Decision Making & Forecasting using the data available to Utilities – Pitfalls, Challenges, and Case Studies of ways forward

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ABSTRACT

Asset Management is increasingly discussed and employed for managing cable systems. Many utilities have limited data that is not amenable to traditional analysis/modelling approaches. The authors propose a number of methods that can be adapted to utilize the types of field data that utilities generally either have available or can be gathered together relatively quickly. These data may then be augmented with diagnostic results and age estimates to provide a basis for planning decisions.

KEYWORDS

Asset Management, Cable Diagnostics, Ageing, Weibull Analysis, Crow-AMSAA, Failure Prediction

INTRODUCTION

The interest in Asset Management for Cable Systems continues to grow. There are many goals, but the most common are to a) wisely use the resources allocated to Operations and Maintenance and b) predict how these resources will need to grow with time as the system continues to age at a rate which is likely to be modified by the remedial actions.

Perhaps the key challenge is to develop the baseline models which realistically estimate the future under the "status quo" operation. In principle, this should be straightforward as all that is required for such estimates are the installation and failure records for the cable system. However, it is the acquisition of these simplest of data that has always been the challenge for people working in this area; as it is often reported that the data are limited, incomplete, and/or inconsistent. As a consequence simple "rules of thumb" (linear approximations of failure rates) / heuristics (age based conditioning) are often used in the base case models; with all the inherent in accuracies in these approaches. Clearly the heuristic approach poses a major hurdle for Asset Management programs which aim to develop a consistent and transferable approach to estimating the value of various intervention strategies. The uncertainty inherent in the base case makes it difficult to determine the optimal strategy either in terms of effectiveness or efficient use of limited resources. Furthermore, the magnitude or direction (smaller / larger) of the base case uncertainty is not known.

Cable System Diagnostics show great promise in guiding Asset Management programs [1-6] that require immediate feedback. However, they have not thus far provided assistance in the arena of predictions. Recent evolutions in the technology have led to the use of Data Driven Health Indices which provide a robust snap shot of current condition and indications of ageing dynamics via Age Lines. Unfortunately, diagnostics are not completely perfect for this application as they are not retroactive, require investment in data collection / collation, and are inherently "sampling-based" as it is not possible to test every circuit.

Historical utility data has always been attractive because they are available now, all encompassing (not sample based), segregated (age / type etc.) and completely historical thereby including all the transients / changes that have occurred on the system. Its use has been limited due to the concerns of data fidelity, changing data management systems, and dispersed storage. However, there have been some recent developments by which the data may be "cleaned" and "re assembled" in a practical and expedient manner. As a consequence much more of this type of analysis may be undertaken.

Thus there are attractions and drawbacks with both of the approaches available to utilities. This paper discusses these issues further and provides illustrations via Case Studies; thereby describing:

- Newly developed algorithms for Diagnostic Data that provide pre conditioning for use in Asset Management Analyses,
- Architecture of utility service data and why this makes "classical" analysis difficult,
- Data fidelity issues that compound the challenges of the architecture,
- Distribution fitting solutions for discrete devices (Parametric Modelling with assumed Failure Sequence),
- Trend evaluation and prediction for lumped failure per year data (Crow AMSAA),
- Modelling using pre-treated utility data (Parametric Modelling with Population Reconstruction)
- Indications of how they might be included in "value" case studies
  - Dielectric Loss tests establishing system health with prognosis of future service performance under different remediation strategies
  - Service Failure Data estimating Survival Curves for different cable system technologies and vintages, thereby providing guidance on the optimal intervention strategies

CLASSIC RELIABILITY ANALYSES

Classic reliability analyses [7] use failure data from the field to fit probability distributions. These distributions allow the engineer to do a number of useful things

1. Consider the whole population, the survivors together with the failures,
2. Obtain a figure print of the failure mode – this is generally the gradient of the curve, and

3. Make predictions of what might happen in the future, if nothing happens.

However, to do this requires that we capture all the failures on the system, we know the ages of the components at failure and that we know the age of all the components that have not failed. The analyses using these data will tell us all that we need to know. Yet the data collection burden can be very significant. In many cases utilities will not have all of the data, especially in the MV arena.

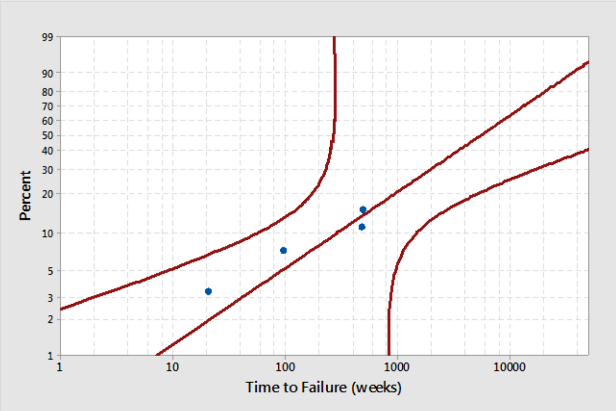

Figure 1 Weibull Curve for time to failure in service

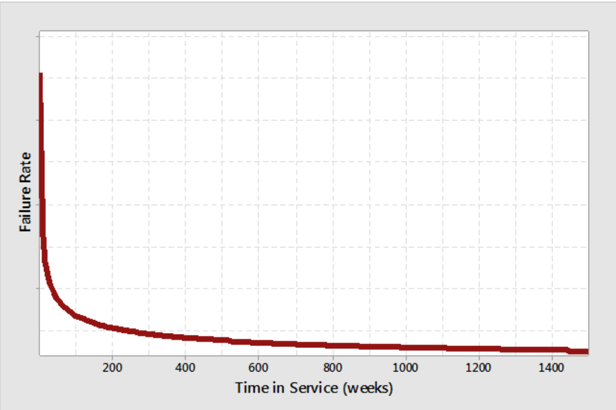

Figure 2 Hazard Curve derived from Weibull Curve

The approach and the requirements can be seen from some synthesised data for the service performance of HV accessories. A series of failures and associated repairs have occured. Consequently the correct data are available:

- Number of accessories involved
- Failure times
- Survival times of the original accessories
- Survival times of the replacement accessories

These data can then be analysed (Figure 1 to Figure 3) show how such classic analyses evolve from Weibull analyses to a Survivor Curve [7, 8]. Although it is common to only inspect the Weibull Curve, there is a benefit in looking at all three of the possible representations. The Weibull Curve provides information on the mechanism and if there is more than a single straight line this suggests two modes of failure. The Hazard Plot is valuable as this enables discussion in terms of the familiar Bathtub Curve and provides a visualisation of the evolution of the Failure Rate that is difficult to extract from the Weibull Curve only.

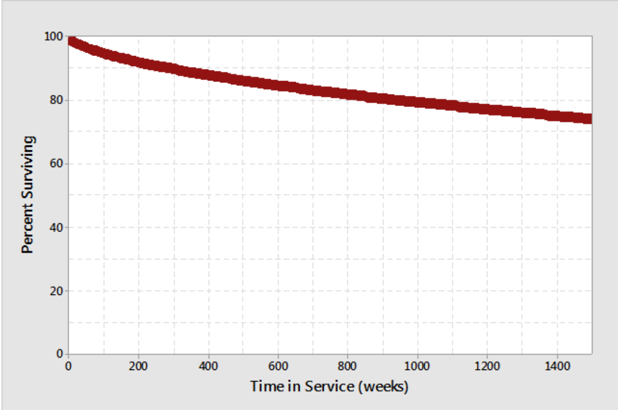

Figure 3 Survivor Curve derived from Weibull Curve

Clearly the reason to conduct the analysis is to understand the future implications of the failures / survivors. This naturally leads to trying to establish a Life Statement. The Survival Curve is perhaps the most convenient way to frame such a Life Statement. In the case of the data represented in Figures 1 to 3 this would be framed as:

When installed in a direct burried configuration and lightly loaded, 80% of the originally installed accessories would be expected to survive 17 years in service.

It is interesting to note that the Life Statement really contains three distinct parts; a statement of the environment / operating conditions, a statement about the expected level of survival, and finally a time frame. All three of these components are required to maximise the usefulness of the statement. Thus there are a number of conversations that typically occur around the analysis of failures and these different conversations are facilitated by different representations.

In this case the Weibull Distribution was used for the analysis, however Log Normal or Exponential Distributions might be chosen [7]. In these cases, an appropriate ”goodness of fit” test should be used to determine which is the most appropriate distribution.

The analysis detailed above requires a level of detail at the component level that is often applicable for HV & EHV systems but is challenging to obtain at MV.

DIAGNOSTIC APPROACHES

One response, being used by utilities [5], to the scarcity of failure data is to utilise field diagnostic measurements. The basic thinking is that the field measurements would let the utility know the status of the cable systems. One of the major drawbacks of the standard embodiment of this approach is that the information is a snapshot – it provides the current condition. This is ideal for making maintenance decisions but is not sufficient to establish the ageing performance trends. This is because the utility knows where they are but not how they got there and thus are unable to make informed judgements on how things might be in the future.

This drawback can be addressed in two ways: Repeat Testing or Testing of a range of ages. Repeat diagnostic testing can be undertaken at suitable intervals. Thus, if consistent measurements are made and the data tracked suitable curves can be developed. Unfortunately diagnostic measurements tend to be inconsistent due to either different operators or evolving technologies. Coupled with this is the difficulty of maintaining a database of results over the 6 to 8 years that it takes to develop the trends. Nevertheless, this approach is valid and represents a way forward if the decades of historical data are not available. The second approach relies on a slightly nonstandard approach to sample selection but has the advantage of being relatively quick to implement, thereby neutralising the problems of evolving diagnostics / operators. The basic technique is to make diagnostic measurements on cable systems that have a representative range of ages and representative service conditions. These data are then interpreted using a set of well-defined rules which allocate membership of condition groups through which a new cable must pass to failure. The relative membership proportion of these classes can be determined along with their evolution with time (i.e. ageing). We have termed such a construct an Age Line as it represents the likelihood that a cable system of a selected age will belong to a particular class.

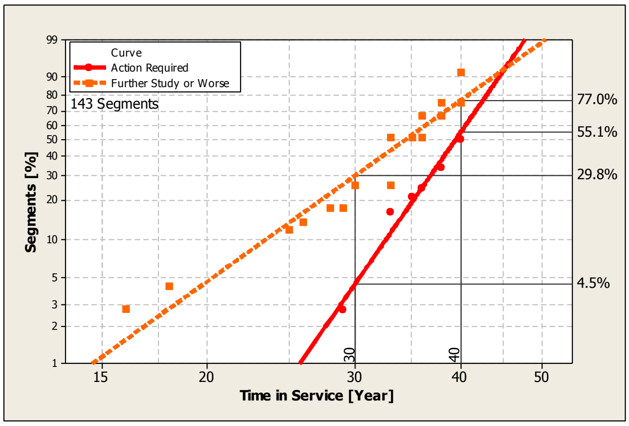

Figure 4: Tan δ Age Lines – "Further Study Advised & Worse" and "Action Required"

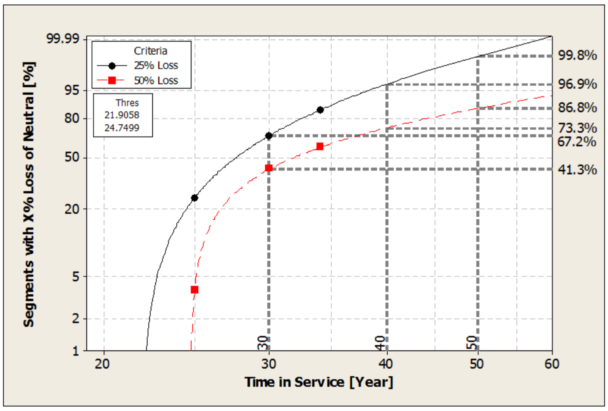

Figure 5: Ohm Check Neutral Assessment Age Lines

Figure 4 and Figure 5 show two examples of this approach for different diagnostics; VLF Tan Delta [8-10] and Concentric Neutral wire integrity (using resistance measurements [5]). The Tan Delta data is segregated into three classes (No Action Required, Further Study and Action Required) using rules based on the voltage and time dependence of VLF Tan Delta data [6]. Clearly, a cable segment will pass through Further Study en route from No Action Required to Action Required; thus there is a direction to the classifications. The analysis makes use of the classification in the analysis. Conducting these assessments on a series of segments of different ages enables the construction of the Weibull Age line in Figure 4. The data used to construct this curve was gathered over an 18 month period, thereby showing the efficiency of the approach. Although this does not represent failures that have actually occurred, the Further Study and Action Required classes represent increasingly likely failures in service. Extrapolation enables the prediction of the system health in future years.

A similar approach is used for the health of the neutral wires shown in Figure 5. In this case there is no need to use classifications as the resistance data themselves represent the loss of cross-sectional area. This approach is perhaps preferred as the utility can choose their own criteria rather than relying on the predetermined ones used in the VLF Tan Delta case.

Although, not directly relating to service failures, this approach does have an advantage in that it enables different degradation mechanisms to be separated out. In this case, a cable system of with significant remaining life is would need to have both good dielectric health and good neutral health. The use can perhaps be best represented in a dual Life Statement of the type set out before:

When considering direct buried un-jacketed MV cables using polyethylene based insulations in the US, at 40 years of age, 73% would be expected to have lost 50% or more of the neutral wire and 55% of the dielectrics would require urgent action.

Clearly, if the end of life criterion for a utility is 50% of the neutral loss then the dielectric health is somewhat better than the neutral health. If the neutral criterion is set at 75% loss then the dielectric health becomes more important.

TREND EVALUATION / RELIABILITY GROWTH

The Crow-AMSAA technique (or Reliability Growth Model) [7] utilizes log-log representations of cumulative performance and cumulative experience. This method is particularly useful for identifying changes in population performance (i.e. lower or higher failure rates). In the case of cable systems as well as other devices, the performance metric is typically taken to be service failures while the experience could be chosen to be length, number of segments, time in service, or some combination. Figure 6 shows an example of a Crow-AMSAA plot for two areas on a utility system. In these areas, the failures have been tracked for a number of years and segregated by the type of failure: cable, elbow, splice, or termination. Unfortunately, the vintage and hence age at the time of failure was not recorded so the detailed Weibull Analysis described earlier is not possible. Nevertheless the Crow-AMSAA analysis is shown in Figure 6. The location of the final points in terms of cumulative failures at a cumulative experience gives the failure rate – end points further to the upper right represent higher failure rates. The gradients of the Crow-AMSAA curves do not provide fingerprints of the mechanism of failure as with Weibull Analysis. These gradients indicate changes in the failure rate; increasing gradients indicate an increasing failure rate. Additionally, any steps that a utility might take to improve the reliability of the system should be represented by the decreasing gradient. Clearly the extrapolation of the curves to large experiences (generally longer times) enables base case (do nothing) scenarios to be evaluated. As an example it is clear that the elbow and splice failures in Area D will outpace the termination failures within a couple of years.

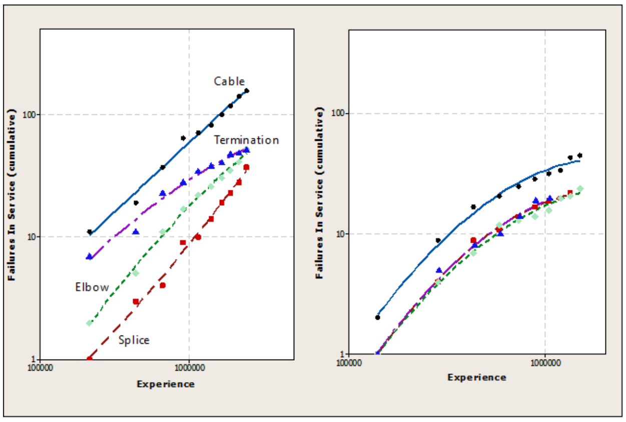

Figure 6: Crow AMSAA Analysis of segregated failures (cable, elbow, splice & termination) for two different utility areas – left Area D & right Area N

The major drawback of the Crow AMSAA approach is that although it readily enables predictions it does not provide guidance on where or how to intervene. This is because the precise details of the failure are not retained. As an example, if the cable failure rate in area N is to be reduced which vintage should be targeted? One consequence of this is that it is not possible to estimate the contribution of future failures from each of the cable system vintages. This information is invaluable in setting the framework for the optimal strategy and budget discussions.

PARAMETRIC MODELING AND POPULATION RECONSTRUCTION

Although Crow-AMSAA provides many benefits, so much more can be done if the failures can be correlated with the vintage of the cables. Unfortunately, there remains the problem of data if these age-segregated data have not been collected in the prior years. The authors have addressed this challenge in a number of applications by using recent failures as one of the sources for the information and then augmenting these data with basic engineering understanding of how the utility operated their system.

The particular approach is demonstrated here using the larger data set from which the area data in Figure 6 were derived. The utility had failure data for a number of recent (last 3) years available to them. These failures had location information, such that it was possible to use the construction records to ascribe an approximate installation date to each. Althought this date will not be precise in all cases, experience has shown that such inaccuracies tend to be evened out as more data are considered. To improve the fidelity of the data further the estimated installation dates were reviewed against engineering and purchase records (i.e. to ensure that a cable is not identified as being installed years before this type was purchased, etc.). In parallel, the purchase records and maintenance practice records were reviewed so that a picture of the complete population could be developed.

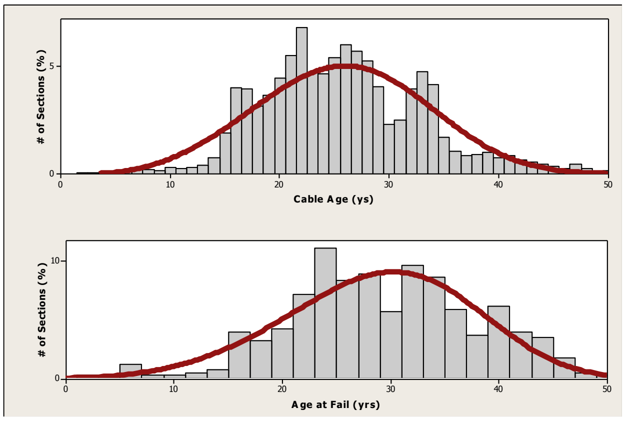

Figure 7: Age Histogram of installed sections (derived from purchase records) – top and failing sections (derived from failure and installation records) - bottom

Figure 7 shows the results of these activities for cables only using XLPE insulations. Similar analyses have been completed for PE & EPR cable and splices and terminations; however these are not presented here. The installed population and the failure population are similar but crucially different with the failures skewing towards the older ones as would be expected. These data were segmented into 10 year bins and subjected to Weibull analysis. As an example, the 10 year bin in Figure 8 is based on all the failures that recently occurred on cables that were 10 years old or less with an allowance for the cables in this age range that did not fail. A similar approach is used for cables failing with ages between 10 and 20 years with an allowance for the cables in this age range that did not fail and for those anticipated to have failed before age 10. The subsequent curves are then built up for the different ages – Figure 8.

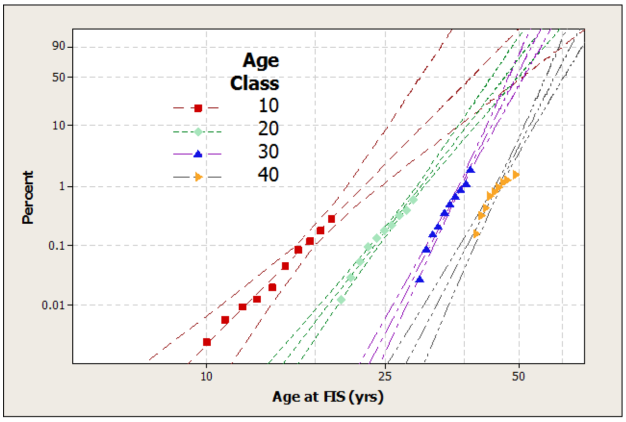

Figure 8: Age segregated Weibull Curves for failures in service

The Weibull Shapes (gradients) are in accord with the anticipated values and naturally become steeper with the increasing age of the bins. This is consistent with the development of a the traditional Bathtub Curve excluding the Infant Mortality which has a time scale that is too short to be resolved in these time bins. Any convenient interval can be chosen for the age bins but care needs to be taken to ensure that the number of data contained in each bin does not decrease too much.

This utility has long had a policy of repairing upon failure rather than generally replacing poor performing cables. Thus, the installed population is relatively stable and known. It is then reasonably straightforward to construct a Survivor Curve from the four separate Weibull Curves in Figure 8 by applying them to the population data shown in Figure 7 (see Figure 9).

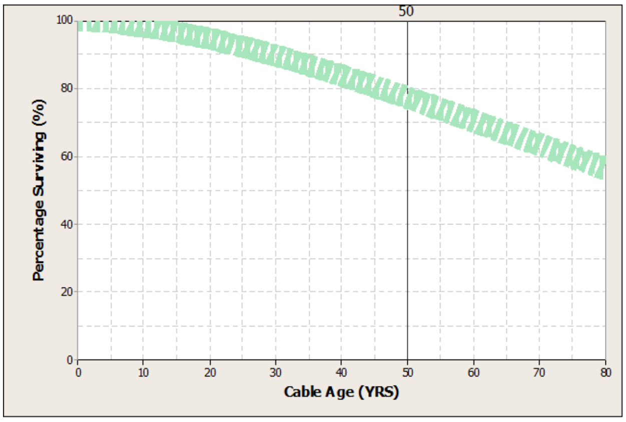

Figure 9: Survivor Curve constructed from the four separate Weibull Curves shown in Figure 8

Thus, Figure 9 makes it quite straightforward to construct suitable Life Statements for this utility cable system:

80% of direct buried un-jacketed MV cable segments using polyethylene based insulations at utility Alpha are expected to survive to age 50.

A 40 year life for direct buried un-jacketed MV cable segments using polyethylene based insulations at utility Alpha is based upon the survival of 83% of the cable segments.

Typically engineers are accustomed to thinking in terms of mean life (i.e. the time at which 50% have failed) and as a consequence the lives are considerably shorter than the >80 years indicated in Figure 9. However, due to the buried nature of cable and the cost of repair / refurbishment / replacement attention is drawn to them at much lower levels of un–reliability, say, 10% (90% survival). It is interesting to reflect upon the paradigm shift that is being engendered by the implementation of SMART devices; in this environment attention is drawn at much lower un-reliabilities of 0.5% (99.5% survival).

One benefit of the Survival Curve in Figure 9 is that it can be used in conjunction with the population to run failure scenarios. As an example, the 5% of the population that is age 33 would be expected to have 90% survival and 85% by age 53. Thus, by addressing each age bin sequentially it is possible to estimate how many failures might reasonably be expected with the current ageing models and which vintage they would be expected to have come from. The result of this calculation for a 20 year horizon is shown in Figure 10. This is interesting as it shows that the cables that have the biggest impact are not the ones that are old today, as there are only a few of them. The biggest impact will come from the ones that we give little thought today as they presently have a low failure rate – the ones at age 34/34 and 26/27/28. These have an impact not because of their currently high failure rate but from the fact that this low rate will rise to a moderate one, but that it will act on a large population.

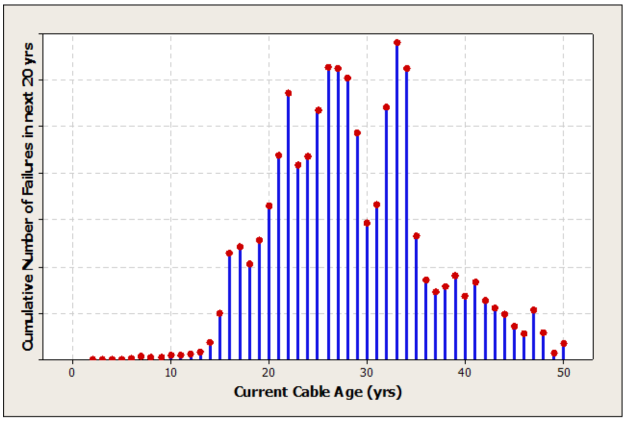

Figure 10: Contributions to the failures in the next 20 years based on current cable age

CONCLUSIONS

There are a number of approaches that the authors have utilized to investigate the service performance of aged cable systems (as well as other devices). These techniques have their advantages and disadvantages. They must be adapted and combined with engineering judgment in order to arrive at reasonable results when data fidelity is limited. The availability of data is a significant issue that can be addressed through other means including targeted diagnostic programs, short term data collecting, etc.

Regardless of the data source, the fact remains that decisions must be made whether there are data to support them or not. This paper shows that there are many ways that these problems can be overcome to yield information that can be used to make better decisions.

REFERENCES

1. Diagnostic Testing of Underground Cable Systems (Cable Diagnostic Focused Initiative), DOE Award No. DE-FC02-04CH11237, Dec. 2010.
2. L. A. Dissado, and J.C. Fothergill, Electrical degradation and breakdown in polymers, IEE Materials and Devices series 9, Peter Peregrinus Ltd., London, 1992.
3. J. Densley, “Aging Mechanisms and Diagnostics for Power Cables - An Overview,” IEEE Electrical Ins Mag, vol 17, no 1, pp 14-22, Jan/Feb 2001.
4. E. Dorison, et al, “Health Index,” *JICABLE07*, Versailles, France, June 2007.
5. R.N. Hampton et al, “Challenges associated with the Interpretation of Dielectric Loss Data,” *JICABLE11*, Versailles, France, June 2007.
6. RB Abernethy, 2006, The New Weibull Handbook 5th Edition Reliability and Statistical Analysis for Predicting Life, Safety, Supportability, Risk, Cost and Warranty Claims, Dr. Robert B. Abernethy, North Palm Beach, FL, USA

7. IEEE, “IEEE Guide for Field Testing of Shielded Power Cable Systems Using Very Low Frequency (VLF) (Less than 1 Hz),” IEEE Std. 400.2-2013, May. 2013.

8. R. N. Hampton, et al; “Practical Issues Regarding The Use Of Dielectric Measurements To Diagnose The Service Health Of MV Cables,” *JICABLE07*, Versailles France, June 2007

9. J. C. Hernandez-Mejia, et al; “Characterization of Ageing for MV Power Cables Using Low Frequency Tan-delta Diagnostic Measurements,” IEEE Trans on Dielectrics and Electrical Ins, Vol. 16, Issue 3, pp 862-870, June 2009.

10. J. Perkel, et al, “Interpretation of Dielectric Loss Data on Service Aged Polyethylene Based Power Cable Systems using VLF Test Methods,” IEEE Trans. Dielectrics and Electrical Insulation, Vol. 20, No. 5, pp. 1699-1711, Oct. 2013.