Interpretation of Dielectric Loss Data on Service Aged Polyethylene Based Power Cable Systems using VLF Test Methods

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ABSTRACT

In the past, cable system management has proceeded on the basis of cable system age, assuming that the oldest has the lowest reliability. It is now recognized that this constitutes a very coarse assessment and that a more targeted approach would bring a more efficient use of resources. The more targeted approach requires an assessment of the health of cable systems. It is increasingly common for the assessment of aged cable systems to be made through the application of diagnostic measurements. A recent study has shown that Very Low Frequency (VLF) Tan δ is the most commonly deployed cable system diagnostic. The practical use of this technique has been supported by the international standards IEEE Std. 400-2001 and IEEE Std. 400.2-2004. A key part of these standards is the guidance provided to a user that is detailed in the "Figures of Merit". These enable users to make practical improvements to the cable system as they help to identify cable systems that are more likely to fail in service in the near future. To aid these decisions a series of criteria have been developed. The benefit of the criteria described here is that the process for their determination is rational, reproducible, and transparent. The outcomes are supported by a probabilistic assessment of service performance.

Index Terms — **Diagnostic techniques, very low frequency (VLF), tan delta, dissipation factor, MV cables, decision tools.**

1 INTRODUCTION

THE use of dielectric loss measurements to estimate the "health" of cable system assets is becoming increasingly common: a study in 2009 conducted by the authors showed that dielectric loss tests were the most commonly implemented proactive diagnostic in North America [1]. The measurement of the dielectric loss on cable systems in the field has been discussed by many authors for frequencies ranging from 0.01 Hz (VLF – very low frequency) to 300 Hz (DAC – Damped AC) [1 - 9]. However, these discourses have tended not to address the practical methods that might be used to determine the levels which define the "health classes" e.g. condition assessment results as: no action required, action recommended, and others.

This paper discusses the interpretation of dielectric loss data from power cable system measurements at the frequency of 0.1 Hz. Only polyethylene (PE) based insulations are considered (i.e. high molecular weight PE - HMWPE, low density weight PE - LDWPE, cross-linked PE - XLPE, and water tree retardant XLPE - WTRXLPE). The discussion is based on the following items or issues:

- Limitations of current methods and standards (i.e. IEEE Std. 400 [2]).

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- Collation of more than 2000 individual dielectric loss data from different cable systems in the field.
- Selection and discussion of traditional and new diagnostic features such as absolute loss magnitude, changes in loss magnitude with voltage (i.e. Tip Up or Tip Down), temporal stability of loss magnitude for a specific voltage level, and stability of loss magnitude between successive voltage levels. These traditional and new diagnostic features are explained and discussed in detail later in the paper.
- Interpretation of the local geographical context of loss data, e.g. effect of isolated high loss regions and neutral corrosion effects.
- Analysis of diagnostic features using Pareto principles that establish the appropriate levels of performance for PE-based cable system insulations.
- Assessment of the in-service performance of the cable systems some years after the initial condition estimates.
- Since, the assessment criteria as typically deployed in the field cover the power cable system accessories. The criteria develop here consider the complete power cable system (cable, terminations, and splices).

This work represents the largest study to date on dielectric loss measurements made on field aged cable systems.

2 VLF TAN δ MEASUREMENTS

Tan δ measurements determine the degree of real power dissipation in a dielectric material (dielectric loss). These measurements are then compared to known reference values for the type of dielectric measured. This comparison allows the user to make a judgment as to the condition of the tested circuit. Reference values can be based on:

- Values measured on adjacent phases (A, B, C),
- Values measured on cables systems of the same design and vintage within the same location,
- Values when the cable system was new,
- Historical values and trending, or
- Industry standards [2-3], or an experience library.

Tan δ measurements have the best benefits if the specific cable and accessory components under test are known. This allows for a direct comparison between the measured value and:

- The expected values for known materials / components,
- Previous measurements on the same circuit, or
- Baseline values.

Tan δ values are obtained typically by applying an AC sinusoidal voltage and measuring the phase difference between the voltage waveform and the resulting current waveform. This phase angle is used to resolve the total current (I) into its charging (I_C) and loss (I_R) components. The Tan δ is the ratio of the loss current to the charging current.

Figure 1 shows an ideal equivalent circuit for a cable, consisting of a parallel connected capacitance (C) and a voltage dependent resistance (R). Table 1 lists some of the advantages and concerns related to VLF Tan δ tests.

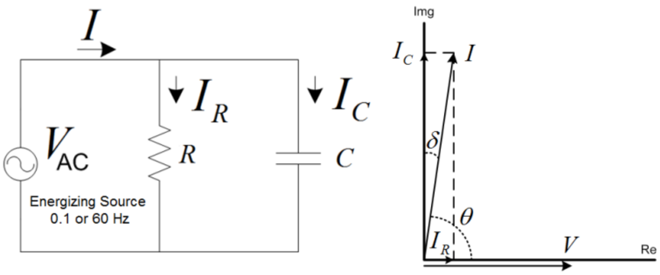

Figure 1. Equivalent Circuit for Tan δ Measurement and Phasor Diagram.

Table 1. Advantages and Concerns of VLF Tan δ.

Advantages	*Concerns*
• Energizing test equipment is small and easy to handle due to the low frequency. • Frequency dependency of Tan δ can be established. • Tan δ is more sensitive at lower frequencies than at 60 Hz due to the reduced magnitude of the capacitive current [1]. • Can test very long cable circuits.	• Testing voltage frequency is not the same as the operating voltage. • Frequencies lower than 0.01 Hz may cause space charge formation [1].

It is recommended that a minimum of 6 measurements should be made at each selected test voltage level in order to determine Tan δ diagnostic features. In general, in this test the "operational U_0" is used to determine test voltages levels [1].

3 TAN δ FEATURES

In principle, there are three types of dielectric loss data that may be reported:

- Tan δ Magnitude - normally reported as the mean of a number of sequential measurements (the median of these measurements may also be used).
- Differential Tan δ or Tip Up - normally reported as the simple algebraic difference between the means of a number of sequential measurements taken at two different voltages (the difference between medians may also be used).
- Tan δ Time stability - normally reported as the standard deviation of sequential measurements. However, the inter-quartile range (span of middle 50% of the data) may also be used.

Degraded power cable systems would exhibit high levels on the dielectric loss data that is reported.

Figure 2 shows examples of measured Tan δ data from a PE cable system in service. The test consisted of sequential Tan δ assessments at selected voltage levels. Following this approach, an extensive collation of VLF Tan δ data for PE-based insulations has been assembled in a database that covers at least 22 discrete test areas and more than 7,300 data entries at different voltage levels. The terminology "PE-based insulations" refers to all cable systems with polyethylene based insulations, including HMWPE, XLPE, and WTRXLPE insulations.

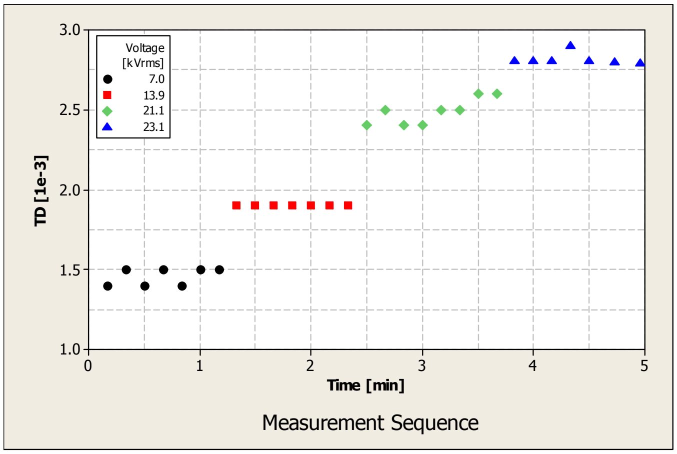

Figure 2. Measured Tan δ data from a PE Cable System in Service (25 kV system operating at 13.9 kV).

This grouping has been adopted by recognizing that in the vast majority of cases, the user will not have the precise details of the cable system at the time of testing – maps are often available but generally do not contain up to date information. The data are presented in box and whisker format [10] - Figure 3 includes three graphs:

- "STAB" – stability vs. time measured by the standard deviation (STD) for sequential measurements made at U_0,
- "Tip Up (TU) 1.5-0.5" – differential Tan δ between $1.5U_0$ and $0.5U_0$, and,
- "TD" – mean Tan δ measured at U_0, where U_0 is the phase-to-ground system operating voltage.

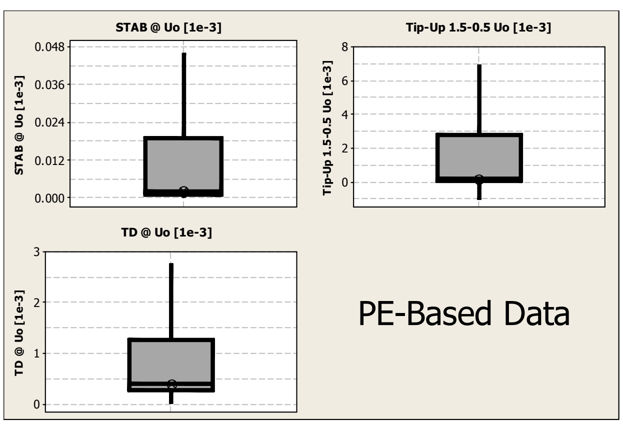

Figure 3. PE Based Cable Systems Dielectric Loss Feature Data in a Box and Whisker Format (the open symbol is the mean of the data).

The authors strongly prefer limiting the maximum Tan δ test voltage to below that prescribed for withstand tests in IEEE Std. 400.2 [3]. Thus, a Tip Up or Differential Tan δ is based on an upper voltage of $1.5U_0$. This has two main advantages: 1) the low risk of failure under test is further reduced compared to traditional higher voltages for withstand tests and 2) the quality of the cable system is assessed before any commitment to a withstand test.

The data presented in Figure 3 represent 2,420 segments with a mean length of 320 m (1,070 ft). The total length for this population exceeds 760 km (475 conductor miles). The horizontal lines within the boxes represent the median while the boxes encompass the middle 50% of the data.

4 TRADITIONAL CRITERIA

In many instances, a condition assessment is attempted using Tan δ as the primary metric. This approach appears in the current data from IEEE Std. 400 [2]. The results of this approach are frequently problematic as the interpretation may be influenced by the length of the cable segment, the type of insulation, and the presence / dispersion of high loss elements (terminations, highly water treed regions, or splices) [1,9]. Applying the criteria suggested in IEEE Std. 400 [2] to the collated data available clearly demonstrates these issues. The standard suggests that cable systems with Tan δ > 4E-3 need to be replaced. However, examination of the data shows that this implies that 47% of the systems measured require replacement. Not only does this appear to be an unreasonably high percentage of "bad" circuits, but the fact that most of these systems remain in service with a failure rate of 11% indicates that the assessment accuracy is not right and needs to be improved. Furthermore, many segments classified at the intermediate levels have proven to fail in advance of those classed more severely. Thus, the authors conclude that the present IEEE Std. 400 [2] criteria and those proposed in Annex F of IEEE Std. 400.2 [3] are too conservative at the most severe level and miss-classify at the mid-level.

IEEE Std. 400 [2] also notes that the critical levels will depend upon the insulation types used for the system. This contention is supported within Figure 3 for the basic insulation classes. The update of IEEE Std. 400.2 [3] will address the critical levels, features, and insulation dependencies. Furthermore, it will revise much of the guidance presently in IEEE Std. 400 [2]. While many engineers focus on a Tan δ level, IEEE Std. 400 [2] also suggests that multiple Tan δ features should be considered (i.e. Tan δ and Tip Up) in the assessment. Unfortunately, the standard does not provide guidance regarding how to make a decision. The use of multiple features, say Tan δ and Differential Tan δ, has proven useful in the analyses (Figure 3) conducted by the authors. In such a scheme, clarity and consistency in determining the critical levels are imperative.

5 METHODOLOGY FOR ESTABLISHING CRITICAL LEVELS WITH MULTIPLE FEATURES

In the past, engineers have tried to find "Perfect" criteria that absolutely separate the Tan δ values of segments that go on to fail from those that do not. It is not possible to define such a "Perfect" criteria since this requires a large database of Tan δ measurements and service performance data. Both of these are difficult to acquire separately, much less together. Even if large amounts of data are available, the multitude of aging scenarios may preclude the value of these data. This is especially true for the dielectric loss data that are typically collected by utilities. However, an alternative approach for defining "Good" criteria, developed by the authors, identifies critical dielectric feature levels that separate "usual" from "unusual" data. This is an application of the classic Shewart or control chart approach, which uses the mean and standard deviation as metrics to define a "normal" value. In the simplest form, data are unusual if either:

a) One value lies more than three standard deviations from the mean, or

b) Two sequential values are more than two standard deviations from the mean.

This technique allows the knowledge rules for Tan δ to be further refined as more data become available. The following discussion describes the current database and its use in determining the critical Tan δ diagnostic levels. This work relies on a hierarchy, established using step breakdown correlations [7], for Tan δ features:

- First Tier – STAB (measured by the Standard Deviation).
- Second Tier – Tip Up or Differential Tan δ.
- Third Tier –Mean Tan δ.

Figure 4 shows the cumulative distributions of Mean Tan δ at U_0, Tan δ stability at U_0, and differential Tan δ between $1.5U_0$ and $0.5U_0$ measurements from the PE-based insulations database including systems with rated voltages of 15 kV, 25 kV and 35 kV.

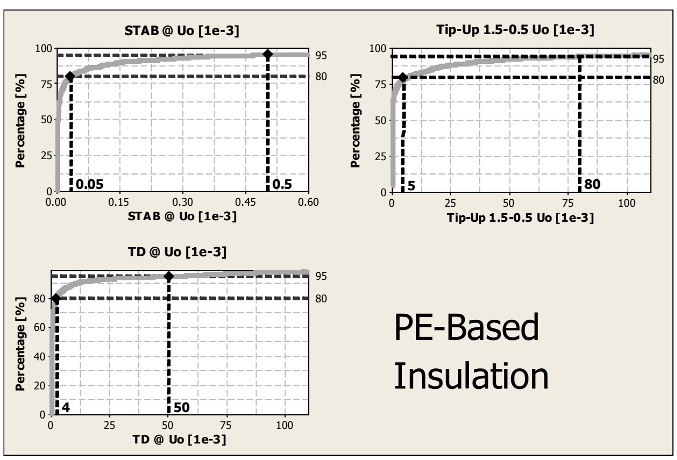

Figure 4. Cumulative Distribution of all Cable System Stability Values at U_0.

To determine Tan δ critical diagnostic feature levels, the authors use the Pareto Principle discussed above to set two critical levels at the 80th and 95th percentiles of the data. The choice of the 80th percentile comes from the principle that says that 80% of the problems come from the worst 20% of the population. In contrast, the choice of the 95th percentile relies on the fact that any data point above this level is considered to be highly "unusual". The power of this approach is that it utilizes the whole data set (cable systems that perform well and those that do not). Thus, it is self-updating as more data becomes available. However, as the decision points are made at the upper percentiles, the updating can cause apparently large changes in critical level values. This is due to the shallow nature of the curves in the upper reaches that produce large changes in value for small changes in percentile.

Taking in to account the 80th and 95th percentiles of the Tan δ features presented in Figure 4, the authors have developed criteria for condition assessment of PE based insulation cable systems. Underlying these criteria is the basic understanding of what values represent good and poor performance. The basic assumption is that unstable time data (high standard deviations), large voltage dependences (high tip ups), and large losses (high Tan δ values) are all characteristic of a poorly performing cable system. Essentially, good lies to the left and poor lies to the right of the graphs in Figure 4. The developed criteria are shown in Table 2. In this assessment scheme, the condition of a cable system is assessed as: "No Action Required", "Further Study", and "Action Required". Each of these assessments is defined by specific percentiles as follows:

- "No Action Required" encompasses the lowest 80% of the data,
- "Further Study" encompasses the next lowest 15% (80% - 95%) of the data, and,
- "Action Required" encompasses the highest 5% (95% - 100%) of the data.

Table 2: Criteria for Condition Assessment of PE Based Cable Systems – Collation of Data to December 2011.

Condition Assessment	*Tan δ Stability at U_0 [E-3]*		*Tip Up ($1.5U_0$ – $0.5U_0$) [E-3]*		*Tan δ at U_0 [E-3]*
PE, HMWPE, XLPE, & WTRXLPE					
No Action Required	<0.05	&	<5	&	<4
Further Study	0.05 to 0.5	or	5 to 80	or	4 to 50
Action Required	>0.5		>80		>50

The above assessment classes are intended to guide the remedial actions, if any, the utility should take to return the circuit to a reliable operating condition. As defined above, most circuits are assessed as "No Action Required" and, thus, do not require additional actions. If a circuit is assessed as "Further Study" or "Action Required," then additional actions should be undertaken as follows:

Actions following a "Further Study" assessment might include:

- Review data for a rogue measurement in the sequence – most common in the first voltage cycle,
- Confirm insulation type to ensure that criteria apply,
- Clean or re-clean terminations and repeat measurements,
- Compare with previous tests or other results from other phases of this circuit if possible,
- Conduct a VLF withstand test (30 min) according to the IEEE Std. 400.2 [3], or,
- Place on "watch list."

In addition to the first four actions following a "Further Study" condition assessment, actions following an "Action Required" condition assessment might also include:

- Conduct a VLF withstand test (60 min) according to the IEEE Std. 400.2 [3],
- Retest in the near future and observe trends, or,
- Place on "watch list" and consider remedial actions for the circuit.

The approach used to determine the critical levels for diagnostic features from these data uses the available collated field data as of December 2011. Inspection of Figure 4 shows that in most cases the data cannot be modeled by a single distribution. In fact, the data set appears to be composed of multiple distributions. The primary interest is to extract the 80th and 95th percentiles. Fortunately, this does not require a model of the entire dataset and so allows a suitable model to be more easily constructed. Given this observation, these probabilities guide the Condition Assessments as shown above and they, together with the previously noted hierarchy, provide the basis for the critical levels shown in Table 2.

The overall condition assessment of the circuit is most simply defined by the most "serious" condition of any of the three dielectric loss features. In other words, if any one criterion indicates the circuit is "Action Required", then the assessment is "Action Required" regardless of what the other two criteria indicate. Prioritizing or differentiating between circuits with the same overall assessment requires looking at and considering all of the criteria together (an approach that combines these criteria into a "health index" is discussed in Section 6).

This scheme is very similar to the level-based systems used for other diagnostic techniques. However, in this case, the knowledge rules (i.e. the critical levels, the level criteria (80% and 95%), and the database) are available to the user. The availability of these numeric data aids in understanding and allows re-interpretation should the critical levels change.

6 SERVICE PERFORMANCE

6.1 OVERALL

Many of the cable systems that have been measured were closely monitored to determine their performance in the field after testing. This work elicits times to failure and the survival times for each of the action classes shown in Table 2. Figure 5 shows these times for PE-based insulations (failure and survival) in Weibull format. Each curve corresponds to the population of circuits in each action class. The performance has been tracked to February 2011.

The failures and survivors in Figure 5 are used to check that the classification criteria in the lowest times to failure (0.1 months) correspond to the dielectric failures on test (FOT). These curves show that the likelihood of failure, if no actions are performed after testing, follow the classifications reasonably closely (e.g. a segment assessed as "Action Required" has the highest probability of failure for any given time). Thus, these data show that there is a strong relationship between the cable system dielectric loss and subsequent service reliability. Hence, an elevated Dielectric Loss feature (Tan δ, Tip Up or Unstable Tan δ) indicates a higher risk of failure in service

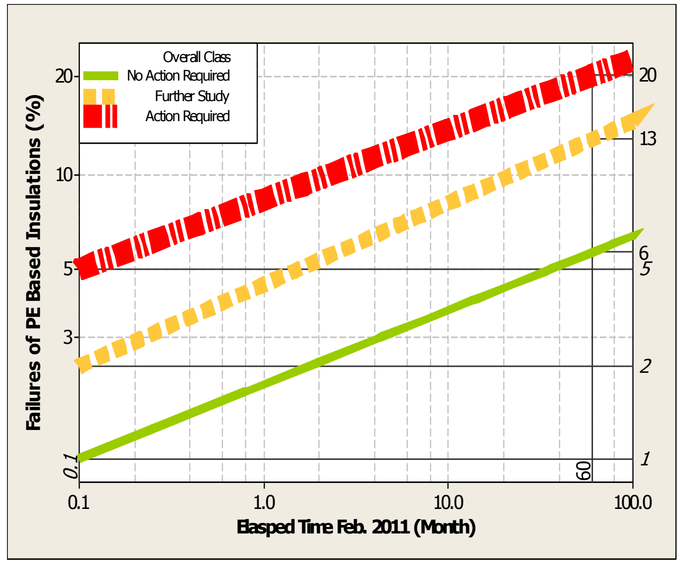

Figure 5. Diagnostic Performance Curves for Tan δ Measurements on Cable Systems with PE-Based Insulations.

In common with almost all diagnostics, even the most severe classification is not necessarily indicative of an immediate "death sentence". It clearly takes time for even the worst segments to fail. Thus, the propensity to failure is identified not the failure itself. The vertical percentile lines in Figure 5 show the probabilities of failure for each condition assessment at selected times after test. Even after five years of service, only 20% of the worst segments failed.

It is instructive to compare the performance achieved here with those from the present IEEE Std. 400 [2] criteria and those proposed in Annex F of IEEE Std. 400.2 [3]. In this case, the same dataset of PE-based cables used for Figure 5 was reinterpreted using these criteria and related to the true level of failures. The most striking feature from this exercise is the fact that for the same circuit population, the worst performers have a failure rate of 12% while the midrange performers have a failure rate of 19% within five years. It would be expected that the highest service failure rate would be associated with the poorest diagnostic class.

6.2 CASE STUDY

Most texts on Tan δ testing note the benefits of comparison with previous measurements. In 2010 a unique opportunity arose to conduct measurements on a system that had been first investigated in 2007. Furthermore good service records were available for the intervening period. Two subdivisions were tested in 2007 using Tan δ Ramp and Tan δ Monitored Withstand. The cable system was a 15 kV unjacketed XLPE system installed in the mid-1970's. The results of the original tests are shown in Figure 6. A full evaluation would require a representation with TD Stability, Tip Up and Mean TD. However, a two dimensional representation is presented here. Nevertheless, even without an all-encompassing classification scheme, it is clear that the performance of the sections in the upper right is different and poorer than the others. Therefore these would be the first candidates for any action.

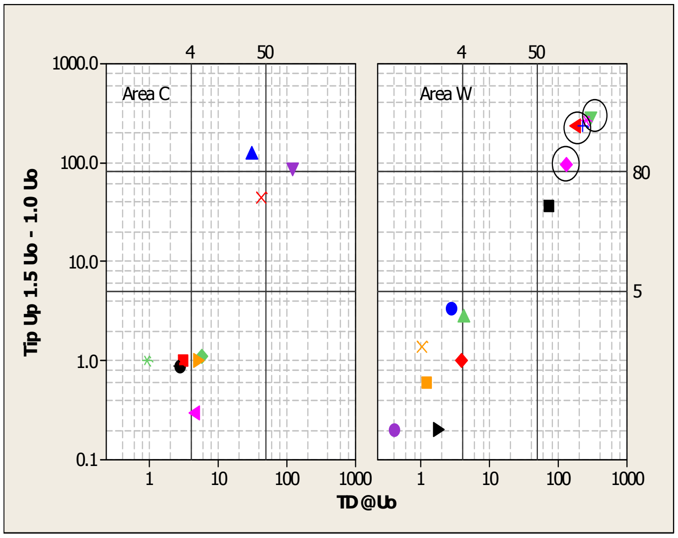

Figure 6. Tan δ Results from 2007 Testing – Open Symbols Indicate Failures in Service in 2010-2011.

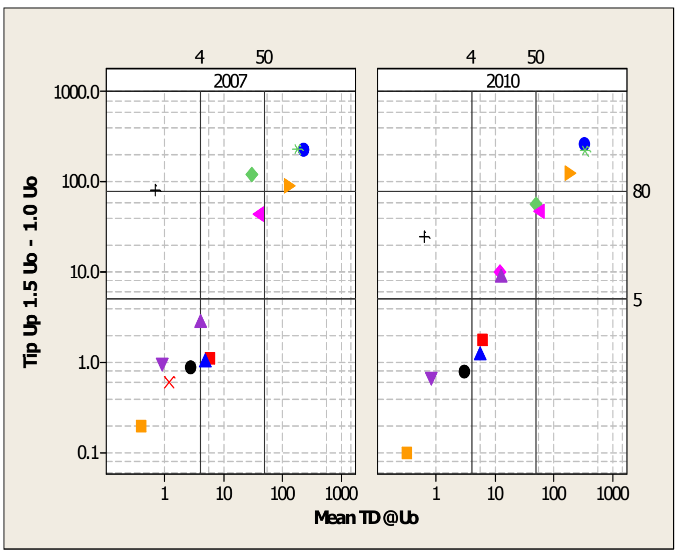

Figure 7. Comparison of 2007 and 2010 Tan δ Results.

During the 4 years since the first tests were completed, three service failures occurred. The failures (circled areas in Figure 6 represent the areas that failed) were restricted to the sections that were identified as "Action Required" in 2007. It is important to note here that these tests were conducted with the goal of understanding the outcomes of diagnostic tests. Thus, the sections were not remediated but were left in service to establish the service performance. If the criteria had been followed in 2007, then these service failures would have been prevented.

Figure 7 shows a comparison of the 2010 results with those obtained in 2007 for all segments tested both years. The changes in condition are summarized in Table 3. As can be observed, the cable sections with the poorest conditions in 2007 (excluding the circuits that failed) showed the largest changes with the general trend to a poorer condition.

The circuits in Area C will continue in service and will be monitored while those in Area W will be replaced within the next few months.

Table 3. Summary of Service Failures and Changes in Condition.

		No Action Required	*Further Study*	*Action Required*
No. per category - 2007		3	4	8
No. failure in service 2007 to 2010		0	0	3
Change 2007 to 2010 on un failed circuits	Degraded but no change in category	0	4	3
	No Change in category	3	0	1
	Improvement in category	0	0	1

7 THE VALUE OF INCREASING THE SIZE OF THE DATABASE

The work presented in this paper is focused on the application of statistical methods to the analysis of Tan δ data. These methods extract useful information from data, discovering relationships that have not previously been known. Additionally, by understanding and obeying clear statistical methods, speculation from knowledge can be separated, as shown by the presented work. Statistical methods are mathematic techniques that involve the following steps: (1) describing data, (2) gathering data, (3) organizing data, (4) analyzing data and (5) interpreting data.

Therefore, the fundamental part of any statistical analysis is the data, which can come in many forms. In this case, the data are sets of numeric values of the diagnostic features, a set of diagnostic features can be seen as a fingerprint for the related specific cable system. In general, as more data is available for analysis and interpretation, results tend to be more statistically significant. The statistical confidence is an indication of the probability of a result not having occurred by chance. The addition of new data is a complex process since these data must be described, gathered, and organized with the same initial criteria. In other words, any additional data must be consistent with the original or previous data sets. This process is critical to the successful development of any criteria.

Thus, in this section the value of adding more data for statistical analysis is explored. To accomplish this goal, the authors have used the data collected over the years for one of the diagnostic features presented in the previous sections, specifically the data for the Tan δ stability at U_0. The data is shown in Figure 8 by means of the probability distribution plots for two selected time periods; all data collected to 2007 and all data collected to the end of 2011.

Figure 8 shows the comparison of the 2007 and 2011 probability distribution plots for the diagnostic feature Tan δ stability and U_0 using Weibull distribution parametric fits with 95% confidence intervals. The raw data is represented by the black dots, the Weibull fits and 95% confidence intervals by the dotted lines. The first case (top of Figure 8) considers the data collected up to 2007 and the second case (bottom of Figure 8) considers all the data collected up to the end of 2011, for comparison the two cases have the same scales and ranges on the two axes.

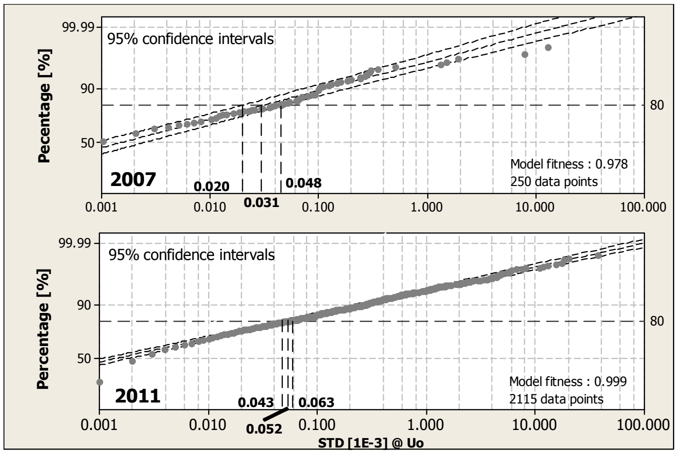

Figure 8. Comparison of 2007 (top) and 2011 (bottom) Probability Distribution Plots for Tan δ Stability at U_0 using Weibull Distributions with 95% Confidence Intervals.

The 2007 dataset includes 250 data points while the 2011 data set includes 2,115 data points. In relative terms, the 2007 dataset represents approximately 12% of the size of the data in the dataset of 2011. Therefore, The 2011 dataset is approximately 750% larger than the dataset from 2007. Table 4 shows a comparison of the 80th percentile estimates from the 2007 and 2011 Weibull curves in Figure 8.

Table 4. Comparison of Estimates of the 80th Percentile for the 2007 and 2011 Tan δ Stability Datasets.

	Case	
	2007	*2011*
No. of data points	250	2115
Model fitness index	0.978	0.999
Estimated Level [E-3]	0.031	0.052
Lower 95% CI[1] [E-3]	0.020	0.043
Upper 95% CI[1] [E-3]	0.048	0.063
Width of 95% CI[1] [E-3]	0.028	0.020

[1] CI: Confidence Interval

As seen in Table 4, adding more data to the analysis produces several clear benefits:

- The level for the feature is more statistically significant since the level for the 2011 case represents a higher population of cable systems; therefore, it can be inferred that the true estimated feature threshold for the whole universe of cable systems is closer to this value than the level obtained in the 2007 case.
- The population of circuits tested through 2007 represents an incomplete sample set as multiple large gaps are present in the data (dataset jumps from 0.55 to 1.4). No gaps are visible in the 2011 dataset up to a stability of 9E-3.
- The width of confidence interval is significantly reduced in the 2011 dataset (by over 28%). This implies that that this estimate has a higher degree of certainty as compared to the 2007 dataset.
- The difference in the 80th percentiles estimates shows that the 2007 dataset was obtained from "healthier" cable systems than those that were tested through 2011. Applying the 2007 dataset estimate would have added 4% of the population to the "Further Study" and "Action Required" classes.

Another important fact that must be noted is that in both cases the model fitness index is acceptable by being higher than 0.90; however, the model fitness index for the second case is better than that observed in the first case, which again shows the value of adding more data to the statistical analysis.

Similar statistical analyzes can be realized for the other Tan δ diagnostic features. Such analyses are actually presented in the section in which the multimodal nature of the data is considered.

8 MULTI MODE ANALYSIS

The previous section has shown the value of adding proper data as time progresses to the statistical analysis of the Tan δ diagnostic features. Specifically, it has been shown that as more data is available, better threshold estimation and confidence intervals are accomplished. However, the preceding section has only shown the analysis for one of the Tan δ diagnostic features, i.e. the first tier that corresponds to the standard deviation of the Tan δ measurements at U_0. In this case, the Tan δ stability data was modeled with high degree of confidence by a single Weibull distribution. However, for the other Tan δ diagnostic features a more detailed modeling analysis is required since they cannot be modeled by a single Weibull distribution.

When data can be modeled by a single Weibull distribution, the probability distribution plot and the data itself form a straight line, as seen in Figure 9. A qualitative assessment of the goodness of model fitting can be accomplished by observing how the model lines for the estimation and confidence intervals correlate with the data points. This qualitative assessment can be expressed quantitatively by the model fitness value; if the model fitness value is high (usually more than 0.90) then the model can be used to completely represent the statistical nature of the data.

In some cases, the data cannot be represented by a single Weibull model. When this situation is present, the data on a probability distribution plot do not lie on a single straight line. However, such data can be modeled by several straight lines over specific ranges defined by limits on both axes of feature values and percentage. In this way, each line would represent the model for the data between the limits. Each separate model in the data is referred to as a mode. Therefore, if one has a case in which data can be represented by two straight lines, it is said that the data has two modes.

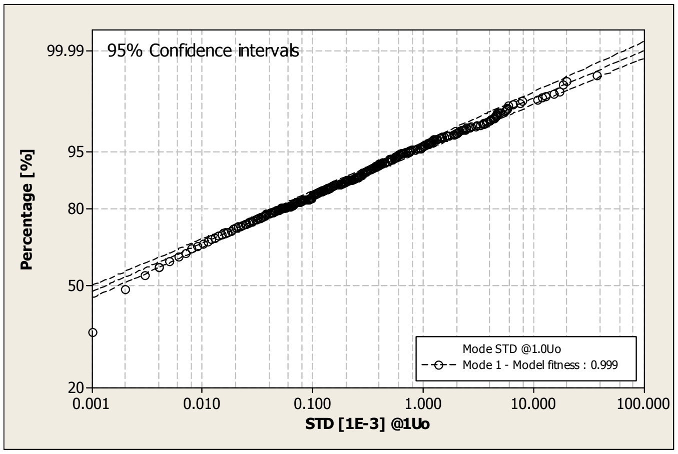

Figure 9. Probability Distribution plot for Tan δ Stability at U_0 by Mode.

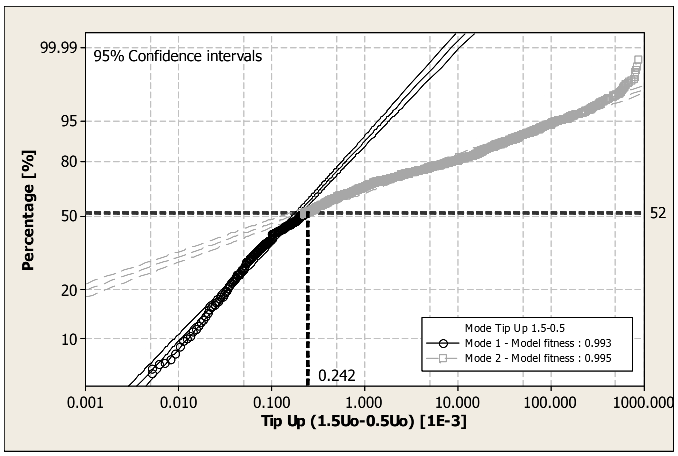

Figure 10. Probability Distribution Plot for Tip Up ($1.5U_0$-$0.5U_0$) by Mode.

Determining the number of modes and their limits is not generally a simple task. Usually heuristic techniques are applied to accomplish this goal. However, determining only the number of modes is a relatively easy task that is generally accomplished by performing a qualitative assessment of the probability distribution plot as the graphical representation enables the critical points to be identified readily. For example, let us consider Figure 10 that represents the probability distribution plot of the second tier of diagnostic feature (Tip Up between $1.5U_0$ and $0.5U_0$). As seen in Figure 10, the data in this case can be represented by two straight lines or models that intersect around the 50%; therefore, it is clear that the data has two modes. Moreover, Figure 11 shows the probability distribution plot of the third tier of diagnostic feature (Tan δ at U_0). As seen in the figure, this feature is also composed of at least two modes. The limit in this case is also around the 50%.

As mentioned before determining the limits between modes is not a simple task. In fact, the authors are not aware of any established methodology to accomplish this. Thus, the authors have opted for taking the approach of determining the limits by solving an optimization problem. Specifically, the limits between modes are determined by maximizing the model fitness for the two modes. In other words, the mode limits are determined in a way that the best model representation is accomplished.

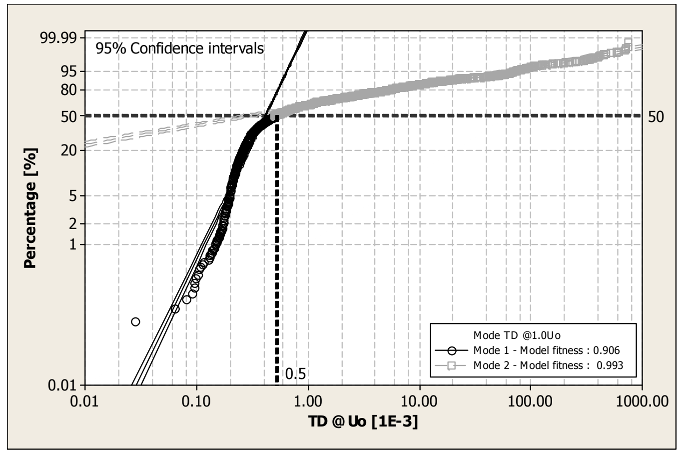

Figure 11. Probability Distribution Plot for Tan δ at U_0 by Mode.

This procedure has been applied on determining the mode limits for the second and third tiers of Tip Up between $1.5U_0$ and $0.5U_0$ and Tan δ at U_0. Results of the procedure are shown in Figure 10 and Figure 11 respectively.

As observed in Figure 10 and Figure 11, both diagnostic features show two modes. The results of the analysis for determining the mode limits are shown in Table 5, including the Tan δ Stability diagnostic features.

Table 5. Summary of Data Mode Analysis for Tan δ Features.

Feature	*No. Modes*	*Mode Limits [%] / [E-3]*	*Model fitness index*
Tan δ Stability - STD (U_0)	1	-	0.999
Tip Up - TU ($1.5U_0$ & $0.5U_0$)	2	52/0.242	Mode 1: 0.993 Mode 2: 0.995
Tan δ - TD (U_0)	2	50/0.5	Mode 1: 0.906 Mode 2: 0.993

As seen in Table 5, the Tan δ stability at U_0 diagnostic features is composed by only one mode whilst the Tip Up between $1.5U_0$ and $0.5U_0$ and Tan δ at U_0 are each composed by two modes. It is instructive to note also that for all diagnostic features and modes, the model fitness index is high which indicates that data is properly modeled when such modes are considered.

The most important use of the mode analysis is that its results can be employed to determine the 95% confidence intervals of the diagnostic features thresholds presented in Table 2. This is a really important contribution since generally, assessment values are seen as crisp thresholds when in fact they are results of statistical analysis of data and therefore there is always a level of confidence related to them. The level of confidence is determined and clarified here by the use of the mode analysis by properly modeling the data. The 95% confidence interval limits for Tan δ features thresholds from Table 2 are shown in Table 6 considering the two levels of 80% and 95% of condition assessment.

Table 6. Modal Analysis Results for the 80% and 95% Confidence Interval Limits for Tan δ Diagnostic Feature Thresholds Shown in Table 2.

Diagnostic Feature	*95% Confidence interval limits [E-3]*					
	80% Level			95% Level		
	Value (Table 2)	Lower Limit	Upper Limit	Value (Table 2)	Lower Limit	Upper Limit
Tan δ Stability - STD (U_0)	0.050	0.047	0.059	0.50	0.41	0.61
Tip Up - TU (1.5U_0 & 0.5U_0)	5.00	4.14	6.04	80.00	64.53	99.17
Tan δ - TD (U_0)	4.00	3.45	4.64	50.00	42.34	59.00

Table 6 shows the modal analysis results for the 80% and 95% confidence intervals limits for Tan δ diagnostic feature thresholds shown in Table 2. For instance, if the diagnostic feature of Tan δ stability at U_0 is chosen at the 80% level, the threshold value is 0.05 (see Table 2) while, in fact, there is a 95% probability that this threshold is between the range of 0.047 and 0.059. Therefore, attention must be taken into account when the threshold values are used considering that they represent a range rather than single crisp values. In practice, when diagnostic features are near or at these threshold values, additional cable system information must be considered to determine a condition assessment. For example, if the condition assessment is between "No Action Required" and "Further Study", actions following a "Further Study" condition assessment (see section 4) could be performed to eventually determine a condition assessment.

9 NONLINEAR VOLTAGE DEPENDENCE OF TAN δ - THE TIP UP OF THE TIP UP – "TUTU"

As the analysis of Tan δ features has progressed, it has become clear that an additional diagnostic feature should be added to the assessment. Up until now, the authors have focused their attention on the Tan δ Stability, Tip Up, and Tan δ. In this approach it was assumed that all the useful classification information, from a voltage dependence perspective, can be captured by a single Tip Up over a range of U_0. However, a number of combinations and ratios of these features have been extensively examined using Principal Component Analysis (PCA) [10, 11]. The analysis has shown that various combinations and ratios did yield useful information for determining the condition assessment of a cable system. However, it was clear that the classification could be improved if the description of the voltage dependence was expanded. In this case, the degree of nonlinearity of the Tip Up with voltage was found to be the most attractive additional feature. This feature is called the Tip Up of the Tip Up or simply the TUTU.

The TUTU looks at the difference in Tip Ups over a 0.5 U_0 span. In other words, the TUTU is defined mathematically as shown in equation (1):

$$TUTU = (TD@1.5U_0 - TD@1.0U_0) - (TD@1.0U_0 - TD@0.5U_0) \tag{1}$$

Physically this additional diagnostic feature provides a measure of the degree of nonlinearity present in the voltage dependence. Thus, a TUTU of zero indicates the voltage dependence is completely linear. On the other hand, a large TUTU would indicate a significant change in dielectric loss with the highest voltage. Thus, the interpretation for classification follows the same scheme as the other diagnostic features namely low numbers indicate good performance and large numbers poorer performance. Figure 12 shows several examples of standard Tip Ups as well as the corresponding TUTUs.

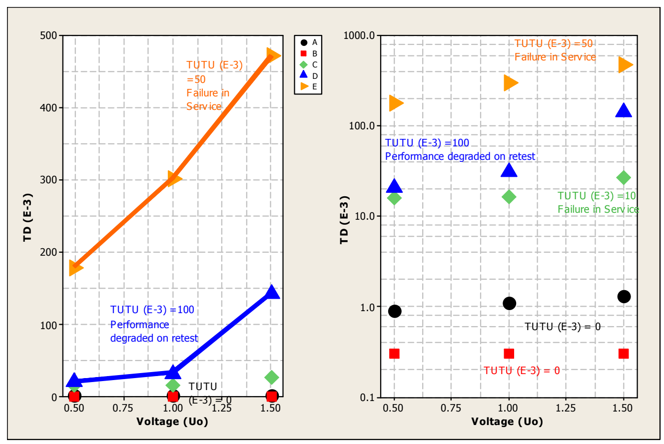

Figure 12. Tan δ Examples for Different TUTU's.

To date, the TUTU's for PE-based insulations have been extracted from the database and the resulting distribution is shown in Figure 13. As in the case of the other Tan δ features, criteria can be extracted from these distributions using the 80th and 95th percentiles to define the "Further Study" and "Action Required" classes, respectively.

Figure 13 shows the 80% level corresponds to a TUTU of 3E-3 while the 95% level corresponds to a TUTU of 58E-3. These threshold levels can be used in conjunction with the three features in Table 2 to aid the condition assessment. There are two ways in which this can be accomplished: (1) add an extra column to Table 2 or (2) try to combine all four diagnostic features into a single "health" indicator that can be used as an index for condition assessment. Although, the two ways are completely plausible, the authors prefer having a single indicator in which all diagnostic features are considered. This would be simpler from the user perspective to understand but more difficult to develop and would likely require more sophisticated tools. In fact, the procedure by which the features are combined is presented in the next section.

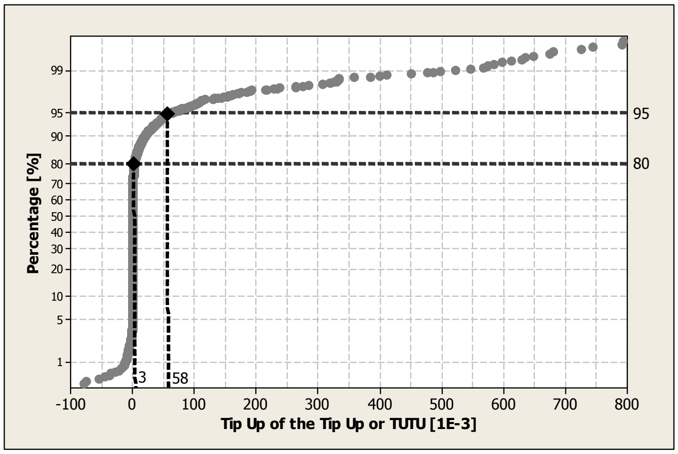

Figure 13. Cumulative Distribution Function for TUTU for PE Based Insulation.

10 COMBINED ASSESSMENT - TAN δ PRINCIPAL COMPONENT ANALYSIS

There is no question that Tan δ criteria are a topic of ongoing study and analysis. Up until now, the approach presented in this paper to Tan δ criteria was to construct a three tier/diagnostic feature approach using three primary useful features: Tan δ Stability (STD-time dependence), Tip Up (TU-voltage dependence), and Mean Tan δ (TD-level of loss). Circuits were classified as "No Action Required", "Further Study", or "Action Required" depending on the most severe assessment from these three Tan δ diagnostic features.

This is very useful information, but at times it can be difficult to interpret. For example, one possible result is that Stability and Tip Up could indicate "No Action Required" but the Mean Tan δ could indicate "Further Study". In this case, it is not clear how to interpret the overall results. The interpretation becomes even more difficult when the fourth proposed diagnostic feature (TUTU non-linear voltage dependence) is considered. Ideally, a method is needed to combine all four features together to create a single "Health Index" that puts any set of measurements in context with the Tan δ database. The PCA method is one means of accomplishing this goal.

In order to obtain a single "Health Index" from all four diagnostic features, the authors have explored a variety of techniques. From all techniques that have been explored, the PCA is the most attractive since it is one of the most popular techniques for reducing the number of feature dimensions. This technique is useful because it takes given a set of points in a high dimensional space and then reduces the dimensionality to a more manageable number. In other words, the PCA technique summarizes the data with several assumed independent variables to a smaller set of derived variables without sacrificing the potential for classification. In fact, the classification capability is enhanced by the PCA.

The technique provides a predictive model with guidance on how to interpret or "weigh" the primary measurement features. It also allows for a physical meaning to be ascribed to the resulting composite factors, i.e. the Principal Components. The PCA approach identifies linear combinations of factors and generates the principal components that better represent the data. The first component has or describes the largest portion of the variance, followed by the second, and then the third, and so on. The PCA redistributes the variance in such a way that the first *k* components explain as much as possible of the total variance of the data. It must be noted that the higher the variance the higher the potential for better classification.

Another important reason for choosing the PCA technique is that in many data analysis/mining scenarios, believed independent variables are highly correlated, which affects model accuracy and reliability. PCA is able to detect such correlations and then essentially exclude the redundant information.

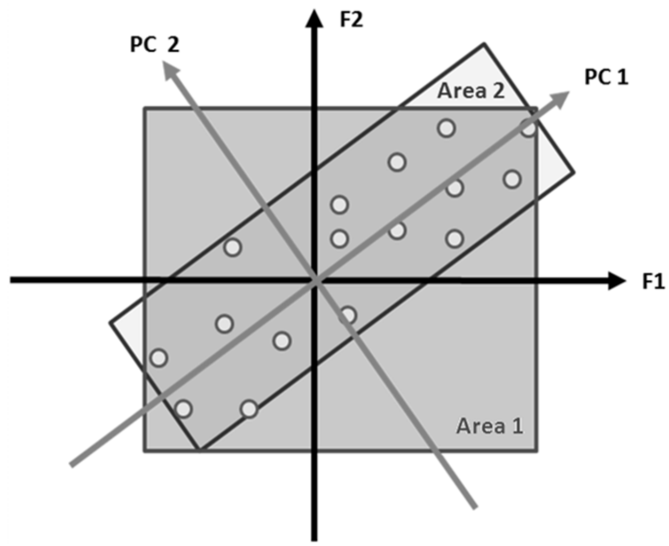

Figure 14. Graphical Interpretation of Principal Component Analysis (PCA).

To illustrate and easily understand the essentials of the PCA technique, Figure 14 shows a qualitative explanation of the technique. The circles represent a dataset in which there are two features (axes) and the variance within this dataset with respect to these features is represented by the area of the rectangle denoted as Area 1. The PCA method attempts to reduce the variance by generating new axes that are linear combinations of the available two features. This causes a rotation/translation of the original axes from F1-F2 to PC1-PC2. The new variance can then be thought of as the area of the rectangle represented by Area 2. By comparing the areas, it is clear that area 2 is smaller and, therefore, has less variance than the original configuration in Area 1. As mentioned above, this process can be used to reduce the dimension of a dataset to as few or as many principal components as are needed.

The PCA technique has been applied to the Tan δ database and Figure 15 shows the transformation from the first two Tan δ diagnostic features (STD and TU) to the first two principal components (PC1 and PC2). As mentioned previously, the PCA reduces the dimensionality; however, this technique does not directly provide a single descriptor by itself, essentially it enables the constructions of simplified and appropriate feature maps that may enhance the classification potential of the diagnostic features when they are combined in the right manner. The principal components features maps can then be used to provide a single condition assessment descriptor as it is shown later in the paper. The transformation can be observed in Figure 15 in which the application of the PCA technique enables for a better relation between PC1 and PC2 (right side of Figure 15) as compared to the original data; in this case, STD and TU (left side of Figure 15).

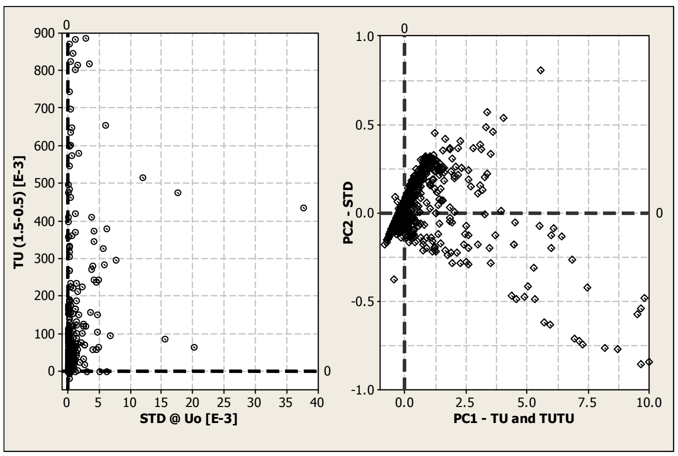

Figure 15. Scatter Plots of STD vs. TU (left) and PC1 vs. PC2 (right).

Table 7. Principal Components Variance Description and theirs Main Diagnostic Feature Contributors.

Principal Component	*Variance Described by Component [%]*	*Variance Described by Component Accumulated [%]*	*Main Tan δ Diagnostic Feature Contributors*
PC1	50	50	TU & TUTU (Voltage Dependence)
PC2	25	75	STD (Time Dependence)
PC3	22	97	TD (Level of Loss)
PC4	3	100	Not relevant since this component only describes 3% of the variability

Subsequently, Table 7 shows the outcome of the PCA procedure. The table indicates the proportions in percentage of each component to the description of the variance as well as main diagnostic feature contributors for each component. The main diagnostic feature contributors are selected on the basis of the analysis of the coefficients related to each feature for each principal component. Features by component that have high coefficients are considered as a main contributor whilst features with low coefficients are considered not to contribute to the specific component. Results from Table 7 indicate that only three principal components are required to describe 97% of the variance; therefore, this is the number of principal components that are considered here. Other important results from Table 7 are that the PC1 describes 50% of the variability and it is mainly composed by the TU and TUTU, features that considers the Tan δ voltage dependence; PC2 describes 25% of the variability and it is mainly composed by the STD, feature that considers the Tan δ time dependence; and lastly, PC3 describes 22% of the variability and it is mainly composed by the TD magnitude, feature that considers the level of loss. Also note that PC4 is not relevant since it only describes just 3% of the variability of the data. Therefore, this principal component is not taken in to account in the analysis.

The main conclusion of the PCA results shown in Table 7 is that they also give an indication of the importance and relevance of the Tan δ diagnostic features. From the analysis, when the variability of the data is considered, the voltage dependence of measurements (TU and TUTU) is the most important factor, followed by the time dependence (STD) and level of loss (TD). These results should not be misunderstood when compared with the results shown in section 5 and reference [7] since in that case the criteria for determining the importance and relevance of the features is based on VLF breakdown correlations as compared to the variability of the data as presented here on this section.

However, a common factor in both approaches is that the voltage dependence, time dependence, and level of loss are independent diagnostic features; therefore, it can be assumed that they carry independent information [8]. Utterly, the question is how to combine all diagnostic features in to a single indicator, which is shown in the next paragraphs.

The use of the PCA technique has allowed also developing a combined diagnostic feature scheme in which all independent features are considered together for an ultimate condition assessment. The combined diagnostic feature scheme is based on the computation of the PCA distance, i.e. given a set of principal components related to a set of measurements, how these component deviate from a known reference point. The PCA distance is computed using the principal components values and a reference point that in this case corresponds to Tan δ measurements of a new cable system. Figure 16 shows the combined PCA distance of the three principal components for all the available data of PE insulated cable systems. In Figure 16, the percentage or rank position is given by the Y-axis values and, in practice, might conveniently be regarded as a "Health Index". The higher the rank position the worse the cable system condition is, relative to all similar systems (i.e. PE-based). The symbols in Figure 16 represent some selected test cases used as examples and their computed PCA distance (Rank) results are shown in Table 8.

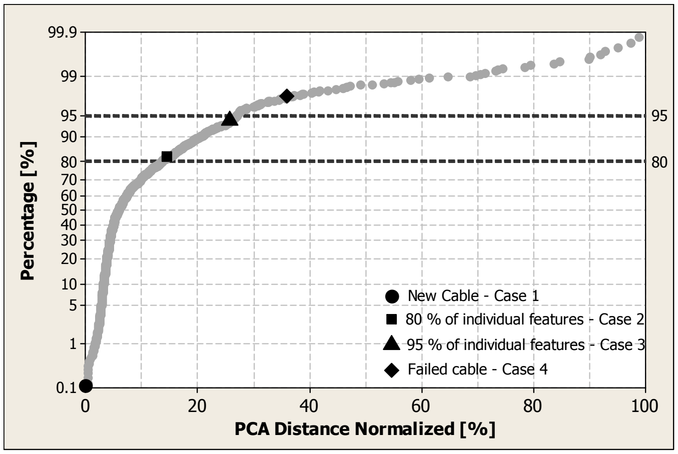

Figure 16. Empirical Cumulative Distribution for the Normalized PCA Distance for PE-Based Cable Systems.

Table 8. Test Cases for Tan δ Principal Component Analysis.

Case No.	*Description*	*STD [E-3]*	*TU [E-3]*	*Tan δ [E-3]*	*TUTU [E-3]*	*Rank [%]*
1	New Cable	0.00	0.00	0.10	0.00	0.05
2	Features at 80% level	0.05	5.00	4.00	3.00	82.00
3	Features at 95% level	0.50	80.00	50.00	58.00	93.90
4	Failed Cable[1]	3.60	247.00	316.00	17.00	97.60
5	Utility test 2007	0.00	0.80	2.80	0.00	79.00
6	Utility test 2010	0.00	1.80	6.00	0.60	84.50

[1] failure after 27 months from test date

In Table 8, the following examples are included:

- Case 1 represents a new PE cable system that lies at the 0.1st percentile. This translates to an extremely good "Health Index". Case 1 is represented in Figure 16 by the solid black circle symbol.
- Case 2 represents the situation in which all diagnostic features are at their respective 80% levels (black square symbol in Figure 16). Note here that all the features at the 80% level yield to a "Health Index" of 82.0%. Therefore, there is a good correlation between the feature levels and the overall assessment considering all features together.
- Case 3 shows the situation in which all the diagnostic features are at the 95% level (black triangle symbol in Figure 16). In this case the "Health Index" is 93.9%. Note again the good correlation between the features levels and the overall condition assessment.
- Case 4 is a real case and represents the poorest performer in a cable system that was tested in 2007 and failed in service 27 months later (black diamond symbol in Figure 16). The PCA indicates that back in 2007, the cable system was within the poorest 3% of all PE-based cable systems.
- Case 5 and Case 6 are also real cases and represent a retest of a cable system after three (3) years of operation.

In Table 8, note the change on the diagnostic features between Cases 5 and 6 after three years of operation, showing that this cable system went from "No Action Required" to "Further Study". The "Health Index" changed from 79.0% to 84.5%, this represents a degradation in the rank position of about 2% per year. Additionally, inspection of mid-range and lower ranks shows that, as might be expected, there is a degradation of rank position here as well, but the rate is much lower: approximately 0.33% to 0.50% per year. Such kind of information is invaluable to an asset manager when determining the most appropriate route forward when deciding on which cable systems to act. Thus, this approach addresses most of the issues associated with simple classification schemes and it is able to provide performance context. However, it is important to recognize that this is not able to ascribe a definite lifetime to the cable system.

11 CONCLUSIONS

This paper has shown that considerable progress has been made in the practical implementation of Tan δ diagnostic tests for medium voltage (MV) cable systems.

The authors have shown how a significant amount of data may be collated to garner data driven assessment criteria for cable systems. The use of a single set of percentiles enables a consistent and relatable set of criteria to be established. To put in perspective the contribution of this paper, Table 9 shows the evolution of Tan δ criteria for condition assessment of PE-based cable system.

Table 9. Evolution of Tan δ Criteria for Condition Assessment of PE-Based Cable Systems.

Year	*Assessment Hierarchy*	*Criteria*
2001	Tan δ Tip Up ($2U_0$ & U_0)	PE criteria only included in IEEE Std. 400 [2]
2007		Qualitative
2008	Tan δ Stability (U_0) Tip Up ($1.5U_0$ & $0.5U_0$)	PE criteria based on data
2010	Mean Tan δ (U_0)	To be included in update of IEEE Std. 400.2 [2] (see Table 2)
2011	Tan δ Stability (U_0) Tip Up ($1.5U_0$ & $0.5U_0$) Mean Tan δ (U_0) Tip Up of the Tip Up (TUTU)	PE criteria based on data PCA analysis Combined diagnostic features

As Table 9 shows, Tan δ criteria for PE-based cable systems have evolved considerably over the last 10 years. The number of diagnostic features has increased and the condition assessment is now made considering a combined "health index". The analyses have been formatted so that they may be readily used in the field to provide real-time guidance on the appropriate decisions that a user might take to proactively manage their cable system asset.

Despite the progress that has been made, there are some challenges that remain to be clearly identified. In particular, the multivariate approach should be extended to Filled and PILC cable systems. The PILC system presents a challenge due to the common finding of a negative Tip-Up and the rarity of large negative values.

Current embodiments of field measurement systems provide real time representation of voltage effects and simple diagnostic factors (mean and standard deviation). Given the progress in the analysis presented here, it is clear that the user would benefit from:

- The calculation of more diagnostic features, for both Tan δ and cable capacitance, such as Tip Ups and Tip Up Ratios, etc.
- A graphical representation of the Tan δ and capacitance evolution with time.

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