INTELLIGENT RECOGNITION OF PARTIAL DISCHARGES IN HIGH VOLTAGE DIELECTRICS

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ABSTRACT

This paper submits the outcome of electrical discharge tests conducted on high permittivity surrogate dielectric samples. A synthesised experiment was performed using contoured electrodes submersed under technical grade insulating oil. Altering magnitudes of common faults within surrogate samples were assessed, these being correlated against magnitude and frequency of activity. The inducement of partial discharge activity up to a point of dielectric failure was observed using a conventional elliptical display partial discharge detector. Concurrent measures of pd activity were also made by virtual scope facilities relaying frame captures to a personal computer. The result of this experimental work was duly processed by artificial neural network programs, a net result indicated harmony between seasoned opinion and software aptitude. This paper describes furthering development of AI techniques for the identification and diagnosis of faults in high voltage dielectrics.

INTRODUCTION

Countless aspects influence dielectric expectancy; applied electrical stress, radiation, temperature, presence of moisture, air or trace salts, mechanical stresses, transient impulses, all of which may act or interact to impair the integrity of a dielectric. Emulating these effects within laboratory confines has provided considerable knowledge concerning these factors individually. Nevertheless the most predominant and widely accepted method of assessing overall pictures, of at times, compounded factors, remains partial discharge analysis (pd). Inevitably, insulation contains voids, gaseous inclusions and colloids either within a dielectric or on boundaries between dielectric disparities. With ensuing influences of both expansive and contractive natures in service, dimensions of these inevitable inclusions may exceed a critical value. Such these are liable to a breakdown, and due to the lower permittivity, remaining vulnerable to relatively high potential gradients in contrast to their limited withstand strength [1,2]. This breakdown creates a progressive deterioration of the dielectric, exhibiting an intermittent electrical breakdown characteristic of attributable causes. Discharge magnitude is determined by the inception voltage at which the encapsulated medium breaks down, the overall volume of the vacuous space, and the dimensions of the surrounding, otherwise sound, dielectric. Levels of pd activity have been extensively researched and links indicate levels of degradation or soundness of dielectrics respectively [2,3].

In spite of widespread acknowledgment as a methodology for condition diagnostics, inadequate analysis methods have otherwise limited prevalent exploitation of this technique. Contemporary techniques and instruments have been developed from detailed studies of material degradation, enabling researchers to extract information of behavioural material degradation previously unattainable with conventional instrumentation. By monitoring analysis of pd behaviour and collating historical behaviour patterns, an accurate assessment of the dielectric condition and a subsequent remaining life prediction may be deduced [1].

NEURAL NETWORKS

Exploited considerably with pattern recognition and/or classification, artificial neural networks (ANN) provide discrimination where there has been a need to correlate characteristic signatures of voltage or current sources [4]. ANN utilise a parallel processing structure composed of a number of surprisingly simple processors: neurons. Thus performing knowledge abstraction and statistical analysis on data presented, information becomes encoded into the network structure, generalising so as to respond correctly to previously unseen data. The most commonly used neural network models are the feed forward back propagation networks such as the multi-layer perceptron (MLP) for which considerable published work has already described [1,3,5]. Equally receiving renewed attention in pattern classification are Radial Basis Functions (RBF) utilising a clustering technique of represented data formations.

Incorporating a supervised learning algorithm unlike MLP (teacher supervised) thus prone to mistakes, RBF function of training remains unsupervised. Encompassing radially symmetric processing; these hidden layer elements combine a Euclidean distance measure with a Gaussian activation function [4]. Potentially use of RBF provides enhanced classification, at improved convergence periods of training routines, forming clustered boundaries in an input space, whereas MLP's tend to create open regions. Thus able to cope with larger numbers of data classifications, RBF networks can be

seen to be superior, thereby used separately or combined as pre-processing with lesser routines, may prove advantageous with processing time and accuracy.

EXPERIMENTAL PROCEDURE

Partial discharges were formed by using a large test cell containing two Bruces electrodes of 2.0cm diameter, and displacement between which two dielectric plates (Perspex) were sandwiched. Machined 3.0mm depth dielectric samples were sterilised to remove surface contaminants, and after applying insulating oil to the edges, sandwiched together under an applied pressure providing a small air entrapment between respective planes. The surrogate samples were submersed under clean insulating oil to further ensure air entrapment between the electrode - dielectric - electrode interface, reducing surface discharge and corona effects. Using a discharge free HV 50kVtransformer, steps of 5.0 kV were applied between the dielectric samples.

Simultaneously observed by a conventional elliptical display pd monitor, the discharge signatures were captured by virtual oscilloscope relaying captures to a personal computer. A parallel HV capacitor provided ready means to monitor the applied voltage to within ± 1%. At relatively low voltage levels (less than 10kV) partial discharges were evident, and as these were occurring at around the expected breakdown level for a displacement within air, these were clearly attributable to the dielectric bounded cavity. See fig 1.

On removing the sample from the experimental tank, a close analysis revealed that the dielectric had suffered no obvious visible damage. Thus introducing a small void to one plane of the dielectric sample, this being of a known and controlled parameter, would allocate groups of pd behaviour against void dimension and multiples thereon.

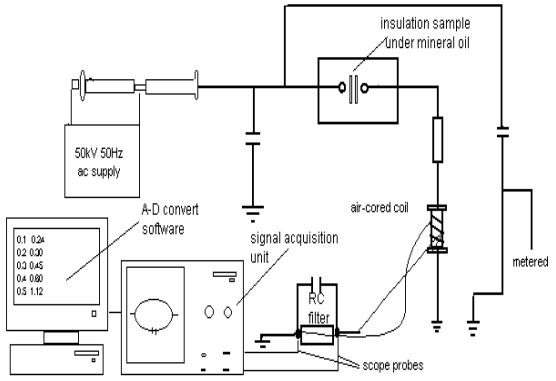


Fig 1. Basic discharge detection circuit [1,6]

Although some surface deposits were evident, a precision-drilled cylindrical impression of 1.0mm was made in the centre of one plate prior to sterilising the sample. This region between the two electrodes contains the more intense uniform field, thus positioning the samples centrally warranted the most likely point of breakdown. A scribed impression matching the diameter of the electrodes was made to the inner of each plate, thus again pre-treating with insulating oil ensured an oil filled perimeter channel maintaining the air encapsulant.

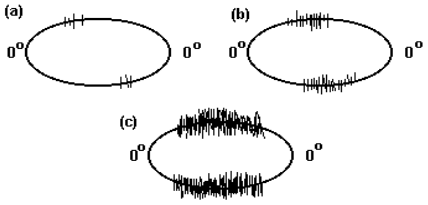


Fig 2a, 2b, 2c.dielectric bounded cavity pd [6]

The high voltage supply was reapplied in more liberal steps based on the previously attained inception level of the dielectric. The partial discharges, appearing as pulses on the elliptical display unit at a fundamental frequency time base, despite remaining at around the previously recorded magnitude, significantly increased in number. In addition to this notable change, the pulses were also noted to have spread around the axis, above and beyond the periods of peak-applied voltage see fig2a. As extraneous influences had been reduced by oil submersion, this being of a higher permittivity than air and thus inhibiting such likelihood, implied that the discharges were solely due to the extended pd active area, namely the artificial void.

After securing a number of captures, the sample dielectric was removed and upon visual examination exhibited little if any permanent damage, other than small tracking deposits within the artificial void. An extended void depth test proved fruitless, suggesting that the inception level of the void, dictated by the encapsulant, was limiting the pd activity to some extent. Thus unless the void were to extend in an axis across the linear region of the electrodes, it was doubtful that any significant variations would be noted, unless the applied HV were to be increased.

Introducing a further two voids to the dielectric plate in a triangular fashion at the central region, samples were again sterilised and pre-treated prior to re-application. The three artificial voids were equally spaced in order to remain within the 2.0cm diameter of the electrodes and oil trap perimeter, encouraging an equal influence to the activity of each void across the linear axis. As expected, discharge activity was again evident at relatively low voltage levels. Once the initial reference level was attained, a significant increase in pulse count was again

very clearly evident, extending further still around the cyclic quadrants of the applied HV. See fig 2b.
Increasing the void cluster further projected an obvious option for an additional test. This was appropriately investigated, and with a somewhat expected increase in count of pd activity, dielectric deterioration was abundantly clear. Activity had indeed increased in line with the authors expectations and the material demise, by now considerable, was exasperating void breakdown so much so, that air encapsulation now represented the bulk of what remained of the surrogate sample. Thus, as channels between voids were now occurring, it would at this stage be difficult to deduce void dimensions, although the lead up to breakdown remained consistent with earlier results see fig 2c. The Pulse count changed in sympathy to the conditions, additionally cyclic position of discharges also varied according to severity of dielectric demise. Thus now presented with attributables, characteristic of source, the captured data was subjected to AI analysis methods, linking partial discharge characteristics with the artificial dielectric failure modes embodied.

NEURAL NETWORK ANALYSIS

The feed-forward, back-propagation network used previously [1,4], produced results that were encouraging. Clearly this was aided by the productive but selective supervised training routine of the operator. As described, Radial Basis Functions (RBF) do not follow this trend, being non-supervised they allocates grouping or clustering as described accordingly. Such, a greater flexibility in operation, permits simple 'top-ups' or additions of further classes, as may be deduced by the network at will. No longer therefore requiring large data captures, signified that fewer nodes were required. Incorporating a commercial mathematical package, a base routine converted time domain captures to Fourier Transforms. Thus finding on conversion to FFT, that the majority of pd detail was contained within the first fifteen components, noise and harmonics showing component values at the upper end of the spectrum. Fewer routines were therefore required for processing, i.e. removing the pre-trigger and reflected wave as displayed in fig 3.

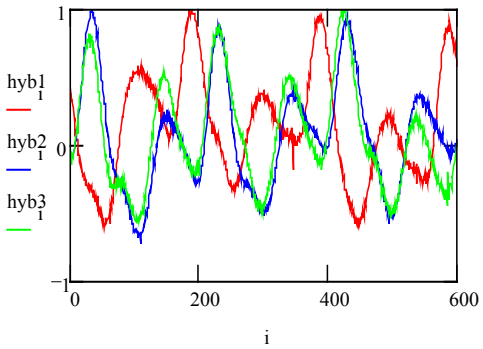


Fig 3 Time domain capture of expanded pd's

Owing to the variable activity allied to partial discharge, non-linear behaviour introduces small variants between each capture. Thus training therefore within a traditional MLP can be both time consuming, from supervisory intervention, and inconclusive if the network cannot convolute. Conversely, upon converting the captures to the frequency domain, a greater level of harmonisation is noted between captures. Thus combined with fewer nodes and the intelligence-orientated training, an unsupervised RBF becomes more feasible. See fig 4 below. Immediately apparent from fig 4, the activity decayed below usable magnitude after 15 data samples. As previously described, activity other than pd of interest, exists in the upper spectrum of the frequency response.

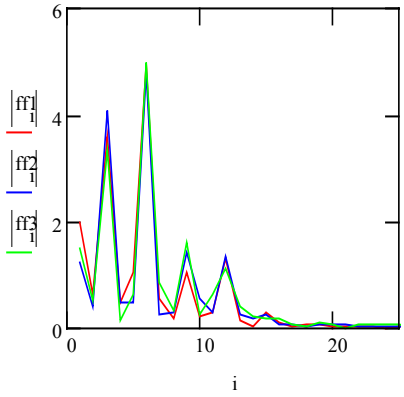


Fig4. Fourier Components of converted captures.

Thus applying arbitrary traces of 15 input nodes, a total of 36 training files were applied to the RBF network for training, these falling into four classes as assigned by the network. A further capture class of eight complete files of varying mix and proportion, were assessed by the network on large-scale cluster width activation functions. The results of this provided a 100% success rate in recognition of pd, rejecting all extraneous readings additionally applied. Improvement was seen to be required however in classification of the four groups applied. By reducing the cluster width of the RBF, increases the level of selectivity the network will distinguish. A magnitude in reduction from 0.1 – 0.01 was applied to the network and re-assessed on both the same test data and additional data previously unseen. In addition to a further full rejection of noise, a significant increase in classification was attained against the training data.

As a comparison, results previously obtained from an MLP network, of it must be said larger data captures were additionally compared. Even though effective in their

own right, in as much as classification of groups (see ref 1,3) these frequently failed to reject extraneous noise of equal or close magnitude. As these still existed in raw capture format, conversion to Fourier component and subsequent node reduction was conducted. Within an assessment mode, all captures representing noise were rejected, similarly the network experienced little difficulty with recognition of less clearly defined 'textbook' pd. Files previously overlooked by an MLP structure were additionally recognised, again higher components of noise having little or no effect where previously errors had occurred. Despite indicating 'possible errors' with group classification other than pd identity, a further and more in-depth analysis would be required to establish such.

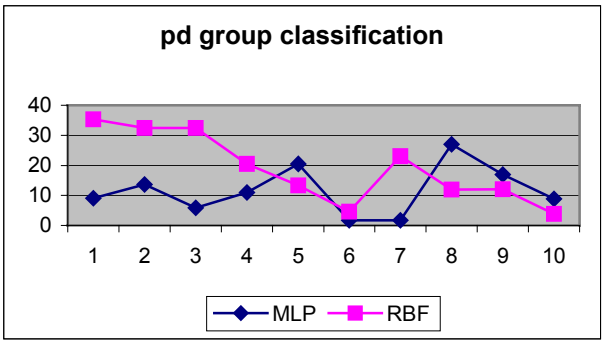


Fig 5. Percentage error of group allotment

The above trace of fig 5 illustrates arbitrarily chosen data captures trained on an MLP network, these the result of large representations to each class, and based over extended data ranges with greater scope of variation. As a comparison the RBF training, although indicating some sizeable errors in allotted groups, received less than one tenth of the data range and only one fifth of the cluster classes. Although no further analysis was made on the above captures, it was considered that fundamental discharge frequencies may co-exist within the captures, and thus although assumed to be wrongly allotted in groups, this may reflect a true case as yet undiscovered. With aims to identify source and/or type of pd, the very much improved level of recognition with excellent rejection of extraneous signals exemplified greater importance. Therefore the results obtained from these base assessment techniques indicated sufficient promise to warrant a further in-depth investigation.

CONCLUSIONS

Observed as an unfortunate drawback, the Fourier/RBF technique required sizeable computational demands, these dictated by pre-processing and FFT frequency conversion. Nonetheless, software routines are already planned to replace much of the commercial software used, thus a time demand reduction by some tenfold is expected. In greater fairness to the RBF training and pre-processing technique, only short data captures of low resolution were used, and thus combined with the controlled limited class numbers applied, offered a reduced scope. It is anticipated that characteristic signatures of specific failure modes, for which there are many, will increase selectivity between classes. Either as a stand-alone system, or in conjunction with MLP as a hybrid, RBF/Fourier technique, offers enormous potential providing the computational demands can avoid 'trade-offs' within selectivity.

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