The Design of a Multi-Agent Transformer Condition Monitoring System

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***Abstract*—Online diagnostics and online condition monitoring are important functions within the operation and maintenance of power transformers. This paper describes how a multi-agent system (MAS) for transformer condition monitoring has been designed to employ the data generated by the ultra high frequency (UHF) monitoring of partial discharge activity. It describes the rationale behind the use of multi-agent techniques, and the problems overcome through this technology. Every aspect of the MAS design is discussed. In addition, the design and performance of the intelligent interpretation techniques are detailed.**

***Index Terms*—Co-operative systems, decision support systems, intelligent systems, monitoring, multi-agent systems, partial discharges, power transformers, UHF measurements.**

I. INTRODUCTION

AN increasingly competitive marketplace, stringent regulatory demands and ageing electrical plant are some of the issues which have established asset management and condition monitoring as key business objectives among asset owners within the electricity supply industry [1].

Effective condition monitoring and asset management plays a significant role in improving the performance, reliability and longevity of electrical plant. The backdrop to this requirement is ever increasing financial constraints married with reductions in manpower and expertise. Technology is seen as a means of solving the asset management problem, driving the research and development of advanced monitoring systems with a view to implementing condition-based maintenance regimes.

As a result, an increasing volume of condition monitoring data is captured and presented to engineers. This leads to two key problems: the data volume is onerous for engineers to deal with; the relationship between the plant item, its health and the condition monitoring data generated is not always well understood. Therefore, the extraction of meaningful information from the condition monitoring data is difficult.

A complete condition monitoring and asset management approach, which tackles these issues, is therefore required. To illustrate this approach, condition monitoring of power transformers has been selected as the major application covered in this research because it represents a significant issue for electrical utilities. Recent research has demonstrated the efficacy of employing ultra high frequency (UHF) measurement of partial discharge (PD) in the monitoring of transformers [1]. This paper describes a condition monitoring architecture that can support the capture and interpretation of UHF diagnostic data and provide engineers with meaningful diagnostic advice using agent-based and intelligent system technologies. The system is extensible and can incorporate the output from other monitoring technologies.

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II. CONDITION MONITORING REQUIREMENTS ANALYSIS

A. UHF Monitoring Data Issues

Electrical discharges, which do not completely bridge the distance between two electrodes, are known as PDs. PD activity exists where an electric field surrounding a conductor exceeds the dielectric strength of the conductor insulation. In practical terms, PDs can occur in items of electrical plant as a result of temporary over-voltage, an incipient weakness in the insulation introduced during manufacturing or as a result of degradation over the plant lifetime [1]. Insulation weaknesses (or defects) manifest themselves in a number of ways. Different classes of defect type result in PD activity in oil filled power transformers. These include: bad contacts, floating components, suspended particles, protrusions, rolling particles, and surface discharges [2]. UHF measurement of PD data is seen as a method of detecting such problems. References [1] and [2] provide extensive details about the implementation of the UHF approach, including details of the separation of noise from actual discharges.

UHF-based PD monitoring suffers from the typical problems associated with all forms of online condition monitoring. A snapshot of PD activity can be taken every few seconds. This leads to an overwhelming volume of data *per transformer* to be interpreted by engineers. When this is multiplied by the number of transformers to be monitored, the problem of data overload becomes insurmountable in terms of manual data interpretation. The second problem is the limited base of experts able to interpret the complex UHF data. The third issue is that UHF monitoring is only one technology applicable to the monitoring of transformers. The monitoring of electrical load, temperature, dissolved gas in oil measurements, acoustic measurements, etc, could complement this. Thus, there is a longer term requirement for the integration of further monitoring technologies. The extensive range of transformer monitoring technologies available are detailed in [3].

B. Functional Requirements of UHF Monitoring System

Based on the problems identified in Section II-A the requirements of an online UHF condition monitoring system are:

- automatic capture and conditioning/formatting of relevant data;

- automatic interpretation of the conditioned/formatted UHF data to identify incipient and serious defects;
- discrimination between a sensor failure and an actual plant failure. This is achieved by corroborating the interpretation results and sensor data with other relevant data sources;
- the provision of clear and concise defect *information* and remedial advice to the operational engineers;
- extensibility and flexibility to include further interpretation techniques and monitoring technologies.

The extensibility criterion is essential for longevity and practical implementation. The architecture must be scalable and support the introduction of new sensors, data sets and interpretation techniques as they become available. This suggests that each of the required functions should be standalone, with the ability to cooperate and exchange data/information as required.

III. Design of the Condition Monitoring Architecture

A. Functional Design

The requirements discussed in Section II led to the design of a "layered" condition monitoring system, where functional modules are grouped by their overall goal. Architecturally, the condition monitoring system uses distributed modules that have no constraints on their physical location. This allows data handling modules to be on the plant or close to it. Importantly, modules are designed such that only relevant data and information enters the telecommunications system, thereby avoiding the current practice of sending all data to a central point.

The layers are:

- the data monitoring layer;
- the interpretation layer;
- the corroboration or diagnostic layer;
- the information layer.

The modules in each layer require fundamental knowledge of how the plant behaves and fails, and how this is exhibited through the sensor data captured. The resulting system is able to integrate various monitoring technologies and data sources, such as oil temperature measurements, electrical loading (from voltage and current sensors), dissolved gas analysis results (online or periodic measurements), UHF PD measurements, tap changer position, and additional relevant data such as records of maintenance and servicing.

B. Requirement for Multi-Agent Systems (MAS) Technology

Based on the functional requirements, MAS technology was seen as an essential technology to underpin this condition monitoring system.

MAS offer a flexible and extensible framework for integrating the necessary data capture systems, monitoring systems and interpretation functions. Nevertheless, MAS do not provide systems integration capabilities only. This technology permits the development of more intelligent and automated diagnostic and monitoring functions. MAS comprise a number of independent software modules (agents) which exhibit four key characteristics: autonomy, social ability, reactivity, and pro-activeness [4]. In engineering terms, autonomy means that each agent will operate in an unsupervised mode, continually performing its diagnostic function while altering its behavior as required. Social ability means that each agent can cooperate and communicate with other agents, supporting data exchange and information exchange for condition monitoring functions. Reactivity and pro-activeness suggest that the agents are imbued with the ability to react to their surroundings and pro-actively take action to solve problems and ensure that they deliver the correct information or initiate the required control activity. Therefore, agents and MAS encompass all of the attributes required to automate diagnostic and condition monitoring applications. Based upon this technology, the transformer condition monitoring multi-agent system (COMMAS) was designed.

C. Detailed Design of COMMAS

A structured agent design approach was used. This has been developed by the authors previously [5]. The stages of the process are the follwing.

1) Requirements capture/knowledge capture.
2) Task decomposition: transformation of high-level requirements into a hierarchy of tasks and subtasks (including those performed by legacy systems).
3) Ontology design: design of the data model and the vocabulary used by the agents to exchange information and data.
4) Agent modeling: identification and design of the independent and autonomous agents which will combine to perform the tasks and subtasks identified previously.
5) Agent interactions modeling: definition of the interactions between different agents.
6) Agent behavior functions: design of the software functions to allow the agent interactions, including the control mechanisms which allow autonomy, reactiveness, and pro-activeness.

Stages 1 and 2 were undertaken in collaboration with UHF monitoring experts and utility representatives. Based on these discussions and knowledge capture, the task hierarchy shown in Fig. 1 was developed.

Stage 3 required the design of an ontology for COMMAS. This is one of the key aspects of a MAS as it underpins the inter-agent communication. It also becomes the basis for extensibility. The ontology is the system vocabulary, and it is within the ontology that concepts and their relationships are defined [11].

As an example, the basic ontology for the transformer monitoring system is shown in Fig. 2. It should be viewed as a class hierarchy of facts. For example, a TxUHFFeatureVector fact will inherit the attributes of the TransformerData fact. This also ensures that a valid TxUHFFeatureVector must be associated with a valid transformer. Therefore, data integrity is ensured. It is assumed that an implementation of COMMAS will operate per substation. As a result, the substation information only needs to be attached when communicating to other higher level systems. The COMMAS fact is used to aggregate all the information for such interactions.

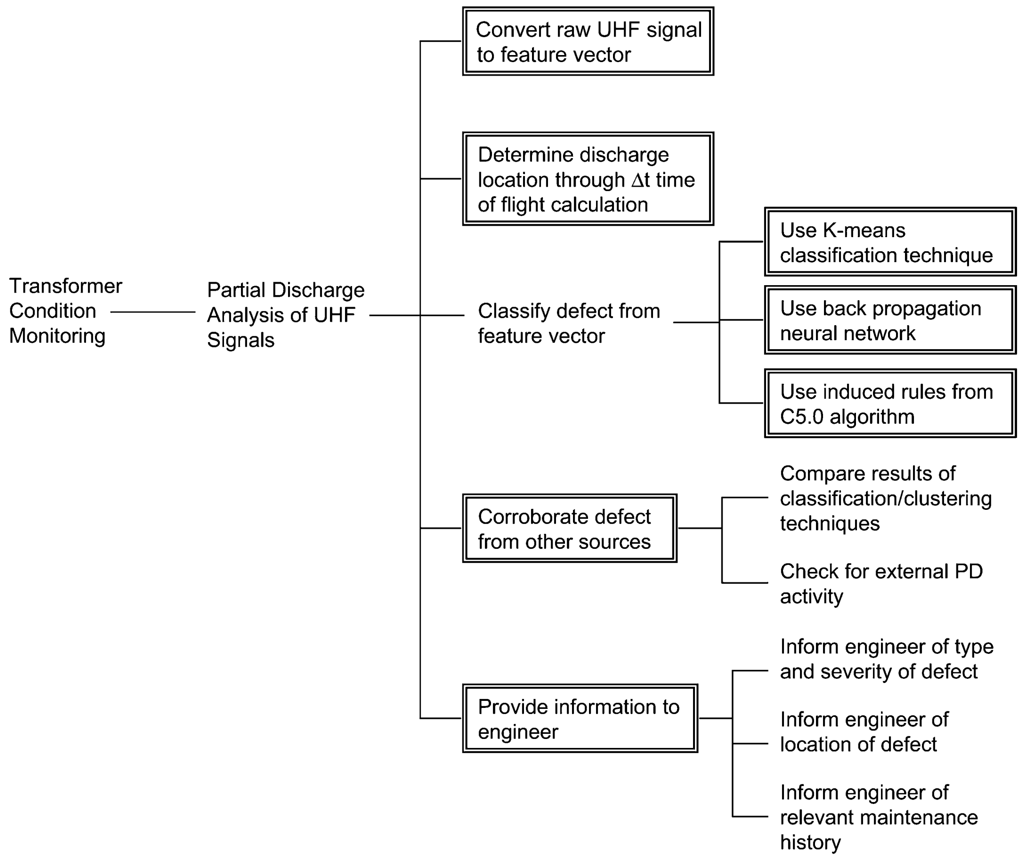

Fig. 1. COMMAS task hierarchy and agents.

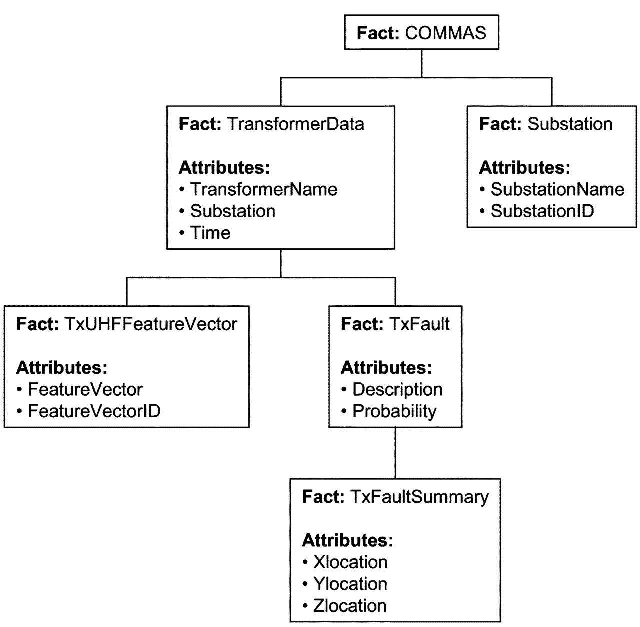

Fig. 2. COMMAS ontology.

D. Design of the Individual Agents

Stage 4 of the detailed design process requires the identification of which functional modules will be independent and autonomous agents. In any system, there is a choice to be made regarding how many functions are combined within a single agent, versus every function becoming autonomous. This is an application specific choice. Within COMMAS, the functions highlighted by a double-lined box (in Fig. 1) were chosen to be individual agents. These agents would embody all the lower level functions indicated.

This choice was driven by the initial requirements, indicated earlier in this paper. The agents were organized into their appropriate condition monitoring functional layer at this point.

1) Data Monitoring Layer Agents: The data-monitoring layer functions as a gatekeeper, the first line of defence in the effort to stop engineers from being overwhelmed by masses of unintelligible data. This first layer in the architecture is intimately associated with the front-end hardware used to monitor physical phenomena relating to plant operation, and is therefore the most plant-specific of the four layers. Raw data from the sensors and associated monitoring systems is received and all necessary pre-conditioning takes place. Therefore, this layer will have two specific agents based on the analysis resulting in Fig. 1. These are the *feature vector extraction agent* and the *Δt calculation agent*.

The *Feature vector extraction agent* was designed to provide the necessary data for the interpretation agents. Under laboratory conditions, UHF sensors were used to detect electromagnetic energy signals radiated by localized electrical discharges, caused by the induced dielectric breakdown of insulating material. A phase-resolved pattern (shown in Fig. 3), representative of the PD activity monitored [2], was generated from the raw

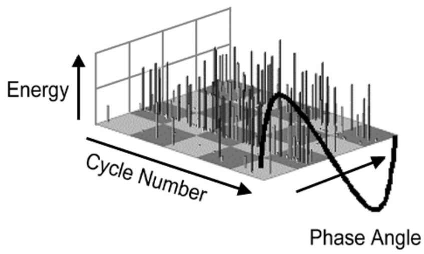

Fig. 3. Phase-resolved data.

sensor data. A phase-resolved pattern can be decomposed into four distinct distributions:

- pulse summation against phase $(\mathrm{H_{qs}})$;
- pulse count against phase $(\mathrm{H_n})$;
- mean pulse height against phase $(\mathrm{H_{qn}})$;
- max pulse height against phase $(\mathrm{H_{qm}})$.

Many parameters may be used to successfully characterize PDs [6]. Basic, deduced and statistical parameters are used to form the feature vector, providing some indication of the shape (cross-correlation), symmetry (skew), and "peakedness" (kurtosis) of the phase resolved pattern, effectively producing a "snapshot" or "fingerprint" of the PD activity. The feature vector consists of parameters (or features), capable of discriminating between different types of PD defect.

The *Δt calculation agent* uses time-of-flight calculations to identify the exact physical location of any discharges and defects.

2) Interpretation Layer Agents: The interpretation layer begins the process of turning the data into information that is of greater use to the plant operator. In addition, the modules in this layer use advanced intelligent system techniques, coupled with codified knowledge and expertise in the area of plant monitoring, to diagnose problems and offer a prognosis. A key aspect of the architecture is that it will support more than one interpretation technique.

It has become apparent over several years of research that no single data interpretation method can completely automate condition monitoring and diagnostic tasks. Instead, the combination of a powerful suite of techniques is required, resulting in a hybrid system. Data interpretation is achieved through three agents, employing K-means clustering, rule induction, and a back-propagation neural network.

The detailed process of training and evaluating the performance of these techniques has been reported previously [7].

The *C5.0 rule induction agent implements* "If-Then" rules derived from the training data set using the C5.0 algorithm [8]. These rules can subsequently be used to classify "unseen" data. Rule-sets and decision trees are induced by segmenting plotted data (feature vectors) using partitioning lines. Sixty rules were derived for the application under consideration. The following is an example of a section of the rule derived for the classification of the "Bad Contact" PD defect type.

Rule for Bad Contact (BC)
if $\mathrm{Negative\ Skew1} > 0.462$
and $\mathrm{Positive\ Phase\ Incp} <= 1$
and $\mathrm{Q} <= 0.365$
then $->$ Bad Contact (115, 0.991)

Predicted	BC	FL	PRO	RP	SD	SP
Actual						
BC	256	3	0	6	16	0
FL	1	251	19	19	20	6
PRO	0	17	224	10	19	32
RP	0	24	0	264	7	5
SD	0	20	21	6	244	9
SP	0	22	22	7	6	240

Fig. 4. Confusion matrix for C5.0 induction rules.

The general observations of PD activity associated with "Bad Contact" defect types interpreted from the above rule, include the following.

- A positive value of skew infers the phase resolved distribution is asymmetric to the left of the zero crossing (i.e. $\mathrm{Negative\ Skew1} > 0.462$).
- Positive phase inception occurs at less than or equal to a value of 1 (i.e. $\mathrm{Positive\ Phase\ Incp} <= 1$).
- $\mathrm{Q} < 1$ infers the discharge is asymmetric over the complete voltage cycle, i.e. discharge distribution over positive half cycle differs from that over negative half cycle (i.e. $\mathrm{Q} <= 0.365$).

Note that a confidence figure is also provided (i.e. 115, 0.991), indicating 115 test cases have been classified as "Bad Contact" defect types by this particular rule, with a confidence level of 99.1%.

For any input, multiple rules can fire. However, a single output is generated using a standard C5.0 algorithm. Each rule can add to the overall probability of any given conclusion. Any time a probability is added, an overall counter is incremented from 0. At the end, the highest probability score is found and then divided by the count of rules fired. For example, three different rules may fire indicating the defect as either a protrusion with 0.4 probability, a protrusion with 0.4 probability, or a rolling particle with 0.9 probability. The algorithm computes the overall probability for each defect by summing the individual probabilities. Therefore, it is either a protrusion with 0.8 probability or a rolling particle with 0.9 probability. The highest output is 0.9 over 0.8. This is now divided by the number of rules which fired (3), giving the result as a rolling particle with a probability of 0.3.

The confusion matrix, shown in Fig. 4, provides information on how effectively the C5.0 rules classify the different defect types represented in the test cases.

The confusion matrix compares the predicted defect types derived from the induced rule sets, with the actual defect types associated with the (previously unseen) test cases. The confusion matrix shows the defect type "Bad Contact" was correctly classified in 256 instances, while being incorrectly classified in 25 separate instances as either defect type "Floating Component" (FL), "Rolling Particle" (RP), or "Surface Discharge" (SD). The strong leading diagonal indicates these rules generally perform very well in the classification of all PD defect types.

C5.0 rules were also derived to successfully classify the insulation type (oil or air) and the electrode type (earth or HV) associated with the PD source.

The *backpropagation neural network agent* employs supervised learning in the training of a neural network [9], [10]. The input data vector is presented to the network input layer while

Predicted	BC	FL	PRO	RP	SD	SP	Unclas-sified
Actual							
BC	261	3	0	0	3	0	6
FL	0	206	14	3	20	15	39
PRO	1	12	195	0	11	34	42
RP	0	18	11	227	3	1	21
SD	0	17	3	4	216	8	17
SP	1	27	15	0	5	212	37

Fig. 5. Confusion matrix for the *backpropagation neural network agent*.

Predicted	BC	FL	PRO	RP	SD	SP	Unclas-sified
Actual							
BC	263	10	0	0	0	0	0
FL	0	95	10	42	80	52	18
PRO	17	11	95	34	47	84	7
RP	0	9	2	246	13	10	1
SD	0	9	3	3	204	37	9
SP	2	17	10	26	24	205	13

Fig. 6. Confusion matrix for K-means.

the output layer is presented with the "target" output (i.e. defect type). The network is refined through a process of error back-propagation, where the resultant error between the actual and target output is minimized.

The confusion matrix shown in Fig. 5, resulting from the backpropagation network analysis, exhibits a strong leading diagonal among those test cases classified successfully, indicating that (from the data classified) most of it was classified correctly. However, a number of test cases remain unclassified by the network. Further investigation may identify other techniques as a more effective means of classifying these particular test cases.

The *K-means classification agent* implements the results of the research into the K-means algorithm for PD monitoring. The K-means algorithm is an iterative procedure in which the cluster centres are continually recalculated, resulting in data points (feature vectors) changing membership between clusters and the subsequent redefinition of these clusters in n-dimensional space [9], [10].

Following the K-Means training phase, each network node is associated with a cluster of feature vectors plotted in n-dimensional space. Each node is then assigned to represent the defect type most prevalent in the cases clustered around the node.

A number of networks of varying cluster size (from 4 to 40 clusters) were tested. By comparing the true positives, false positives and false negatives associated with each defect type classified by the K-Means networks of varying size, the most accurate network was identified.

The network providing the most comprehensive classification of this particular defect type, (i.e. highest proportion of true positives and lowest proportion of false positives and negatives) consisted of 40 pre-defined K-Means nodes.

The confusion matrix of the forty-node K-Means network (shown in Fig. 6) illustrates the difficulty experienced by the network in distinguishing between FL and SD defects, and between PRO and SP defects.

The lack of symmetry evident in the matrix also provides a useful insight into how the network performs. It is evident that while there are 84 instances of PRO defects being mis-classified as SP defects, only 10 instances of SP defects were mis-classified as PRO defects. Therefore, while the network may experience difficulty in classifying PRO defects it experiences no such problems in classifying SP defects. This knowledge is built into the agent within the corroboration layer.

The *K-means classification agent* is coded in Java with the ability to upload weights. Thus, it is a re-usable condition monitoring agent.

An ongoing research issue is the general applicability of the three techniques, and the requirement for re-training and testing the when applied to transformers of different ratings, sizes, insulation types, etc.

3) Corroboration Layer Agent: The corroboration layer is composed of a single agent, the *transformer diagnosis agent*. This takes the output from each of the interpretation layer agents and composes an overall diagnostic conclusion. It employs the confidences provided by the interpretation agents to determine an overall diagnosis and confidence. The corroboration currently used in COMMAS is based on a basic statistical analysis of the messages received from the various analysis agents. The technique is designed to allow the various different outcomes to be aggregated in a statistically reasonable manner whilst allowing full flexibility in both the number of analysis techniques and the number of possible outcomes. It is designed to reflect that the K-Means classification algorithm is able to provide an indication of the probabilities of more than one type of defect for a single PD phase resolved data set.

To perform corroboration, the *transformer diagnosis agent* maintains a database of events, within which it tracks the various techniques that have submitted conclusions and the probability of each conclusion. Initially, a table is built with technique tabulated against conclusion. The cell data is then populated with the various probabilities that have been submitted to the corroboration agent. After this is complete, the table is checked to ensure that the sum of conclusions for a technique sum to 100%. If they do not, the difference between the sum of probabilities and unity is split between all techniques that do not have an explicit probability set. If all possibilities are set, the set is not altered. Each time a new probability is added, the corroborated conclusion is recalculated. After the table is fully populated, the mean probability is found for each conclusion and these probabilities form the corroborated result set. An example is shown in the case study.

This agent can also use the input from the *Δt calculation agent* to identify the exact location of the defect. This can be used to determine the confidence of the diagnostic conclusion. For example, if the location is known to be in the oil, then a floating component is more likely than a protrusion. This agent also makes use of the knowledge concerning the performance of the different techniques. For example, it will make use of the knowledge detailed in the previous section that the K-means algorithm may experience difficulty in classifying "PRO" defects but it experiences no such problems in classifying "SP" defects.

4) Information Layer Agent: This layer contains an *Engineering Assistant Agent*. This is designed to present the information to the relevant engineer. This has been designed to present a three dimensional image of the transformer with the defect superimposed on its actual location. A graphical delivery of

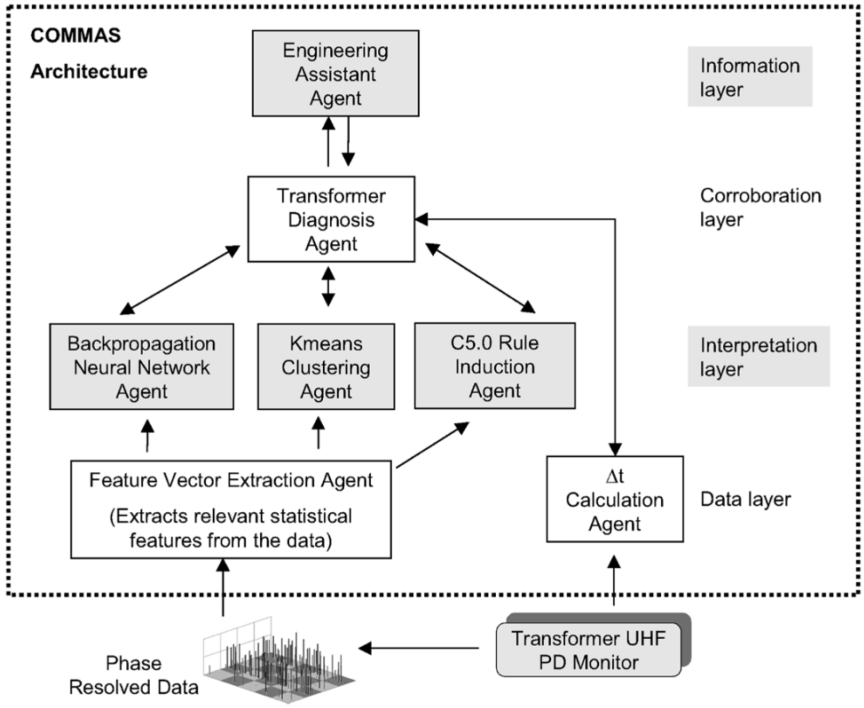

Fig. 7. COMMAS architecture.

summarized defect information is seen as the optimum delivery method of condition monitoring alerts. This *engineering assistant agent* is designed to handle diagnostic information from a number of transformers for which the engineer is responsible.

The resulting multi-agent architecture from this complete design process is shown in Fig. 7.

E. Agent Interactions and Agent Functions

Stages 5 and 6 of the design process deal with the agent interactions and agent functions respectively.

In order to build an extensible system, standard agent conventions have been used. This means that all inter-agent communications are handled using just a few types of message, examples of which are "subscribe", "query-ref", "inform", and "confirm".

Of these, "subscribe" and "query-ref" allow agents to request information updates automatically and to ask for answers to specific queries respectively. The "inform" message type is used in response to both query types. "Confirm" is used to indicate the success of an activity.

The MAS is supported by two utility agents. The *nameserver* manages the network addresses of all the agents. The *facilitator* records and manages all the services offered by each agent. When each agent starts up, it registers with the *nameserver*. The *facilitator* then requests the agents' addresses from the *nameserver* and queries each about what services are available. The agent sequence diagram in Fig. 8 provides an example of this for the *backpropagation neural network agent*. Each agent would initiate a similar process at startup.

When agents come on line, they will find everyone capable of providing them with required information and send the appropriate subscription request. In order to ensure the system has missed nothing during the offline period, or in the period during which the subscriptions were set up, the system will also issue a query and check the resulting information with its own knowledge. A similar technique is adopted whenever it is detected that communications between agents has failed and been re-established. This is facilitated through each agent registering the "Services" it is able to offer. These include "UHF data provision", "UHF data interpretation", "diagnostic corroboration", and "diagnosis display". By registering their services with the *facilitator* agent, other agents can search for the services they require. Once informed of the agent(s) which provide the relevant services, subscriptions can be initiated. A sequence diagram demonstrating the *backpropagation neural network agent* finding and subscribing to the *feature vector extraction agent* is shown in Fig. 9. Each agent uses an identical process to find and subscribe to the relevant data or information source.

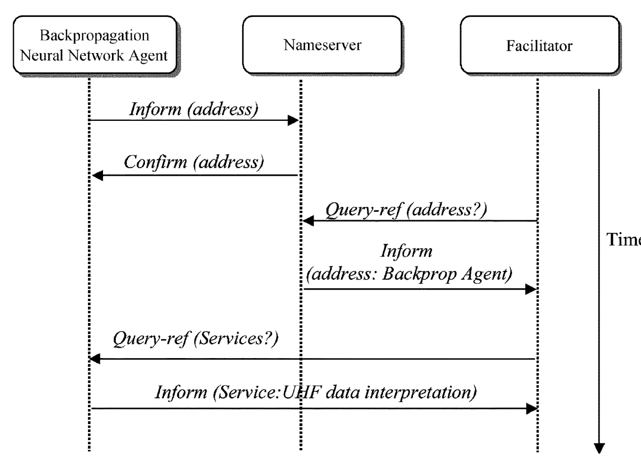

Fig. 8. Registration of backpropagation agent.

From Fig. 7, it can be seen that data is initially passed from the data monitor to the analysis systems. From here, the pro-

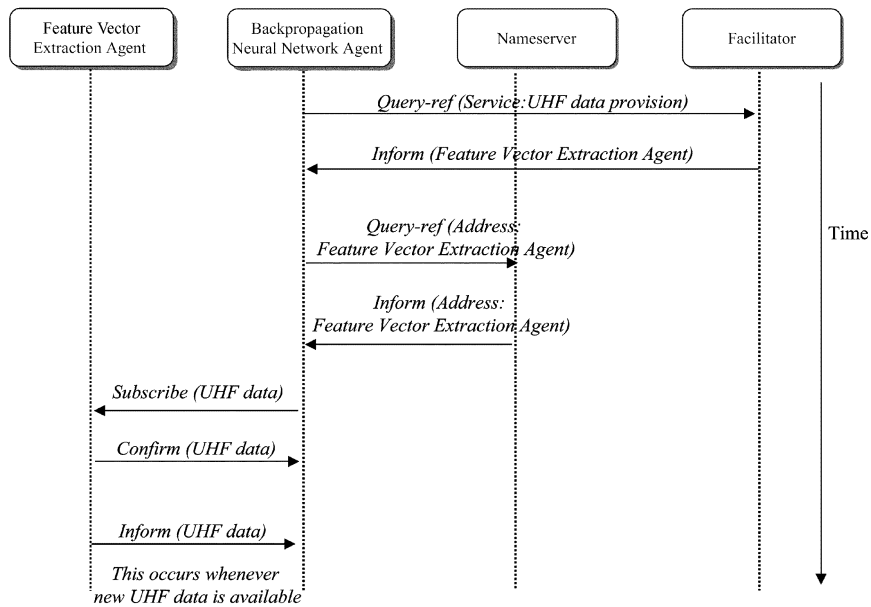

Fig. 9. Backpropagation agent subscribing to a data source.

TABLE I
CORROBORATION TABLE: RESULTS FROM K-MEANS AGENT

	FL	SP	SD	PRO	RP
K-Means	0.423	0.308	0.173	0.058	0.038

posed conclusions of each interpretation agent are passed to the corroboration agent. It is then up to this agent to use its own knowledge of the analyses to compute the overall conclusion using all of the available information.

The addition of this extra reasoning layer allows new techniques to be rapidly added to the system simply by adding the agent to the community and reconfiguring the corroboration agent. Depending on the type of data this agent is dealing with, it will use either manually set rules or weights, or adaptive algorithms in order to generate conclusions with probabilities for each proposed outcome.

IV. CASE STUDY

A transformer defect was set up in the laboratory and the UHF PD data was captured. The phase resolved data was generated by the monitoring equipment [1], [2], passed to the *feature vector extraction agent* and processed as described in Section III-D. This is now sent, via agent subscription and messaging, to each of the interpretation layer agents. From these, the first conclusions are generated by the *K-means clustering agent* and this passes the result to the *Transformer Diagnosis* Agent using the ontology and agent interactions described previously. The K-Means agent can return multiple results detailing the probability of the discharge being due to one of the possible defects: FL, SP, SD, PRO, or RP. Therefore, the corroboration statistical table is as shown in Table I.

Next, the *backpropagation neural network agent* provides its result. Due to the way this technique works, it has a single result which in this instance is SD at a probability of 30.4%. Thus, the corroboration statistical table becomes that shown in Table II.

The italicised average numbers have been calculated. Those in the backpropagation row balance the overall probability at unity, and those on the *average* row are the mean probability of each defect type. At this stage, floating electrode is the most likely with a confidence of 29.9%.

TABLE II
UPDATED CORROBORATION TABLE: RESULTS FROM BACKPROPAGATION AGENT

	FL	SP	SD	PRO	RP
K-Means	0.423	0.308	0.173	0.058	0.038
Backprop.	0.174	0.174	0.304	0.174	0.174
Average	*0.299*	*0.241*	*0.238*	*0.116*	*0.106*

TABLE III
UPDATED CORROBORATION TABLE: RESULTS FROM C5.0 AGENT

	FL	SP	SD	PRO	RP
K-Means	0.423	0.308	0.173	0.058	0.038
Backprop.	0.174	0.174	0.304	0.174	0.174
C5.0	0.031	0.031	0.876	0.031	0.031
Average	0.209	0.171	0.451	0.088	0.081

The last result passed to the *transformer diagnosis agent* is the conclusion from the *C5.0 rule induction agent*. This technique has also yielded a single result, which is SD with a 87.6% confidence. When added to the corroboration table, the result is shown in Table III.

As can be seen, spreading the balance to unity out amongst the other possibilities has the effect of reducing their overall scores and keeps the final conclusion vector still summing to 100%. At this stage, the *transformer diagnosis agent* concludes its calculation of the corroborated result. It determines that there was a SD, with a 45.1% confidence. This is now passed to the Engineering Assistant Agent for display.

This is the correct result, as a SD defect fingerprint was fed into the agent network.

The corroboration layer's approach to combining the outputs from the different interpretation agents is an ongoing research activity. This will be enhanced through further laboratory-based experiments, and site tests. However, the current approach is generic and extensible enough to allow other interpretation agents to input conclusions and probabilities. It will also use further knowledge of the performance of each technique as detailed in Section III-D-3).

V. Conclusions

This paper has presented the design of a multi-agent condition monitoring system for online transformer monitoring, using UHF PD analysis. This research has explored the viability and benefits of a multi-agent approach to transformer monitoring.

The next stage of the research is to extend the system in terms of its coverage. Therefore, future research will prove the COMMAS architecture for the monitoring of multiple transformers in a substation. In addition, it will be extended for application at a number of different substations, allowing all the transformers' health assessments to be available through a single *engineering assistant agent*. Currently, plant lifetime models are being developed for integration into the system. The use of further monitoring systems as part of the architecture will also be addressed.

During the course of the research, significant expertise in UHF data analysis was created throughout the research team. Therefore, knowledge elicitation is under way to capture and structure this expertise. Future work will consider the implementation of a knowledge-based agent, offering further corroboration of the system diagnosis and improved explanation of the system output.

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