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Electrical Treeing Diagnostics - An Approach Combining Optical Measurements and Partial Discharge Statistics

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Abstract: *Many post-mortems on failed polymeric insulation have revealed electrical treeing as one of the final causes of electrical breakdown. This paper combines the laboratory constrained optical measurement techniques of electrical tree growth with the statistical analysis of associated captured partial discharge analysis, providing a consolidated approach to further study electrical treeing and improve in-situ diagnostics. A critical review of the available and commonly employed optical measurement techniques is outlined. This review is accompanied by a theoretical survey of statistical distributions potentially applicable to model partial discharge activity. The methodology to amalgamate these two diagnostic methods is presented, thereby describing the software development automating enhanced electrical tree growth measurements using image-processing techniques while correlating statistical partial discharge analysis.*

Keywords: *Partial discharges, electrical treeing, Weibull distribution, image processing, software development.*

1. Introduction

Electrical treeing, a common polymeric ageing mechanism eventually leads to insulation failure. Timely detection of this extensively studied electrical ageing mechanism, prior to imminent insulation failure employing diagnostic tools and techniques is paramount to achieving improved asset management practice yielding improved levels of power system security. Consequently, a comprehensive understanding of electrical tree (ET) growth is imperative if one needs to maintain system reliability and up time. Applying optical tools to visually observe and monitor progressive ET growth has traditionally and practically been limited to fundamental laboratory oriented research on electrical insulation ageing mechanisms. Consequently partial discharge (PD) diagnostics have been globally embraced and are now accepted by the electrical insulation industry for in-situ measurements.

PD activity, both a cause and effect of insulation ageing, progressively deteriorates the integrity of the dielectric, reducing insulation life by several orders of magnitudes (Montanari, 2008). The cumulative effect of PD within solid dielectrics, particularly polymeric, is the formation of numerous, branching partially conducting discharge channels or ETs, which can ultimately cause system failure. PD can occur at operating voltages in ETs, voids, cuts, cracks, fillers, and contaminants with poor adhesion to the polymer, delaminating sites at insulation interfaces (Densley, 2001) and along the boundary between different insulating materials.

The three stage defined process of electrical treeing (Dissado and Fothergill, 1992) in Figure 1 illustrates each stage representing a visual change in ET structure is associated with a change in PD activity. During the inception stage, the magnitude of PD, of the order of picocoulombs (pC) and can only be detected by very sensitive measurements. The propagation stage represents the ET growth in small branches from inception until they reach the opposite electrode. These branches are not continuously conductive; they can penetrate the insulation without causing breakdown. In the runaway stage, the small branches widen into pipe-shaped channels. These hollow channels are considered to be dangerous to the insulation because conduction usually occurs leading to insulation breakdown. The magnitude of the PD increases to the order of nanocoulombs (nC) during the runaway stage, which can be used to detect this change of tree structure in the insulation (Vogelsang et al., 2005).

Figure 1 modelled the general ET growth characteristics. Given the evolution of insulation operating conditions, the stresses influencing insulation ageing, electrical and otherwise are now many (Bahadoorsingh and Rowland, 2008). This evolution of the network can be linked to demand side management, distributed generation, power system expansion and increased power electronic loads contributing to changes in power flows in the quest to develop the "smart grid".

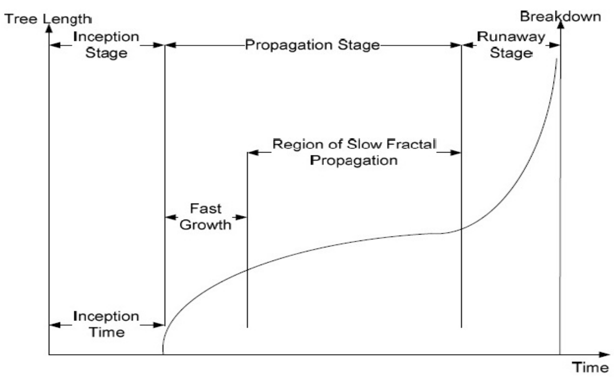

Figure 1. Stages of electrical tree growth
Source: Abstracted from Dissado and Fothergill (1992)

This paper puts forward an approach to merge the optical measurements and PD activity captured from ET growth. This approach will combine two commanding diagnostic measurands (Bahadoorsingh and Rowland, 2008) in an attempt to improve ET growth modeling. This paper critically reviews the optical techniques and statistical modeling of PD activity describing the benefits of amalgamating these techniques and application of documented approach.

2. Optical Measurements

Employing relatively high speed and high resolution cameras have advanced the acquisition of progressive, two dimensional digital colour ET growth images shown in Figure 2. There exist few published techniques, usually applied post experimentation, to quantify the ET growth captured by these images. ET growth measurements were previously limited to manual offline techniques, proven to be tedious and error prone. Recent advances in computing and optical technology have enabled fast and improved accuracy of ET measurements.

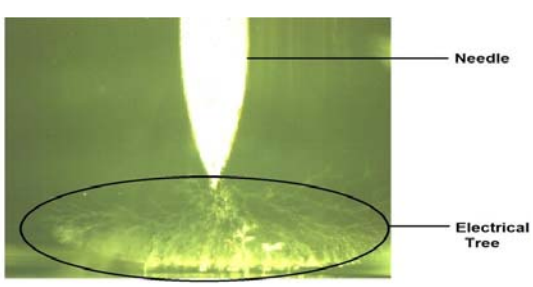

Figure 2. Experimentally captured electrical tree image

3. Critical Review of Electrical Tree Measurement Techniques

Some of the documented electrical tree measurement techniques quantifying ET growth include:

1) *Distance from the initiation site or tree length* - This method measures the maximum length of the tree from the needle along the needle plane (Hozumi et al., 1990, Noskov et al., 2000).
2) *Tree Width* - This method determines the maximum horizontal distance of the electrical tree from the needle (Song et al., 2009, Zheng and Chen, 2008).
3) *Length Width Product* - This method determines the area of the rectangle that encloses the electrical tree (Morita et al., 2003). Figure 3 shows the length and width dimensions of a typical electrical tree. The length width product is given by Equation 1.

Length Width Product
= Electrical Tree Length x Electrical Tree Width Eq.1

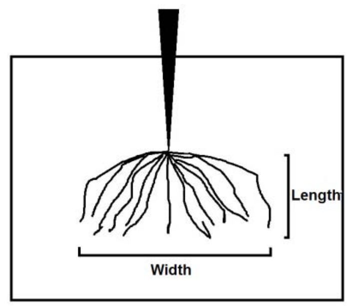

Figure 3. Length and width dimensions of the electrical tree

4) *Width Length Ratio* - This ratio illustrates how the width is changing with respect to the length (Bahadoorsingh and Rowland, 2010b). A large ratio would indicate that the electrical tree's width is larger than its length. The width length ratio is given by Equation 2.

$$\textit{Width Length Ratio} = \frac{\textit{Tree Width}}{\textit{Tree Length}} \quad \text{.... Eq.2}$$

5) *Fractal Dimension* - This method utilises the box counting method to determine the fractal dimension (Chen and Tham, 2009, Ding and Varlow, 2005, Dissado et al., 1997, Kudo, 1998, Kurnianto et al., 2007). The electrical tree is covered by N boxes of equal size r. Thus for a fractal structure, a plot of $\log N$ against $\log r$ should yield a straight line whose gradient corresponds to the fractal dimension, D_f, expressed by Equation 3.

$$D_f = \frac{\log N}{\log r} \quad \text{.... Eq.3}$$

The fractal dimension describes the tree structure, space occupied and complexity (see Figure 4).

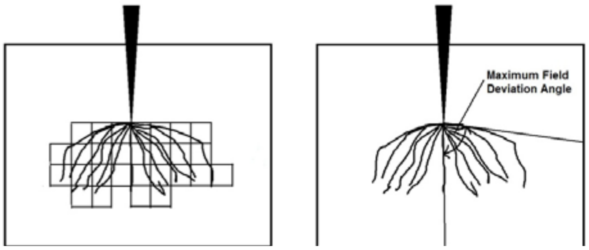

Figure 4. Box counting measurement to determine fractal dimension (left) and maximum field deviation angle of electrical tree (right)

6) *Time to Breakdown* - Measurement of time to insulation breakdown under electrical stress does not provide an indication of the actual tree growth. Only one value is presented per sample, hence this method is applicable for breakdown analysis between different samples (Vogelsang et al., 2006).
7) *Number of Cracks* - This technique calculates the number of cracks from the energy level at the considered high electric field tip relative to the critical energy level (El-Zein et al., 2009). This technique is limited since the value obtained is an estimate.
8) *Electrical Tree Shape* - This technique uses the shape of the electrical tree to measure tree growth (Qiong et al., 2009). The shape of the electrical tree is visually analysed.
9) *Maximum Field Deviation Angle* - This method measures the maximum angle of the electrical tree from the tip of the needle (El-Zein et al., 2009).

Table 1 shows the comparison of the electrical tree measurement methods described. A “good” technique is indicated by chronological electrical tree growth measured in two or more dimensions.

Table 1. Comparison of previously utilised electrical tree measurement techniques

Method	Growth Dimensions	Growth Analysed with Time	Measurement Technique Analysis
Tree Length	One	Yes	Limited
Tree Width	One	Yes	Limited
Time to Breakdown	One	No	Limited
Width Length Ratio	Two	Yes	Good
Width Length Product	Two	Yes	Good
Fractal Index	Two	Yes	Good
Number of Branches	Two	Yes	Limited
Tree Shape	Two	No	Limited
Maximum Deviation Angle	Two	Yes	Good

3. Methods Developed and Recommended for ET Growth Measurement

The review of published literature suggested caution must be exercised when employing selected techniques. This section outlines six methods selected which can be easily implemented to measure ET growth. These are:

- Area
- Perimeter
- Fractal Index *(recommended)*
- Length Width Ratio *(recommended)*
- Intensity Frequency Analysis *(developed)*
- Estimated 3D Volume *(developed)*

The area and perimeter methods are simple mathematical extractions which can convey ET growth, often forming the base calculation for further complex algorithms. The area method counts the number of pixels covered by a binary image; providing a physical measurement of the coverage of the electrical tree. The results obtained can be used to quantify the ET growth in relation to the size of the insulator. This can give an indication of ET growth coverage, providing easy comparison to images and values obtained from other experimental research. The perimeter method traces the edges of the ET. It does not merely trace the outer edge but the internal edges also. This result gives valuable information about the tree shape and its structure. For example, a large perimeter may indicate a large amount of branching or a bushy tree like structure.

The fractal index and length width ratio have been identified as good techniques in the previous section having the facility to chronologically capture ET growth in one or more dimension. The fractal index method, a very popular method in the research community, utilises the box counting method for ET measurement. The fractal index is a very useful indicator of branching within the ET structure. This value indicates the structure density relative to the outer length. A small fractal index indicates the ET area is small relative to its boundary, suggesting the ET structure is not dense but is plagued with pockets of free space.

Conversely, a large fractal index indicates a dense ET structure. The width length ratio describes how the ET width changes with respect to its length. A ratio greater that unity suggests the ET is growing much wider than it is longer, with the reverse relationship occurring for a ratio less than unity. A unity value of this ratio is indicative of equal on both dimensions which can occur during short intervals until the ET traverses the insulation gap.

A new approach known as the intensity frequency analysis technique has been developed and described here. The frequency in an image corresponds to the number of times an intensity level occurs in a greyscale image. Therefore a histogram of a greyscale image produces a frequency intensity spectrum. This method is based on the assumption that the change in intensity from subtracted chronologically successive images yields ET growth. The area under the intensity spectrum for each image is computed and divided by a defined constant to produce the intensity frequency index. This method is the most accurate since the data is obtained directly from greyscale images. Therefore the results are an almost exact representation of the ET growth.

The estimated volume method utilised a three-dimensional modeling technique for ET growth analysis. All the techniques described previously have been limited using two-dimensional analyses. Employing the image intensity yielded an estimate of the image depth in the third dimension facilitating an estimation of the ET volume.

The processes involved in the measurement techniques developed for electrical tree analyses are shown in Figure 5.

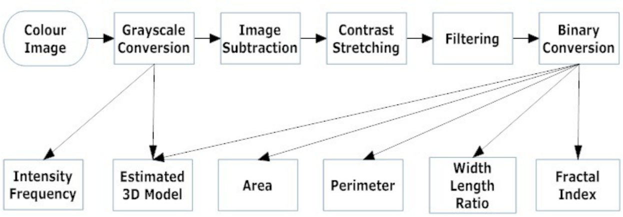

Figure 5. Flowchart of modules for measurement techniques

There are several steps illustrating the processes involved in binary conversion of the electrical tree growth images. These are:

1) Two sample colour images are selected. A colour image can be defined as a three-layer array of pixels where each layer corresponds to the red, green and blue components of the image at specific coordinates (see Figure 6).
2) Gray-scale conversion. A colour image can be converted to a greyscale image producing a single layer array of pixels where each layer corresponds to an intensity value ranging from 0 to 255 (see Figure 7).
3) Image Subtraction. In this process the arithmetic difference between subsequent images is used to detect changes between these images. Two images characterised by the same size and background must be employed (see Figure 8).
4) Image Crop. The image is then cropped from the bottom of the needle (see Figure 9).
5) Contrast Stretching. Contrast stretching is utilised when an image contains low contrast or is within a narrow band of intensities. The process involves the 'stretching' of a desired intensity range to occupy the intensity range of 0 to 255 (see Figure 10).
6) Filter. The filtering of the images with a Gaussian low pass filter removes noise and other irregularities in the image. It is a blurring filter that utilises the Gaussian function to determine the transformation that should be applied to each pixel. This results in a blur which preserves boundaries and edges (see Figure 11).
7) Image to Binary. This process converts a gray-scale image to binary image. The output image replaces all pixels in the input image with luminance greater than the level specified with the value one and replaces all other pixels with the value zero. This produces an image in which the intensity values have two distinct values (see Figure 12).

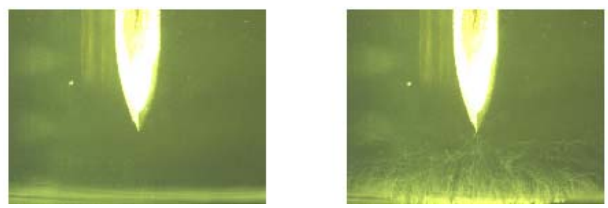

Figure 6. Sample colour electrical tree images

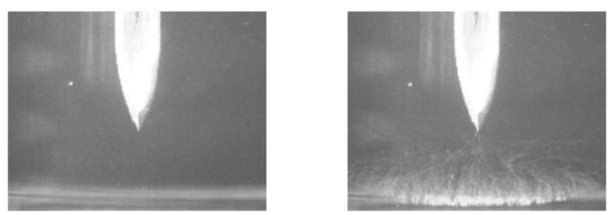

Figure 7. Sample colour images converted to gray-scale

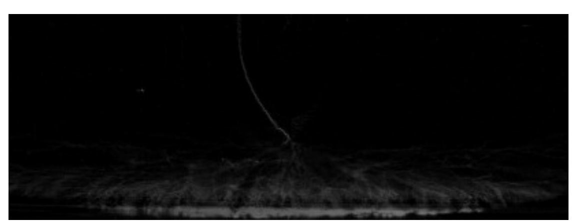

Figure 8. Resultant image after image subtraction

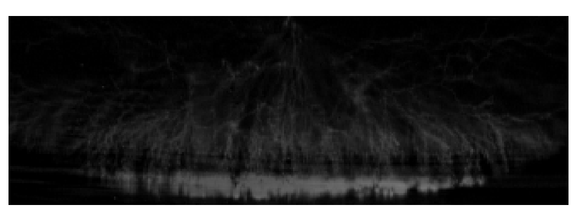

Figure 9. Resultant image after cropping

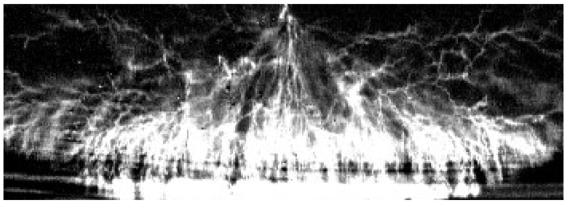

Figure 10. Contrast stretched image

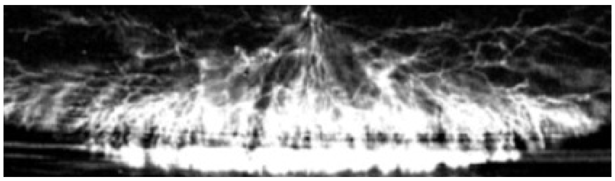

Figure 11. Image after filtering

Figure 12. Binary image

Image processing of two dimensional electrical tree images and subsequent application of the developed measurement techniques can therefore give constructive insight into various aspects of ET growth. As aforementioned, this includes factors such as area covered, density, shape, length width characteristics and complexity of the electrical tree structure. Whilst this method of analysing ET growth is useful, it can be complemented by concurrent PD analysis.

4. Statistical Application of PD Activity

PD in insulation systems may be due to different sources depending on the nature of the deterioration mechanism or pre-existing defects (Contin et al., 2000). Discharges can be generated by sharp points or protrusions where electric field concentration causes corona effect, by discharges on insulation surface or in defects such as micro and large voids (Dissado and Fothergill, 1992). PD is considered both a cause and effect of electrical treeing. There are usually several competing ageing processes occurring simultaneously at defective spots. PD, often the fastest degradation mechanism, remains the main measurand for insulation system diagnosis (Montanari, 2006). PD measurement and analysis is an advantageously non-destructive and non-invasive technique which monitors insulation integrity whilst the system is still functioning.

Statistical life distributions as well as processing techniques reviewed for applicability to PD analysis are shown in Figure 13.

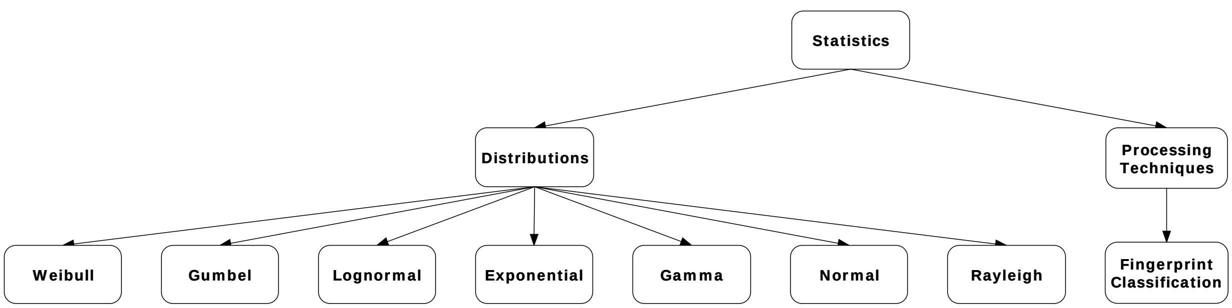

Figure 13. Statistical distributions and processing techniques considered for PD analysis

5. Fingerprint Classification

Fingerprint classification is a commonly employed diagnostic tool. A set of 29 parameters is used to create a fingerprint of the PD data. Three groups which can be used to describe the characteristics of a discharge were identified (Gulski and Kreuger, 1992). These are:

1) Basic quantities, which are quantities observed during one voltage cycle;
2) Deduced quantities, which are integrated values of basic quantities from the first group observed throughout several voltage cycles; and
3) Statistical operators, which are operators for the statistical analysis of the deduced parameters.

Statistical operators introduced include discharge asymmetry, phase asymmetry, cross-correlation factor, modified cross-correlation factor, skewness (Sk) and kurtosis (Ku) (Gulski and Kreuger, 1992). This method, however, assumes that the voltage waveform is a pure sinusoid. Hence, it is not applicable for use with PD data obtained using harmonic influenced waveforms.

6. Review of Statistical Distributions

Reliability engineers use life data analysis to determine capability of parts, components, and systems to function accurately and efficiently for certain time frames without failure, in specified environments (Weibull.com, 2011).

Life data analysis involves fitting a statistical distribution to produce life data models from a representative data set. The distribution parameters are used to find important characteristics such as probability of failure and mean life. Statistical analysis of electrical treeing PD activity is one of few existing avenues for investigating ET growth. Life data analysis can be employed since the electrical treeing ageing mechanism leads to breakdown or insulation failure.

6.1 The Normal Distribution

The Normal (or Gaussian) distribution is a continuous, bell-shaped distribution which can be used to describe continuous random variables which are symmetric about a mean value. Applications of the normal curve include physical measurements in meteorological experiments, rainfall studies and manufactured parts (Walpole et al., 2007). The associated probability density function (pdf) is given by Equation 4, where μ and $\sigma 2$ are the mean and variance, respectively.

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)2}{2\sigma^2}} \qquad \text{.... Eq.4}$$

The Normal distribution has no shape parameter; hence it has only one shape which does not change. The mean represents the location parameter whilst the standard deviation represents the scale parameter. The probability of a normally-distributed value greater than a few standard deviations from the mean drops off very rapidly. Consequently, statistical inference using a normal distribution is not robust to the presence of outliers.

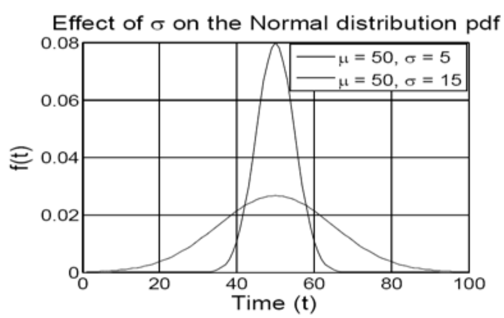

Figure 14. Effect of the standard deviation on the Normal distribution

6.2 The Lognormal Distribution

The Lognormal is a two-parameter distribution used to model the life of components which fail as a result of fatigue-stress including most mechanical systems. The Lognormal distribution is similar to the Normal distribution to some extent. If the logarithm of a variable is normally distributed, then the variable is lognormally distributed (Weibull.com, 2006). The pdf of the Lognormal distribution is expressed by Equation 5 where T values are the times to failure, $T' = ln(T)$, μ = mean (scale parameter) and $\sigma_{T'}$ = standard deviation (shape parameter).

$$f(T') = \frac{1}{\sigma_{T'}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{T'-\mu}{\sigma_{T'}}\right)^2} \qquad \text{.....Eq.5}$$

The Lognormal distribution is skewed to the right, with the pdf starting at zero, increasing to its mode, and decreasing thereafter. For a given μ value, the degree of skewness increases as $\sigma_{T'}$ increases, whilst for a given $\sigma_{T'}$ value, the skewness of the pdf increases as μ increases. This is illustrated in Figure 15.

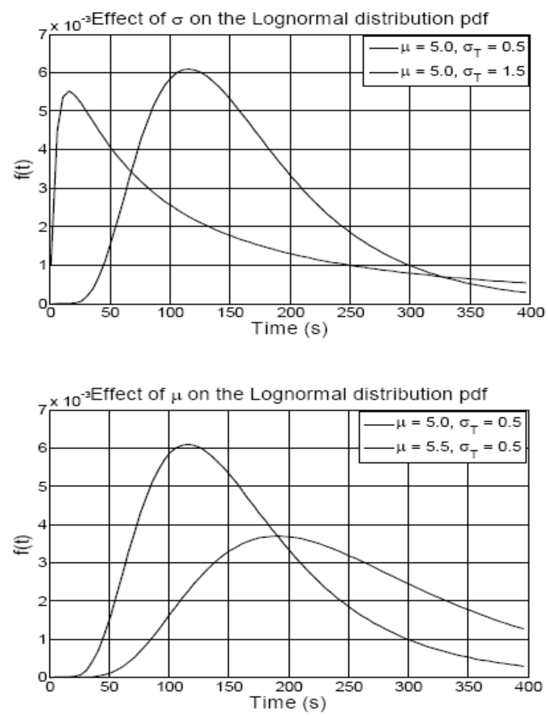

Figure 15. Effect of the shape and scale parameters on the lognormal pdf respectively

6.3 Exponential Distribution

The exponential distribution, pdf expressed by Equation 6, is extensively used in reliability engineering to model the behavior of units which have a constant failure rate. It is a special case of the Weibull distribution when β = 1.

$$f(x) = \lambda e^{-\lambda x} \qquad \text{.....Eq.6}$$

This distribution has only one shape; hence there is no shape parameter. The scale parameter, given by 1/λ, is the mean value where λ is the failure rate. The exponential pdf is always convex and is stretched to the right as λ decreases in value (as shown in Figure 16).

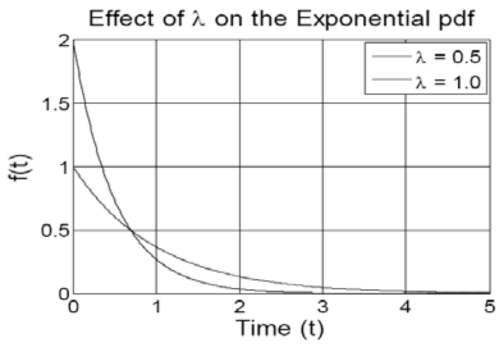

Figure 16. Effect of the failure rate on the exponential pdf

6.4 Gamma Distribution

The gamma distribution is a flexible life distribution model which is suitable for use with some sets of failure data. However, it is not widely used as a life distribution model for common failure mechanisms (Weibull.com, 2005). Its pdf is expressed by Equation 7, where z = ln(t) - μ, e^{μ} = scale parameter and k = shape parameter. When k = 1, the gamma becomes the exponential distribution (see Figure 17).

$$f(T) = \frac{e^{kz-e^{z}}}{t\Gamma(k)}, \ where\ 0 < t < \infty, -\infty < \mu < \infty \text{ and } k > 0 \qquad ...Eq.7$$

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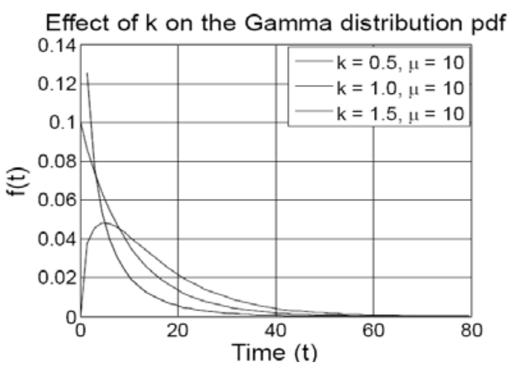

Figure 17. Effect of the shape parameter on the Gamma distribution

6.5 The Rayleigh Distribution

The Rayleigh distribution is a continuous probability distribution, which is often observed when the overall magnitude of a vector is related to its directional components. The pdf of the Rayleigh distribution is expressed by Equation 8, for parameter $\sigma \geq 0$.

$$f(x;\sigma) = \frac{x}{\sigma^2} e^{-x^2/2\sigma^2}, \ where \ \ x \geq 0 \qquad ...Eq.8$$

One example where the Rayleigh distribution is naturally found is when wind speed is analysed into its orthogonal two dimensional vector components. The Rayleigh is also used in the case of random complex numbers whose real and imaginary components are independently and identically distributed Gaussian. The absolute value of the complex number is Rayleigh distributed. Where the Rayleigh distribution is a poor model for a given location, it may be appropriate to fit the data to a Weibull distribution since the Weibull is identical to the Rayleigh when β = 2.

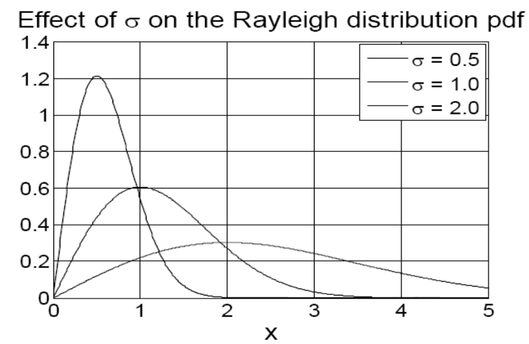

Figure 18. Effect of the standard deviation on the Rayleigh distribution

6.6 The Gumbel Distribution

The Gumbel distribution, pdf expressed by Equation 9, is an extreme value distribution where μ and σ are the location parameter and scale parameters respectively. Uses of the Gumbel distribution include modeling strength as well the life of products that experience very quick wear-out after reaching a certain age (Weibull.com, 2005).

$$f(x) = \frac{1}{\sigma}\exp(-z - \exp(-z)) \ \ ; \text{where}$$

$$z = \frac{(x-\mu)}{\sigma}, \sigma > 0 \qquad ....Eq.9$$

The Gumbel distribution is skewed to the left and has one constant shape since there is no shape parameter. The distribution is non-symmetrical about its μ; hence μ is equal to the mode but differs from median and mean. The pdf shifts to the left as μ decreases, and shifts to the right as μ increases. As σ increases, the pdf spreads out and becomes shallower; and conversely, decreasing σ causes the pdf to become taller and narrower (see Figure 19).

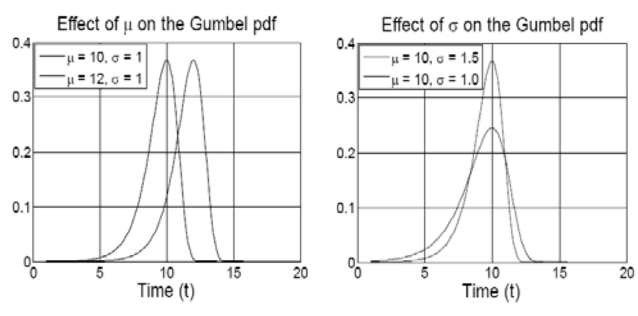

Figure 19. Effect of the location and scale parameters on the

Gumbel pdf

6.7 The Weibull Distribution

The Weibull distribution, whose pdf is expressed by Equation 10, is one of the most extensively used lifetime distributions in reliability engineering. For a (usually time dependent) variable x, the Weibull is described by two parameters, the scale (α) and shape (β) parameters.

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} \exp\left(-\left(\frac{x}{\alpha}\right)^{\beta}\right), \textit{where} \quad \alpha \geq 0, \beta \geq 0 \qquad \textit{... Eq.10}$$

The Weibull is a robust and flexible extreme value distribution which adopts the characteristics of other distribution types, based on the shape parameter value, β. When β =1, the Weibull distribution reduces to the Exponential model and when β =2, it is identical to the Rayleigh distribution. It also approximates the Normal distribution when β =3.5; hence justifying its use in modeling a variety of life behaviors. The Weibull pdf is skewed to the right and its shape changes as the β value changes (as seen in Figure 20). Increasing the scale parameter α value decreases the height and increases the width of the Weibull pdf. The Weibull distribution has been widely employed in electrical treeing studies (Bahadoorsingh and Rowland, 2010a, Bozzo et al., 1998, Bozzo et al., 1996).

Research has shown that the PD height values from a single PD source are often characterised by the two parameter Weibull distribution. A mixed Weibull model or five parameter Weibull function can be utilised to separate Partial Discharge Height Distribution (PDHD) due to different simultaneously active PD sources (Cacciari et al., 1995). PD magnitude, often an indication of the aggressiveness of the PD activity is represented by α whilst the source of the PD activity is denoted by β. A conducted study examined the ability of the shape parameter β to identify concurrent yet distinct varied PD phenomena (Contin et al., 2000). Shape parameter values characterising discharges in voids in epoxy are $1.4 \leq \beta_{\text{void}} \leq 2.3$ (Contin et al., 1998). β values for discharge activity due to electrical treeing in XLPE and EVA (ethylene-vinylacetate copolymer) lie in the range $0.7 \leq \beta_{\text{tree}} \leq 1.5$ (Bozzo et al., 1998).

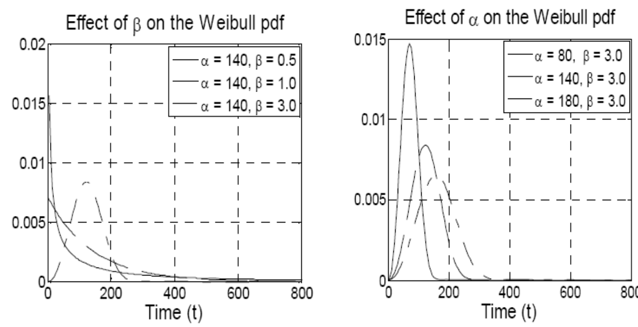

Figure 20. Effect of the scale and shape parameters on the Weibull pdf

7. Assessment of Statistical Distributions

As outlined in Table 2, the Gumbel, Exponential and Normal distributions have no shape parameter; hence the pdf has a constant shape. The model provided by these distributions would be limited relative to distributions which have a shape parameter. Additionally, a normally-distributed variable has a symmetric distribution about its mean and is not robust to the presence of outliers, hence this distribution would not easily accommodate PD magnitudes at least two standard deviations from the mean.

The Raleigh distribution is used in vector analysis and with random complex numbers whose real and imaginary components are independently and identically Gaussian distributed.

Table 2. Evaluation summary of surveyed statistical distributions

Distribution	Characteristics	Application
Gumbel	• No shape parameter. • Non-symmetrical about its mean. • Pdf skewed to the left.	Modeling strength and modeling the life of products which experience very quick wear-out after reaching a certain age.
Weibull	• Has both shape and scale parameters. • Robust, flexible. • Adopts characteristics of other distributions based on the shape parameter value. • Pdf skewed to the right.	Used to model life behaviors, extensively employed in electrical treeing PD data analysis.
Lognormal	• Has both shape and scale parameters. • Pdf skewed to the right.	Used to model life of components which fail as a result of fatigue stress.
Exponential	• Has scale parameter, but no shape parameter.	Used to model units with constant failure rate.
Gamma	• Has both shape and scale parameters.	Suitable for some sets of failure data.
Normal	• "Bell"- shaped • Symmetric distribution about its mean • Not robust to presence of outliers	General purpose distribution.
Rayleigh	• One parameter	Applicable when overall magnitude of a vector is related to its directional components e.g. wind speed modeling.

The Gamma distribution is not extensively used, and is only applicable to specific sets of failure data, as previously described, while the Lognormal distribution is used to model the life of components which fail as a result of fatigue stress.

A thorough review of the previously presented statistical distributions revealed that the Weibull distribution was the most applicable. It is the most robust and flexible technique for analysing the variability in PD activity. The Weibull distribution inherently encompasses several distributions. Although traditionally used with time to failure (breakdown) data, it has been successfully applied to model PD diagnostic data (Bozzo et al., 1996, Bozzo et al., 1998).

8. Application of the Weibull Distribution to PD Data

The cumulative distribution function (cdf) of the two-parameter Weibull distribution is expressed by Equation 11; where q represents the charge in the PD under investigation and α and β are the scale and shape parameters of the Weibull function, respectively.

$$F(q;\alpha,\beta) = 1 - \exp\left\{-\left(\frac{q}{\alpha}\right)^{\beta}\right\} \qquad \text{...... } Eq.11$$

$$\alpha \geq 0, \beta \geq 0$$

In life data analysis, the scale parameter α represents 63.2 percentile of discharge activity and is analogous to the mean of the Normal distribution. The shape parameter β is a measure of the range of the failure times. The larger β is the smaller that is the range of breakdown voltages or times. In the case of diagnostic PD data; α is indicative of PD magnitude whilst the β indicates the degree of data variability. PDHDs can be linearly modeled by logarithmic Weibull plots. This is particularly applicable when an active known single source of PD degrades an insulation medium. The straight line graph is obtained by transforming the two parameter Weibull function into logarithmic form, which is given by Equation 12.

$$\ln[-\ln(1 - F(q))] = \beta \ln(q) - \beta \ln(\alpha) \qquad \text{......} Eq.12$$

By defining:

$$Y(q) = \ln(-\ln(1 - F(q)))$$

$$X(q) = \ln(q)$$

$$K = -\beta \ln(\alpha)$$

Equation 12 becomes:

$$Y(q) = \beta X(q) + K \qquad \text{......} Eq.13$$

Figure 21 shows the Weibull charge plot of PD data for electrical treeing occurring at an excitation voltage of 14.4 kV peak. Note the minimum detected PD captured > 10 pC. This is equivalent to the form of a straight line graph, where β is the gradient and K is the y-intercept; hence α can also be computed.

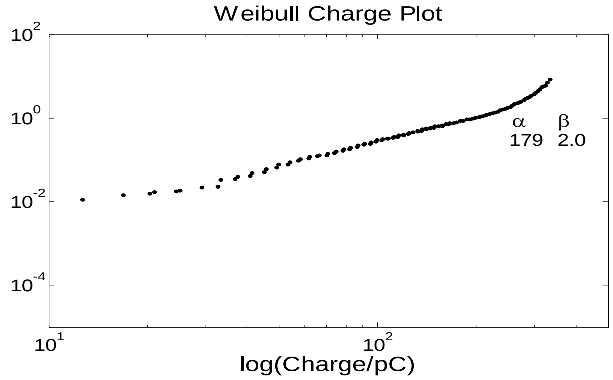

Figure 21. Weibull charge plot of PD data for electrical treeing

9. Discussion

A potentially powerful tool has evolved that merges the extraction of ET growth indices from images and the statistical parameters of PD data as described in the previous sections. The main advantage of such an extended approach is the ability to simultaneously extract the many indices used in defining ET growth using the parameters of the Weibull distribution based on the polarity of the electrical treeing PD activity. This application lends itself to the investigation of the many other PD based degradation phenomena which often lead to visual dielectric damage.

While increased PD magnitudes provide a direct correlation to the aggression and acceleration associated with the dominant insulation ageing mechanism, caution must be exercised as the Weibull scale parameter represents the 63.2 percentile of PD magnitude. In PD diagnostics the maximum PD magnitude is employed to estimate the insulation ageing state.

This tool will facilitate further study of ET growth under variable conditions including but not limited to harmonic influenced electrical stress. There is a dearth of published literature documenting research investigating ET growth (not failure) as a consequence of specific harmonic orders polluting the power frequency at varying magnitudes.

The tool therefore provides the wherewithal to critically analyse, recorded progressive visual images and partial discharge data to investigate potential relationships between harmonic content and ET growth. The mechanics of the experimental setup required to conduct such laboratory based exercises are critical and are well documented (Bahadoorsingh and Rowland, 2010b, Bahadoorsingh and Rowland, 2010a).

Figure 22 graphically illustrates how captured experimental results can be decoupled by the approach outlined and reintegrated providing unique perspectives and insights in the quest of extracting potential relationships amongst attributes of the measurands and ET tree growth.

Further research to improve and optimise the existing methodology and equipment would include:

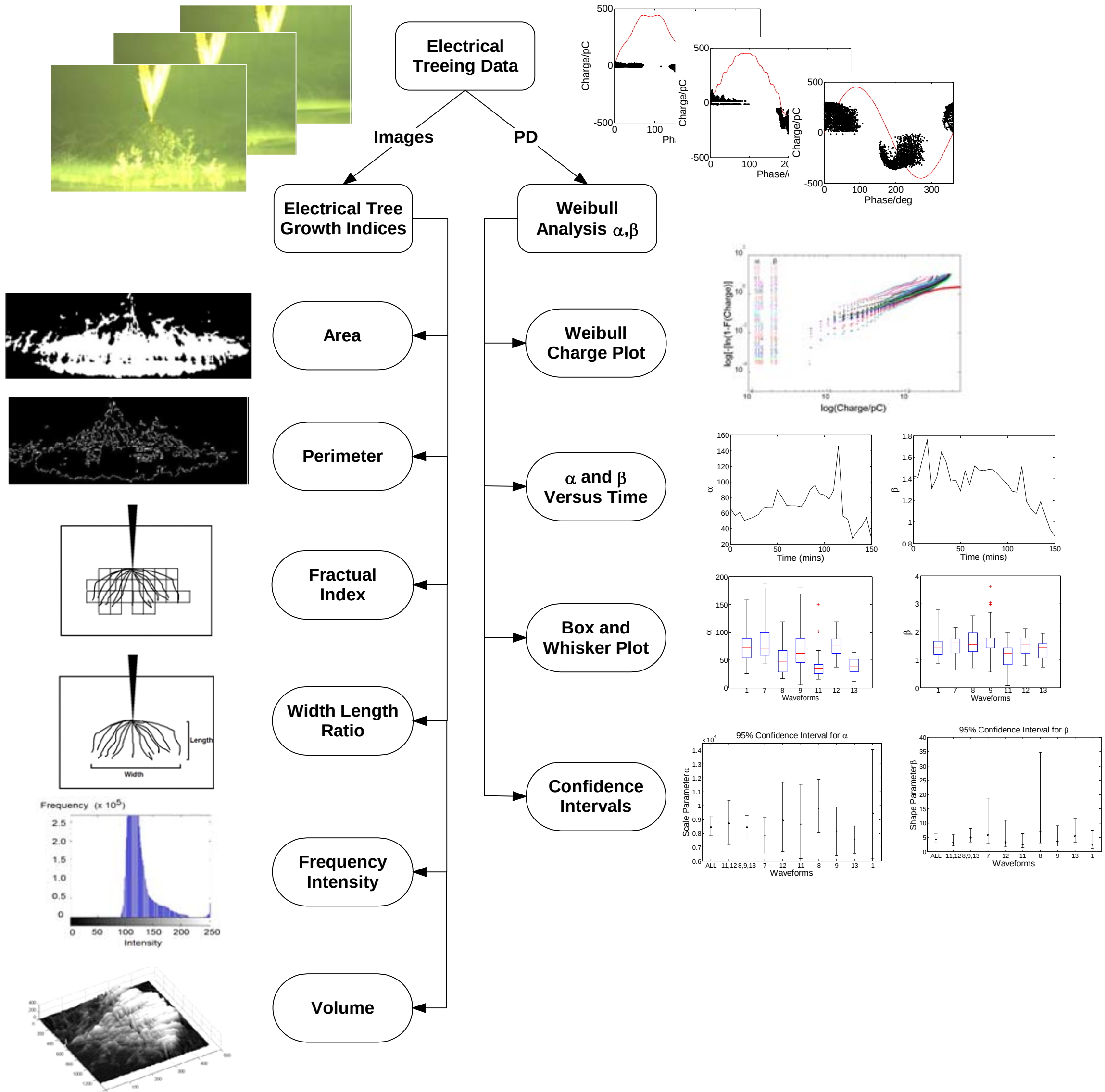

Figure 22. Proposed approach for amalgamation of optical and statistical processing techniques for ET data

1) The use of higher resolution cameras during the experiments producing more detailed images. There are cameras of 15 megapixels and above readily available today. These can produce higher resolution images and therefore more electrical tree growth information can be extracted.
2) Employing multiple cameras in the experimental procedure that produces images at 90º apart can produce a more accurate 3D model. This 3D model will improve image capture and accuracy of the observed progressive electrical tree growth.
3) Improved automated optics including lighting and camera focal length adjustments before and during the early stages of the experiment. This will focus and enhance the clarity of captured images of ET growth.
4) Improving the minimum detectable PD level (currently recorded at 5 pC) and the sensitivity of the experimental equipment.
5) Using increased sampling rates and onboard digital buffers to facilitate improved real-time processing of the captured PD data.
6) Development of software to automate the entire process - from the experimentation to the testing and analysis of captured data.

10. Conclusions

This paper introduced and discussed an analytical approach for ET data processing, employing both image processing and statistical techniques. It further discussed the technical requirements of image processing to quantify ET growth, using six defined methods, two of which were novel. The mathematical mechanics of the justified Weibull distribution were also outlined, unconventionally modeling PD data. Assessing ET images and PD data can provide an opportunity for further investigation to determine if there are any relationships which may exist between ET growth and corresponding PD activity as a function of time. This is the next step in the research to fully comprehend the multidimensional problem that is dielectric ageing and more specifically ET growth.

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