AGENT-BASED TECHNOLOGY FOR DATA MANAGEMENT, DIAGNOSTICS AND LEARNING WITHIN CONDITION MONITORING APPLICATIONS

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ABSTRACT

Online condition monitoring systems are used to prolong the life of electrical power equipment by continually monitoring for any signs of faults. To be of most use, a condition monitoring system should be flexible enough to accommodate various sensors and different data interpretation techniques. To provide such flexibility this paper proposes an agent-based architecture, where autonomous modules (agents) perform separate parts of the data management and interpretation tasks. This means that only the agents associated with required tasks need to be deployed. This paper presents an example of a flexible agent-based system that can be used to diagnose defects in a power transformer using data from various sensors.

The agent-based architecture also provides an extensible framework to integrate different types of data interpretation. This paper shows this by detailing the addition of further interpretation agents for pattern recognition, diagnosis and learning. One employs a knowledge-based approach to diagnose defects in transformers, based on fundamental partial discharge behaviours. Other agents provide on-line learning of the plant behaviour, automatically identifying normal and abnormal modes, leading to advanced anomaly detection capabilities.

KEYWORDS

Condition Monitoring, Multi-Agent Systems, Power Transformers.

INTRODUCTION

Power transformers are valuable pieces of high voltage equipment. Detecting faults within the transformer has many economic benefits. These include providing time to take action, reducing unplanned power outages and improving the safety of personnel. Condition monitoring is intended to detect a fault by continually monitoring a transformer. The earliest sign that a fault is occurring within the insulation in a transformer is the presence of a partial discharge (PD) signal.

Defects cause PD by lowering the dielectric strength of the insulation system. In a power transformer, this may take the form of protrusions, metallic particles, moisture, or poor contacts, and could be introduced during manufacture, or result from degradation over time. Different types of defect display different partial discharge patterns [1], but the relationship between discharge characteristics and defects is not well understood.

A PD generates an electromagnetic signal in the Ultra High Frequency (UHF) range. This signal can be captured by UHF sensors mounted on special dielectric windows [2]. Each pulse can be plotted on a three dimensional axis consisting of the *pulse's relative amplitude*, the *cycle number* on which the pulse appears and the *phase position* of the pulse on the voltage cycle. Consecutive pulses generated by a defect present in the transformer can be combined to create a 3D Phase-Resolved Partial Discharge (PRPD) pattern representing a one second (50 cycle) snapshot of PD activity, see Figure 1. Artificial Intelligence techniques can use this PRPD pattern to diagnose a defect within a transformer.

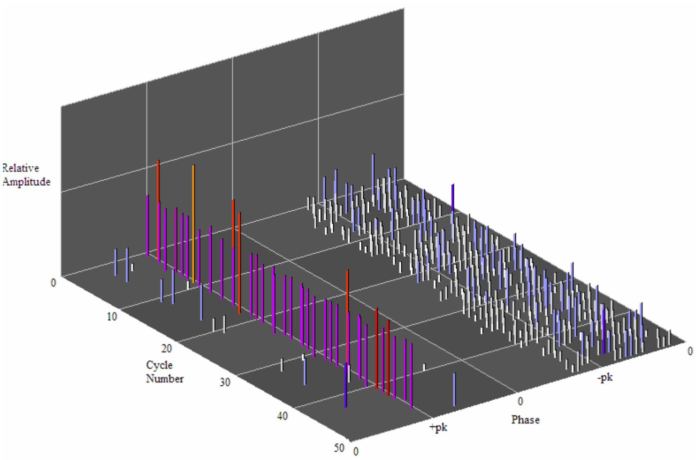

Figure 1 – PRPD Pattern showing a one second snapshot

An alternative way to measure the PD is by using conventional equipment to measure the apparent charge (IEC 60270) levels [3] within the transformer. This data can also be used to diagnose a defect. This paper describes an agent-based condition monitoring architecture and how it can be used to diagnose the data captured from these two sensors. This paper also describes how two specific sets of interpretation agents can individually achieve defect diagnostics from the data captured by the UHF sensor, along with how they can be incorporated in the agent-based architecture.

AGENT-BASED ARCHITECTURE

The COndition Monitoring Multi-Agent System (COMMAS) [4] is an overall transformer monitoring system, which employs an agent-based approach to the diagnosis of PD data, see Figure 2.

Why Agents are Required

Diagnosing the cause of the discharge gives information about how urgently it must be dealt with, and what type of maintenance is required. For this reason, a number of Artificial Intelligence techniques were trained to classify defects on the basis of PRPD patterns [4]. However, no single technique proved accurate at classifying all types: rather, each technique had strengths and weaknesses. It was recognised that an accurate system of diagnosis would incorporate many different data interpretation methods, and preferably use multiple types of sensor, to give the most complete picture of plant health.

Such a system requires a way of integrating different components, allowing sensors and interpretation techniques to be easily added and removed from the diagnosis process. This can be achieved with agent technology, where different tasks are encapsulated by individual autonomous agents, co-operating to fulfil their goals. Agents can be designed to conform to certain standards for communication, such as protocols and message formats developed by the Foundation for Intelligent Physical Agents (FIPA) [5], ensuring that messages sent between agents can be understood and data exchanged as needed.

Agents pass messages, rather than directly invoking the functions of other system components, allowing new agents to easily be added to the system without reprogramming existing ones. Agents advertise the services they offer through a facilitator agent, which others can consult to locate the services they need. For example, an agent which classifies a defect type from PRPD patterns may advertise a service called DefectClassification, and others looking for transformer health information can find and contact all the agents offering this service. When a new classification agent is added to the system, it only has to notify the facilitator that it offers the DefectClassification service before others can find it.

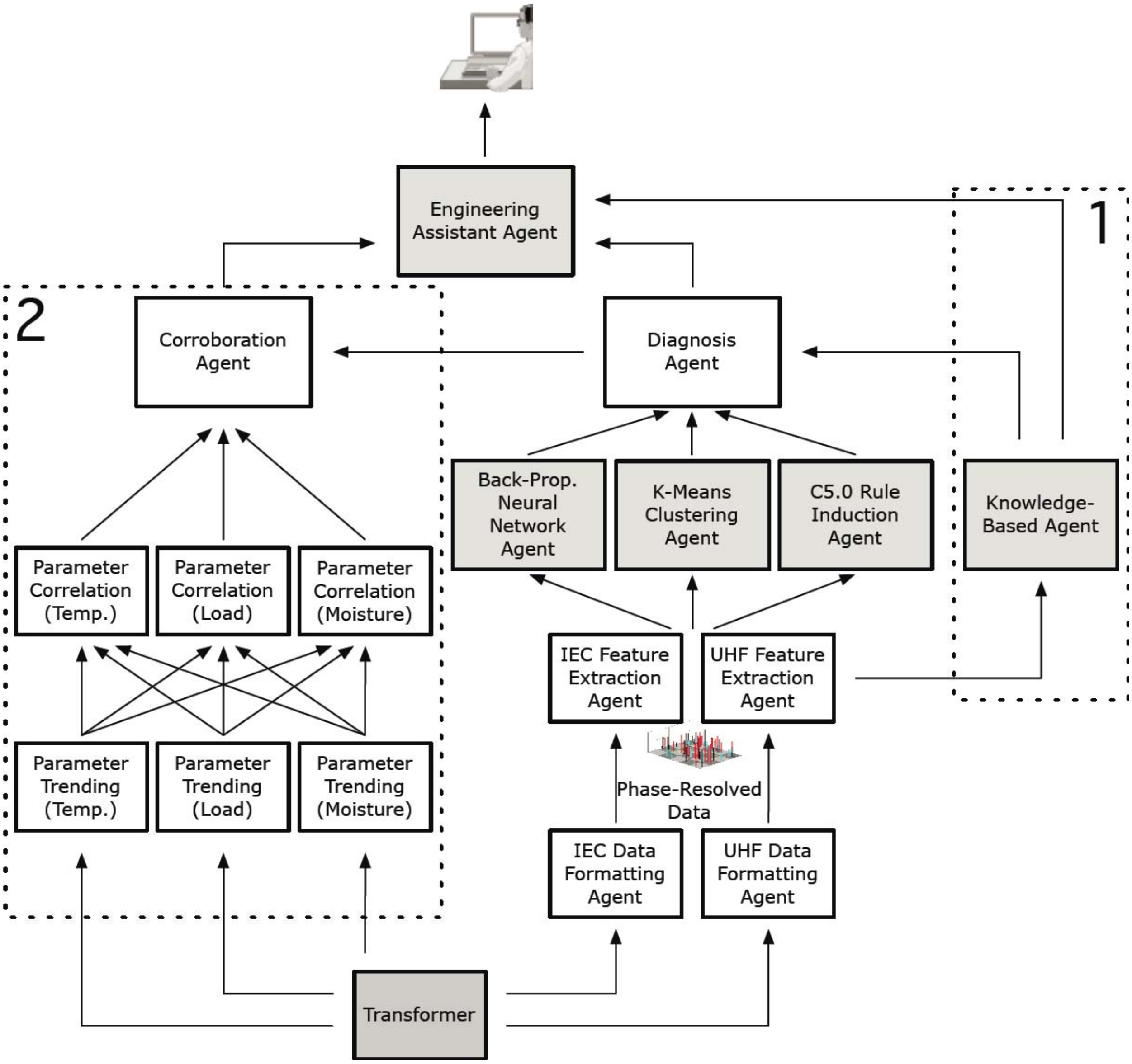

Figure 2 – COMMAS Architecture showing the integration of two specific sets of interpretation agents in the dashed boxes

This property of flexible integration of different components matches the requirement that the partial discharge diagnosis system accommodates multiple data interpretation techniques and sensors. Initially, agents for three different classification techniques and two types of sensor were developed: these are described in the following section. The remaining parts of the paper examine how easily new interpretation methods could be added to the existing system, and the benefits they give to the health monitoring process.

Initial System Agents

Two different types of sensor were used to capture partial discharge data. The first, a UHF sensor, detects electromagnetic energy radiated from a partial discharge, while the second uses an electrical connection to detect the apparent charge of a discharge (specified by IEC 60270). Both types of sensor can be correlated with the input voltage at the time of the discharge, giving a phase-resolved partial discharge pattern (see Figure 1).

The task of the two Data Formatting Agents is to collect data from each sensor and parse it into a standard format for other agents to understand (Figure 2). The Feature Extraction Agents take formatted data from their corresponding Data Formatting Agent, and calculate from it a set of 101 features. These include basic, deduced, and statistical features shown to help identify defect types [6]. The feature vectors produced by these two agents contain the same features, allowing any feature vector-processing agent to understand vectors originating from either type of sensor.

This means that all three Interpretation Agents (C5.0 Rule Induction, K-Means Clustering, and Back-Propagation Neural Network) can classify defects from either Feature Extraction Agent, despite being trained only on data from UHF sensors. These three agents diagnose each feature vector as being caused by one of six defect types: bad contact, floating component, suspended particle, protrusion, rolling particle, or surface discharge.

The Diagnosis Agent is responsible for corroborating evidence of defects, and determining the most likely state of the transformer. It gathers diagnoses from the Interpretation Agents, and also historical information about each agent's accuracy. This is used to construct a Bayesian Belief Network, and calculate the probability of each defect being the cause of the partial discharge. The defect type with the highest probability is the one with the most supporting evidence, and is therefore determined to be the partial discharge cause.

Finally, the Engineering Assistant Agent automatically collects information from the Diagnosis Agent about any defect diagnoses produced, and displays it to engineers. If the engineer requests it, this agent can also collect lower level data, such as the PRPD pattern.

Options for Extension

This initial set of agents give a system for classifying which type of defect is most likely responsible for each PRPD pattern. It can automatically alert engineers to new defect diagnoses, and allows investigation of each diagnosis by examination of lower level data. However, there are some areas where the usefulness of the system could be improved.

The first issue is that the data-driven approach of defect classification gives no explanation of why a particular defect type was chosen over another. Each of the Interpretation Agents turns a feature vector into a defect class and probability, which the Diagnosis Agent uses to provide an overall defect class and probability. However, other than the set of classifications and probabilities, the feature vector, and the phase-resolved pattern, there is no information available about where the diagnosis came from.

Giving the engineer an indication of which features of the pattern caused a particular diagnosis would increase the confidence placed in that diagnosis. An explanation of how a defect type could cause partial discharge to occur in this pattern would show the engineer how the conclusion was reached, and allow verification of the reasoning process. This can be achieved using a knowledge-based approach to the interpretation of PRPD patterns, and is described in the knowledge-based approach section.

In addition to partial discharge, other parameters of the transformer are often measured, such as temperatures, gas levels, and power factor. These give information about the health of the transformer, but in a more plant-specific way than partial discharge. Deviations from normal operating levels may indicate degradation, but the normal operating levels of each parameter may differ from transformer to transformer.

As a result, making use of these parameters for health monitoring really requires learning their normal envelope on a plant-by-plant basis. Additionally, this has to be as generic a process as possible, to handle whichever parameters are being measured. The learning process and agents required are described in the on-line learning section.

INTERPRETATION AGENTS

Due to the extensible framework offered by the agent-based architecture different types of interpretation agents can be incorporated into the system to perform further defect diagnostics. Figure 2 illustrates how the two additional sets of interpretation agents mentioned in this paper can be integrated to the previously described agent-based architecture.

Knowledge Based Approach

In the past, research into new interpretation agents included the "black box" natured techniques of neural networks and clustering algorithms. These techniques required little knowledge regarding the PD behaviours and defect types. As further knowledge was gained about the PD behaviours it became possible to employ a knowledge-based system to automatically diagnose a defect from the PRPD pattern. This type of system not only offers further classification of the defect but also introduces explanation of the diagnosis, which provides the user with confidence in the system output. To create a knowledge-based agent first the knowledge needs to be captured and modelled, which is achieved through knowledge engineering techniques.

Knowledge Engineering

Knowledge elicitation is the first stage of the knowledge engineering process. Interviews and case studies are exercised to capture the knowledge that has become second nature to the expert. This type of knowledge is called tacit knowledge and is the hardest to articulate. Once this knowledge has been captured it needs to be represented in model form. Displaying the knowledge in this way makes it easier for the expert to understand and validate. A range of tools are available to support the knowledge representation stage, with CommonKADS [7], an extension of KADS (Knowledge Analysis and Design Support), being the most widely applied.

CommonKADS is the product of research since 1983 and is the leading methodology to support structured knowledge engineering. "A major contribution of the KADS approach is its proposal for structuring the Expertise Model" [8]. This model splits the knowledge into three categories; the task knowledge, inference knowledge and domain knowledge. Each of the three categories are modelled using Unified Modelling Language (UML) diagrams [9].

The first knowledge category identified in CommonKADS is the task knowledge, which describes the goals and how they can be accomplished through the use of subtasks and the inferences. The inference knowledge describes the steps that are required to be taken to reach a goal. This is achieved by making use of the domain knowledge, which is knowledge about the overall topic in an application. Once the knowledge has been acquired and represented it needs to be validated by the expert. Any changes to the knowledge are incorporated and the knowledge is then able to be constructed as rules in a rule-based system.

Diagnosis Process

Knowledge elicitation interviews with experts highlighted an incremental process to the diagnosis of the PRPD pattern. This process is shown in a UML activity diagram in Figure 3. The expert knowledge is required at each of the five stages in the diagnostic process. This knowledge, captured using the knowledge engineering techniques described previously, is used in the system in the form of *IF* condition *THEN* action. These rules are implemented in a forward chaining rule-based system, which takes in the data and matches the condition part of the rules to reach the actions. Placing these actions in working memory allows them to be incorporated in later stages of the system to diagnose a defect.

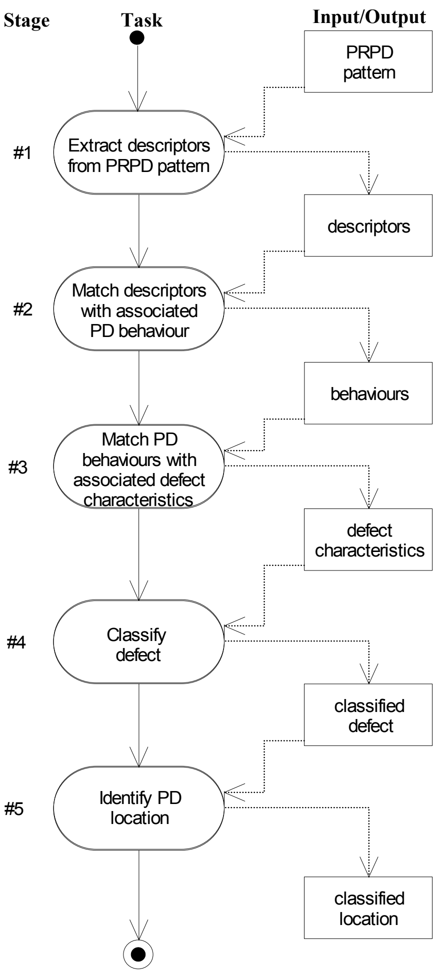

Figure 3 – UML Activity Diagram of the PD diagnosis

Stage #1 extracts descriptors from the PRPD pattern by using Gulski's statistical features [6]. These descriptors, identified and defined by the expert during interviews, include magnitude, phase position, symmetry, shape, skewness, phase range and density. The data used to extract these descriptors is supplied by the feature vector generated from the UHF Extraction Agent, see Figure 2. Once these descriptors have been identified they are passed into stage #2 of the system. Here the PD behaviours associated with these descriptors are matched and displayed to the user. The PD behaviours are also passed back into the system where they are matched with the defect characteristics in stage #3. These results are also displayed to the user and are then used to classify the defect in stage #4. Once the defect has been classified it is utilized along with the knowledge already gained to identify the PD location. Displaying the associated expert knowledge at each stage of the system will provide the user with confidence in the final classification by explaining how the system reached its conclusion.

Since the expert knowledge is separated into the five individual stages described above, as new knowledge of PD behaviour, defect characteristics or defect classification are introduced by additional experts, or through further understanding of the PRPD pattern, additional knowledge can easily be added to the corresponding stage of the knowledge-based system. This offers an extensible system for automated PD diagnostics. It is also believed that the knowledge used by this system could be generic for different electrical apparatus, which would offer a flexible system for PD diagnosis in equipment other than the transformer.

The dashed box in Figure 2 depicted with a 1 shows how this knowledge-based system can be integrated within COMMAS to provide further data handling and interpretation functions. Not only will the integration of this system provide additional diagnostic capability, but it will also introduce a practical explanation for why a particular defect was diagnosed, and so enhance the user's confidence in the diagnosis. The diagnosed defect is sent to the Diagnosis Agent to determine the most likely state of the transformer, while the explanation is sent to the Engineering Assistant Agent to be displayed to the user.

On-line Learning

The original set of agents were trained to recognise patterns of discharge captured from defects constructed in the laboratory. A potential issue is that transformers do not all behave in the same way, and what is normal behaviour in one may be indicative of incipient failure in another. One way of overcoming this is to learn normal patterns of behaviour on a per-transformer basis. It would also be useful to corroborate partial discharge data with other available data sources, such as temperatures, load levels, and moisture content of the oil.

However, there is no standard set of parameters used for transformer monitoring; rather, there is a large set of health indicators of which an arbitrary subset may be available for any particular transformer. Most transformers have periodic off-line oil sampling, which reveals levels of dissolved gases and moisture. This would be available from a database, but live information will be available for some transformers from on-line sampling. Many transformers will have one or more temperature sensors, and some will have measurements such as the dissipation factor of the insulation (tan delta), voltage, and current.

The challenge is to treat all data sources in a generic way, in order to simplify the handling of whatever types of sensors are available without making a requirement of particular parameters. Additionally, normal behaviour of each parameter must be learned for each transformer, to distinguish normal changes from concerning ones.

Parameter Behaviour

The trend of a parameter can be characterised by four things: its maximum and minimum values, its maximum positive rate of change, and its maximum negative rate of change. These can be learned over a period of time when the transformer is expected to behave normally, such as near the start of its life, or a typical month in service. Comparison of the learned values with measured values will indicate whether a parameter has experienced no change, gradual drift, or dramatic change since the learning period.

However, health of the transformer is related to the parameters in a fairly complex way. If a single parameter changes dramatically while all others remain within normal bounds, this could be due to a sensor failure or a problem with the transformer. Looking for changes across parameters is not fully reliable either, as an increase in transformer load would legitimately be associated with an increase in temperature. Indeed, an increase in temperature without an increase in load is more of a cause for concern.

This leads to a requirement for two levels of learning. The first level is to characterise each parameter, in terms of its maximum, minimum, maximum positive rate of change, and maximum negative rate of change values. The second is to learn how pairs of parameters change. Each pair could be labelled as:

- unrelated (a change in one does not affect the other),
- related (an increase in one is associated with an increase in the other), or
- inversely related (an increase in one is associated with a decrease in the other).

The two levels of learning can occur together, and may be occasionally repeated to adjust to normal ageing of the transformer. After the learning period, changes to parameters can be compared with the others to assess the significance of the change.

A subject for continued investigation is setting the precise level of significance of changes. Initial consultation with industry suggests that transformer condition should be classified as Serious, Unusual, or Normal on the basis of parameter changes as follows:

- Serious: a change of 25% to any maximum or minimum value; or a change of 10% to any single rate of change; or three or more Unusual changes.
- Unusual: a change of 10% to any maximum or minimum value; or a change of 5% to a rate of change.
- Normal: Maximum and minimum values within 10% and rates of change within 5% of learned values.

Indications of Serious or Unusual behaviour to engineers may optionally be inhibited if the changing parameter is accompanied with a predicted change in a related or inversely related parameter, as learned from previous behaviour. An example of this would be if a change of load went above 10% of the maximum learned value, and this was accompanied by similar increases in top oil temperature and winding temperature. The Engineering Assistant Agent could be set to not alert the engineer to this Serious condition (three Unusual changes) because all three parameters are changing consistently. This would prevent engineers being overloaded with reports of parameter changes when the behaviour is in response to unusual but non-fault conditions.

The percentage changes for determining each state will be verified in future work by experimentation with historical data.

Parameter Agents

Monitoring parameters in this way gives an indication of health, rather than diagnostic information. Coupling it with the interpretation of partial discharge data can produce a more holistic view of the transformer's health, and help determine how serious a defect may be. This can be achieved by implementing parameter monitoring as agents, and deploying them within the community as shown by dashed box 2 in Figure 2.

Each parameter has an associated Parameter Trending Agent, for learning its characteristics and measured data comparison. Additionally, a Parameter Correlation Agent learns how that parameter varies in relation to the others, characterising each pair as unrelated, related, or inversely related, and detecting deviations from the learned relationship. Finally, the Corroboration Agent monitors parameter trends and correlations, and partial discharge diagnoses, to classify transformer health as Serious, Unusual, or Normal. This information is sent to the Engineering Assistant Agent to alert engineers to changes in state.

CASE STUDY

This case study shows the diagnosis of a protrusion defect in a power transformer. A protrusion defect is caused by fixed, sharp metallic objects on conductors inside the transformer. A UHF sensor was used to capture a PRPD pattern from a protrusion defect set up in the laboratory (such as that shown in Figure 1), which was passed to the COMMAS agents for diagnosis.

Passing this PRPD pattern into COMMAS showed the following output from the agents in the original architecture:

Interpretation Agents	**Diagnosed Defect**	**Probability**
C5.0 Rule Induction	Protrusion	84.8%
K-Means Clustering	Protrusion	58.6%
Back-Propagation Neural Network	Surface Discharge	27.6%

Table 1 – COMMAS Diagnosis

The Diagnosis Agent then corroborated these results and correctly gave an overall diagnosis of a protrusion defect.

Passing the same PRPD pattern into the knowledge-based system described in this paper supports this diagnosis of a protrusion defect. This knowledge-based system also provides explanation to its classification at its various stages of diagnosis, see Table 2. Each stage of the diagnosis can be acquired by the user, allowing him to gain justification of the classification at a desired level.

Stage	Task	Output
1	Split PRPD Pattern into Descriptors	Skewness of distribution in negative and positive half cycles close to zero *implies* the "discharges are located on the voltage peaks".
2	Match Associated PD Behaviour	The discharges located on the voltage peaks *implies* "discharge dependent on absolute voltage". This suggests that the discharge is governed by external field, which *implies* minimal space charge present i.e. little "memory" effect.
3	Match Associated Defect Characteristics	Minimal space charge present i.e. little "memory" effect *implies* "discharge at an SF_6 to metal interface".
4	Classify Defect	Discharge at an SF_6 to metal interface **AND** Energetic discharge (knife blade shape on positive half cycle) implies "Protrusion Defect in SF_6".
5	Identify PD location	"Protrusion Defect in SF_6 **AND** Magnitude on Positive Phase > Negative Phase" implies "Protrusion in SF_6 on High Voltage Conductor".

Table 2 – Knowledge-Based Diagnosis

The integrated system, shown in Figure 2, displays to the user the output of the three original classifiers in COMMAS along with the diagnosis from the incorporated knowledge-based agent. Not only will the addition of the knowledge-based agent provide a further diagnosis but it will also give the user an explanation as to why this defect was identified, thus increasing the confidence in the overall result.

CONCLUSIONS

Power transformers currently have a life span of 25-50 years. This can be increased by the use of condition monitoring techniques. This paper has described how an agent-based architecture, COMMAS, can be used to diagnose a defect from PD data captured from a transformer. The flexibility of this agent-based architecture has made it possible to diagnose defects from various sensors, as illustrated in this paper.

This paper also shows the addition of further sets of interpretation agents for pattern recognition, diagnosis and learning. One agent, described in this paper, achieves automatic PD diagnosis by a knowledge-based approach. At present only a limited number of experts are able to identify features from a PRPD pattern and therefore classify the defect that created the pattern. Introducing a knowledge-based system, with this expert knowledge, to COMMAS will not only provide further diagnosis, but it will also introduce a practical explanation of why such a defect was diagnosed, and so enhancing the user's confidence in the diagnosis.

Other agents, which can be incorporated into COMMAS extensible framework, provide on-line learning of the plant behaviour, automatically identifying normal and abnormal modes, leading to advanced anomaly detection capabilities. These on-line learning agents are described in this paper to achieve further data interpretation handling.

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