method is most accurate for different classes[4]. One of the key benefits of

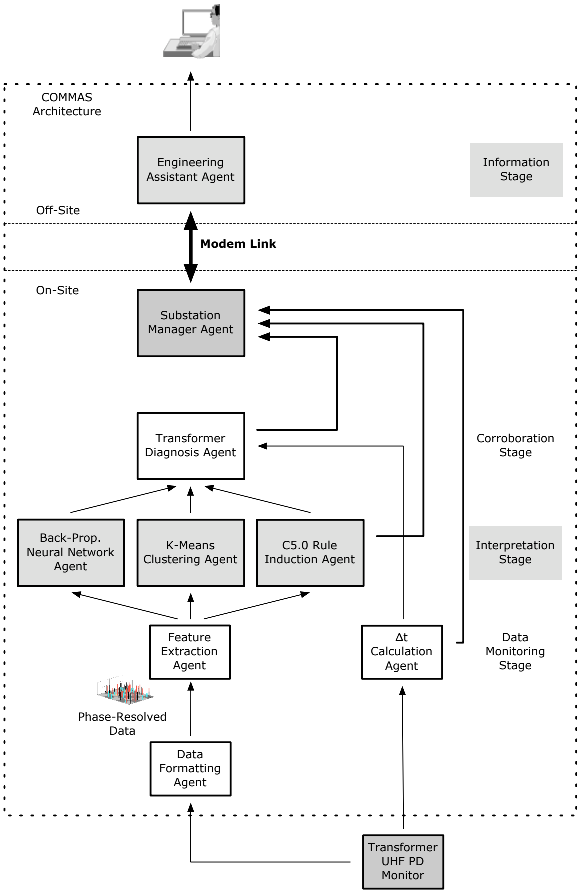

Fig. 1. The Agent Architecture of COMMAS

the COMMAS architecture is its ability to integrate complementary interpretation techniques, and use all available data to corroborate the final diagnosis.

It was believed that knowledge of the particular strengths of each of the interpretation agents could be used to enhance the corroboration process in the Diagnosis Agent. A more complex scheme for arbitrating amongst the diagnoses has the potential to produce more accurate results than the weighted average technique. In order to determine the validity of this hypothesis, a number of arbitration schemes were examined and the results compared.

III. Reflection in COMMAS

A. Reflective Agents

Reflection is a process of reasoning about where agent inputs come from, in addition to what those inputs are. A reflective agent has the ability to reason about other agents' behaviour, and why they are sending particular inputs[9]. This can help assess the meaning of messages received, by introducing a layer of meta-reasoning which gives perspective on the message content.

The agent behaviours producing reflective abilities can be divided into six categories[9]. A reflective agent need not implement them all, but useful abilities would generally arise from a selection of these behaviours. They are:

- Own Process Control: reasoning about their own abilities and goals;
- Agent Specific Tasks: the core behaviour of the agent;
- Agent Interaction Management: reasoning about the messages the agent is receiving or not receiving from other agents;
- Maintenance of Agent Information: ensuring the model of other agents' behaviour is consistent;
- World Interaction Management: reasoning about the inputs the agent is receiving or not receiving directly from the environment; and,
- Maintenance of World Information: ensuring the model of the agent's environment is consistent.

Reflection has been shown to be effective in a variety of arbitration situations[10], where meta-knowledge of situations in which classifiers perform well is used. The design of systems for on-line vehicle detection[11] and on-line workflow adaption[12] using reflective agents have been reported. However, reflection has not yet been applied to the power engineering or condition monitoring domains, and most work remains at the theoretical or demonstrative levels, rather than being used in industrial applications.

B. Making COMMAS Agents Reflective

The meta-reasoning abilities of reflective agents can be applied to the corroboration process in COMMAS, allowing the Transformer Diagnosis Agent to discriminate between any conflicting diagnoses received from other agents. This is done by providing the agent with meta-knowledge of the interpretation agents' strengths and weaknesses. It can then reason about where the diagnoses are coming from, instead of simply what the diagnoses are.

This means the Diagnosis Agent must hold information on every technique used in the system. If this knowledge were programmed into the Diagnosis Agent, it would remove flexibility from COMMAS, as new interpretation agents could not be added to the system without the Diagnosis Agent having prior knowledge of their abilities. To prevent this, interpretation agents should know their own strengths and weaknesses, and when they join the community they should send this knowledge to the Diagnosis Agent.

Applying the reflective task classification outlined above, each interpretation agent gains reflection on the Agent Specific Task. Rather than only providing defect diagnoses and probabilities, they now provide meta-knowledge of the situations in which they perform best.

The Transformer Diagnosis Agent gains the reflective tasks of Agent Interaction Management and Maintenance of Agent Information. This is due to the comparison between incoming defect diagnoses and the knowledge of the sending agent's abilities, which requires gathering and maintaining information on each interpretation agent. Additionally, the reflective Own Process Control task is needed to reason about which situations need discrimination between diagnoses. The task decomposition of the reflective Transformer Diagnosis Agent is shown in Figure 2.

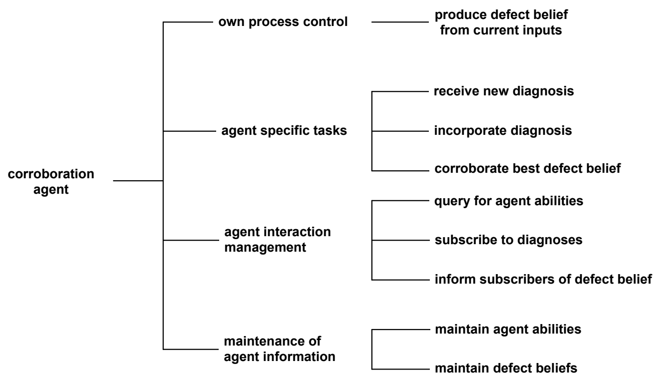

Fig. 2. Task decomposition of the reflective Transformer Diagnosis Agent

		Predicted Defect						
		BC	FL	PRO	RP	SD	SP	Undef.
A	BC	263	10	0	0	0	0	0
c	FL	0	95	10	42	80	52	18
t	PRO	17	11	95	34	47	84	7
u	RP	0	9	2	246	13	10	1
a	SD	0	9	3	3	204	37	9
l	SP	2	17	10	26	24	205	13

TABLE I

COINCIDENCE MATRIX FOR THE K-MEANS AGENT ON BAD CONTACT (BC), FLOATING ELECTRODE (FL), PROTRUSION (PRO), ROLLING PARTICLE (RP), SURFACE DISCHARGE (SD), AND SUSPENDED PARTICLE (SP) DEFECTS

IV. EVIDENCE COMBINATION

Whether the Transformer Diagnosis Agent uses reflection or not, it requires some algorithm to combine all the available evidence into useful and coherent defect information for the engineer. This process can be called data fusion or evidence combination, and there is a range of methods available, from the computationally simple to more complex schemes.

To assess the most accurate method of evidence combination for defect diagnoses, a number of schemes were compared. These are outlined in the following sections.

A. Non-Reflective

1) Weighted Average: This is the scheme previously employed by COMMAS[1]. Every interpretation agent produces probabilities of the defect belonging to each of the six defect classes. The overall probability of a defect class being correct is then calculated by:

$$\frac{\sum_{i=1}^{n} P_i(x)}{n} \tag{1}$$

where n is the number of agents who have submitted diagnoses, and $P(x)$ is the probability submitted by an agent of the defect class x being correct.

This technique tends to give a majority verdict, making it accurate in most cases, but it is susceptible to being misled by agents which are very confident of their diagnosis. Ultimately, agents with lower confidences can be correct. A detailed examination of this situation can be found in [2].

2) Dempster's Rule of Combination: This is a process for combining experts' testimony of the probability of particular outcomes[13]. In this application, the experts are the interpretation agents offering diagnoses, and the event outcomes are the six defect classes. Each expert produces probabilities of the defect belonging to each class, as in the Weighted Average process. This is used to calculate a probability mass for each agent, where probabilities are assigned to every set of outcome combinations.

For an example, let there be two defect classes, denoted FL (floating component) and SD (surface discharge). An interpretation agent may make the diagnosis that there is a 60% probability of the defect being FL, 20% of it being SD, and 20% unsure. This would give a probability mass of:

$$\emptyset = 0, \{FL\} = 0.6, \{SD\} = 0.2, \{FL, SD\} = 0.2$$

The agents' probability masses are then aggregated to produce an overall mass, according to Dempster's Rule:

$$m_{12}(A) = \frac{\sum_{B \cap C = A} m_1(B) \cdot m_2(C)}{1 - \sum_{B \cap C = \emptyset} m_1(B) \cdot m_2(C)} \tag{2}$$

Once the overall probability mass has been calculated, it can be used to generate degrees of *belief* and *plausibility* of each outcome. This is known as Dempster–Shafer theory. Assuming three agents' diagnoses have been combined, the equations are:

$$Bel_{123}(\{FL\}) = m_{123}(\{FL\}) \tag{3}$$

$$Pl_{123}(\{FL\}) = 1 - Bel_{123}(\{SD\}) \tag{4}$$

The defect class with the highest belief is the one for which there is most supporting evidence among the agents, and so this is the Diagnosis Agent's final decision.

B. Reflective

During the testing stage of the development of each interpretation agent, a coincidence matrix was compiled of the actual class and predicted class of each test defect[4]. This gives precise information about the accuracy of each interpretation technique diagnosing the six classes. Table I shows the coincidence matrix for the K-Means interpretation agent. This matrix is used as the report of agent abilities, which the Transformer Diagnosis Agent needs to reflect on the agents' diagnoses. Every method described in the following sections will use this information to reason about the messages it receives.

1) Winner-Takes-All: Computationally very simple, but reportedly very successful[10], this requires reflective capabilities to assess which agent is most often accurate for the defect class they are diagnosing. The class chosen by this agent is then taken as the final diagnosis.

For example, if one agent diagnoses a surface discharge with 80% probability, and another concludes the defect is a rolling particle with 65% probability, a comparison is made between the accuracy of the first of diagnosing surface discharges and the second of diagnosing rolling particles. If the coincidence matrices reveal that for 300 surface discharge defects, the first agent was correct 78% of the time; and for 300 rolling particle defects, the second agent was correct 95% of the time; then the diagnosis of the second agent is taken over that of the first. The final conclusion of the Diagnosis Agent will be that the defect is a rolling particle.

2) Evidential Reasoning: Based on Dempster–Shafer Theory, with its foundations in Dempster's Rule of Combination, Evidential Reasoning is a way of assessing the strength of evidence supporting a particular defect diagnosis. It has been previously applied in the domain of transformer condition monitoring[14], but not specifically to defect classification.

It is better suited to condition assessment, as it requires the definition of a range of grades where H_{n+1} is always better than H_n, such as:

$$\begin{aligned} H &= \{H_1, H_2, H_3\} \\ &= \{Critical, Poor, Normal\} \end{aligned}$$

In COMMAS, the grading would contain the six defect classes, but there is no simple way of defining them as better or worse than each other. Future research may investigate the use of similarity measurements to allocate a grading of defects, but Evidential Reasoning is currently not applicable to COMMAS.

3) Bayesian Inference: Bayes' Theorem is used to determine the probability of an event based on some evidence, when the causal probability of the event on the evidence is easier to assess. In its simplest form, Bayes' rule is:

$$P(D|E) = \frac{P(E|D) \cdot P(D)}{P(E)} \quad (5)$$

$$= \frac{P(E|D) \cdot P(D)}{P(E|D)P(D) + P(E|\neg D)P(\neg D)} \quad (6)$$

where $P(D|E)$ is the probability of a defect D occurring, given some evidence E. This can be used to infer how likely a defect type is, given the evidence of an agent diagnosing it.

For example, if an agent diagnoses a surface discharge with 87% probability, and the coincidence matrix indicates that this agent correctly diagnoses surface discharges 81% of the time, the probability of the defect being a surface discharge, given that the agent is saying it is, is calculated by:

$$P(D_{SD}|E_{SD}) = \frac{0.81 \cdot 0.87}{0.81 \cdot 0.87 + (1 - 0.81)(1 - 0.87)}$$

The defect class with the highest probability, given the evidence, is the Diagnosis Agent's final decision.

4) Bayesian Belief Network: A Belief Network is a graphical representation of the influence certain variables have on others. The design of such a network begins with the identification of root causes, which become the first nodes in the network. Next, variables which are directly affected by those root variables are added, and then variables directly affected by these new nodes. This process is repeated until all variables are included in the network. Probabilities are then assigned to each node: independent probabilities to the root nodes, and dependent probabilities to all others.

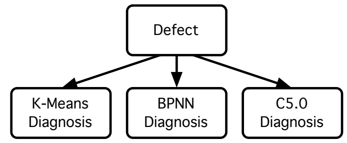

Fig. 3. A Bayesian Belief Network of defect diagnosis

The Belief Network for defect diagnosis is quite small (see Figure 3). There is only one root node: a defect; and the diagnoses of each interpretation agent are dependent on it. The coincidence matrices are used to calculate the dependent probability tables for each of the non-root nodes.

This network is used to find the probability of a certain defect class, given the situation that two agents diagnose a surface discharge and one a rolling particle. This is given by:

$$P(D_{RP}|KM_{SD} \wedge BP_{SD} \wedge C5_{RP}) = \frac{P(KM_{SD}|D_{RP})P(BP_{SD}|D_{RP})P(C5_{RP}|D_{RP})P(D_{RP})}{P(KM_{SD})P(BP_{SD})P(C5_{RP})}$$

where KM_{SD} means the K-Means agent diagnoses a surface discharge, BP_{SD} means the Back-Propagation agent diagnoses a surface discharge, $C5_{RP}$ means the C5.0 agent diagnoses a rolling particle, and D_{RP} means the defect is a rolling particle. The defect class with the highest probability, given the diagnoses of the other agents, is the Diagnosis Agent's final decision.

V. Results

In order to determine whether reflective knowledge improves diagnosis, and reach a conclusion about the most accurate technique for COMMAS, the five schemes discussed above were implemented in separate Diagnosis Agents. All five Diagnosis Agents were then deployed in COMMAS simultaneously, and the resulting diagnoses from a series of test datasets were compared.

The datasets were captured from defects simulated in laboratory experiments. In total, 3700 partial discharge patterns were classified: 327 bad contacts, 917 floating electrodes, 733 protrusions, 447 rolling particles, 871 surface discharges, and 405 suspended particles. This gives an average of 617 patterns per defect type.

The results are shown in Table II.

VI. Discussion

The results support the hypothesis that reflective reasoning about the strengths of each Interpretation Agent improves the accuracy of the Diagnosis Agent. The original Weighted Average scheme is correct 63% of the time, whereas all reflective techniques are over 72% accurate. The more complex non-reflective technique—Dempster's Rule of Combination—performs even more poorly than Weighted Average, suggesting that the reflective schemes are not better just because they are more complicated.

Of the reflective methods of evidence combination, Winner-Takes-All and Bayesian Inference performed very similarly.

Defect Class	Weighted Average	Dempster's Rule of Combination	Winner Takes All	Bayesian Inference	Bayesian Belief Network
BC	83.79	85.63	86.85	86.85	97.55
FL	50.96	38.40	65.54	63.36	68.05
PRO	34.59	34.38	57.84	56.07	59.75
RP	65.32	36.24	83.45	83.45	81.21
SD	70.03	69.35	60.73	60.39	61.88
SP	73.09	62.72	82.47	84.69	82.72
Average	63.0	54.5	72.8	72.5	75.2

TABLE II

PERCENTAGE ACCURACY OF THE FIVE DIAGNOSIS TECHNIQUES

By re-examining these algorithms, it can be seen that Bayesian Inference is a more complex way of choosing a winning agent, but essentially still a winner-takes-all technique. Bayes' Theorem is used to calculate the likelihood of an agent's diagnosis being correct, and the diagnosis with the highest likelihood is the Diagnosis Agent's final decision. The Winner-Takes-All algorithm calculates likelihoods directly from the coincidence matrices without using Bayes' Theorem, but is otherwise the same. Therefore, it is to be expected that their accuracies are similar.

The most accurate algorithm is the Bayesian Belief Network. It differs from the other reflective techniques in that it considers all available evidence in one equation, rather than determining the 'best' agent's diagnosis. This means it has the potential to give counter-intuitive results that no other technique could provide, such as a particular combination of diagnoses making an undiagnosed defect class most likely.

The Bayesian Belief Network is constructed flexibly: when diagnoses are produced by Interpretation Agents, nodes are added to the network. This is only at the conceptual level; in the implementation of the Diagnosis Agent, terms are added to an equation to accomodate new diagnoses. As a result, we can integrate new Interpretation Agents and data sources in the future; no modification of the Diagnosis Agent will be required.

VII. CONCLUSION

The accuracy of the diagnosis produced by COMMAS is dependent on the output of the interpretation agents, and on how this is combined to create a final defect diagnosis. This paper presents a number of schemes for evidence combination, and explains how they can be applied to COMMAS. A comparison of the accuracy of each method reveals that reflective knowledge significantly benefits the diagnosis process, and that within the reflective techniques, the Bayesian Belief Network performed best.

A Bayesian Belief Network populated by reflection is therefore the method of evidence combination used by the COMMAS Diagnosis Agent.

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