Nuclear Power Plant Instrumentation and Control Cable Prognostics Using Indenter Modulus Measurements

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ABSTRACT

As the fleet of nuclear power plants (NPPs) approach their original qualified life (typically 40 years) and operators seek license extensions, regulators require assurance that they can continue to operate safely in the decades to come. Some of the most important, yet often overlooked components, are the cables that provide the signal paths for instrumentation and control (I&C) systems used to ensure safe and efficient operation of NPPs.

In response to this, the authors explore the use of expanding indenter modulus (IM), an industry-accepted technique for cable condition monitoring, into a prognostic tool for predicting the remaining useful life (RUL) of I&C cables. Not only is this technique non-destructive, but it can be performed while NPP cables are in service, thus making it practical for adoption into existing cable condition monitoring programs. In this paper, the authors describe an accelerated aging cable test bed used to acquire several types of measurement parameters as cables age. Additionally, practical techniques are described in which simple IM measurements can be leveraged for condition monitoring and RUL estimation.

Error analysis indicates the proposed method is superior to conventional RUL estimation techniques, such as simple trending and curve fitting. The authors demonstrate that using IM can potentially provide a non-destructive, in-situ estimation of RUL for I&C cables. As described in this paper, the IM data clearly shows trends as a function of cable age, and shows promising performance for RUL estimation especially compared with conventional techniques.

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1. INTRODUCTION

As existing nuclear power plants begin to operate beyond their initial design lifetimes, it becomes increasingly important for plant engineers and operators to be able to monitor aging and degradation of critical plant equipment and components. The extension of plant life, coupled with power uprates and shorter outage durations results in aging plants that are not only operating for longer periods, but are also being driven harder than in the past. Along with the next generation of NPPs, existing plants need to be able to maintain reliable operation to meet the energy demands over the coming decades. The need for more reliable operation has prompted the nuclear industry to explore alternatives to traditional time-based maintenance practices in favor of condition-based maintenance strategies that employ advanced surveillance, diagnostic, and prognostic techniques (Coble, Ramuhalli, Bond, Hines, & Upadhyaya, 2012).

Prognostic and Health Management (PHM) technology has been given consideration by research organizations and other experts as a promising avenue that can be used by the nuclear industry. The majority of this research, however, has been focused on end-device components such as bearings, pumps, motors, batteries, etc. As a result, little attention has been paid to an important part of the I&C chain: the electric cabling (Villaran & Lofaro, 2009). Cabling is one of the largest cost factors in adding new instrumentation to existing NPP equipment and one of the most difficult to replace. Cable aging, in particular, is primarily concerned with degradation of the polymer material by thermal oxidation while exposed to heat, humidity, radiation, and other environmental stressors (Toman, 2002). Consequently, as the polymer degrades, it embrittles, cracks, and becomes susceptible to moisture intrusion that can cause shorts and shunts in the cable circuits.

The following details the results of performing prognostic analysis on data collected from accelerated aging of instrumentation and control (I&C) cables, and uses this data to empirically assess the use of a non-destructive mechanical measurement known as indenter modulus (IM) for the prediction of cable RUL. Over the course of the accelerated aging, IM measurements are taken at regular intervals. After the completion of the experiment, two data driven prognostic techniques, trend evaluation and the General Path Model (GPM), are used to estimate the RUL of the cables at various points in the cables' life and these estimates are compared with the actual RUL to empirically determine the error.

The following sections will first present a background of research previously conducted on the mechanisms behind aging of I&C cables. Next, a summary of the prognostic techniques used for RUL estimation is presented. After summarizing the details of the accelerated cable aging experiment and results, the data is then used to perform RUL estimations. Finally, an analysis and discussion of the results of the selected RUL methods is presented, as well as an estimation of the error present in each method.

2. CABLE DEGRADATION MECHANISMS AND CONDITION MONITORING

As discussed by Toman (2002), low-voltage cable aging is dominated by the effects of radiation and thermal stress on the polymer material comprising the cable's insulation and/or jacket. Generally speaking, this results in a net hardening of the material over time, although the exact behavior is specific to the type of polymer (e.g., amorphous vs. semi-crystalline). This hardening can eventually result in cracking of the material, thus exposing the current conductors to the environment .

Conventionally, the nuclear industry has used a destructive mechanical measurement known as Elongation-at-Break (EAB) to quantify the condition of the polymer material of a cable's jacket or insulation and to determine if it is qualified for continued use. EAB is measured using a specimen of the cable's polymer material stretched on a tensile strength machine (Figure 1) until the sample breaks. EAB values for new cables typically range from 250%-650%. Higher EAB values for new cables do not reflect superior quality, but the nominal properties of the material as engineered by the manufacturer (Toman, 2005). As stated by Villaran and Lofaro (2009), the conservative acceptance criterion for a nuclear power plant cable is an EAB of 50% or more. That is, if a sample specimen stretches by at least 50% of its original length before it breaks, it is qualified for nuclear service. In addition to using EAB to characterize the condition of cable polymer materials, the Electric Power Research Institute (EPRI) showed that the predictability of EAB could be used to estimate a cable's RUL. This was done by correlating the EAB of the cable-under-test to typical EAB curves, and calculating the time until 50% EAB (Toman, 2005).

Figure 1. EAB Testing Equipment

Because of the destructive nature of EAB, significant work was carried out in the 1980's and 1990's by EPRI and other institutions to develop a non-destructive method for characterizing the mechanical condition of cable polymer material. Like EAB, compressive modulus is a mechanical property that can be used to assess the condition of a material that exhibits an orderly change in mechanical properties as it ages (Toman, 2003). Further, testing a cable's compressive modulus is non-destructive. This eventually led to the development of a portable device known as an indenter (Figure 2) for calculating the compressive modulus (i.e., indenter modulus) of materials. The device uses a small probe to gently press into the material while recording the relationship between force and displacement. The IM is then calculated as the ratio of the change in force to the change in displacement (Figure 3). Typically, several IM measurements are collected from various locations around the circumference of the cable and averaged to account for local changes in cable configuration. Experimental research has shown that the correlation between IM and EAB is strong for several common polymers found in NPP cables, such as Ethylene Propylene Rubber (EPR) and Chlorosulfonated Polyethylene (CSPE) (Toman, 2005).

Figure 2. IM Testing Equipment

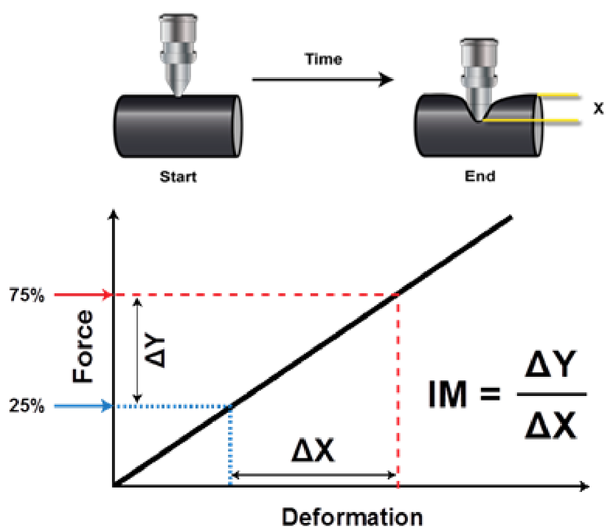

Figure 3. Principle of Indenter Modulus

3. USING PROGNOSTICS FOR REMAINING USEFUL LIFE ESTIMATION

As described by Hines, Garvey, Preston, and Usynin (2008), data-driven prognostic techniques can be classified into three categories. Type I techniques use historical failure data to generate failure distributions and predict the behavior of the average component in average conditions. An example of this type of method is Weibull Analysis, which is commonly used in reliability engineering. Type II methods quantify the effect of specific conditions, environments, or parameters on the average component. The Cox Proportional Hazards Model, for example, is commonly used in analyzing the different factors that impact survival rates of those affected by particular diseases. Type III methods aim to make predictions based on specific conditions and a specific component.

For RUL estimation, this paper compares three techniques for RUL estimation: trend evaluation, and two applications of the General Path Model (GPM). Application of these techniques generally requires the selection of a *prognostic parameter* – essentially a measurement over time that increases or decreases in a predictable manner until failure. An individual prognostic parameter in a set is known as a *degradation path*. Because it is not always known a priori what measurements will make suitable prognostic parameters, a variety of metrics can be used to quantify how well a candidate parameter would perform for RUL estimations. Researchers at the University of Tennessee have developed a set of three metrics for quantifying a candidate parameter's fitness for development into a prognostic model: *monotonicity*, *trendability* and *prognosability* (Coble, 2010). A high degree of monotonicity is characterized by a path whose slope is always positive or negative. To have high trendability, all of the measured degradation paths must have the same underlying shape. Finally, prognosability defines the degree to which the degradation paths end at the same level of damage. Each metric is scaled from zero to one and the sum is used to quantify the fitness. Therefore, a good prognostic parameter will have a fitness value close to three.

3.1. Trend Evaluation

Trend Evaluation is one of the simplest types of data-driven prognostic methods, using standard regression techniques to extrapolate degradation data to failure (Sikorska, Hodkiewicz, & Ma, 2011). An assumption of this method is that the degradation parameter, typically originating from a single sensor or a fusion of several sensors, displays some repeatable behavior over time that could be modeled using a mathematical function. As new data is collected, it is assumed that the data continues to follow the same underlying shape, and the new data is used to generate an updated extrapolation to failure. Assuming that the selected mathematical model always describes the degradation behavior, this method can provide reasonably accurate results if sufficient degradation data is available. On the other hand, this method can contain a large amount of error in the estimation when little data is available. With little data, regression error is typically higher and can often result in unreasonable RUL estimations (e.g., infinite RUL). Figure 4 shows a simple illustration of this method. The degradation parameter data from the device under test is used to regress the selected mathematical model and extrapolate this model to the failure threshold. The difference between the time at the current data point and the point at which the extrapolated behavior crosses the failure threshold is the estimated RUL.

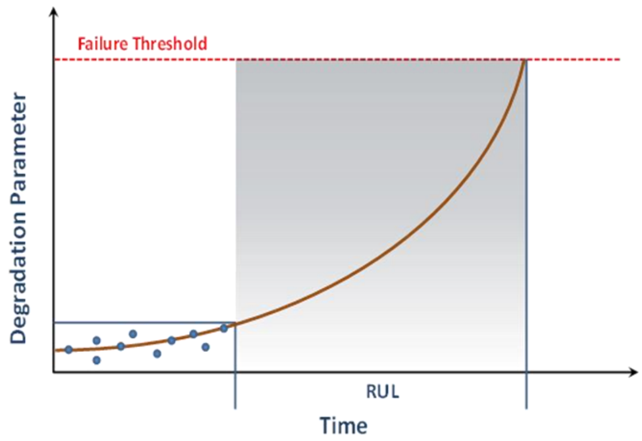

Figure 4. Example of Using Trend Evaluation to Estimate RUL.

3.2. General Path Model

The General Path Model (GPM) was first adapted for reliability estimation by Lu and Meeker (1993). For prognostics, the GPM technique constructs a model based on a population of degradation paths. In a similar manner to trend evaluation, building a GPM consists of fitting a selected function to a degradation path. However, the GPM fits this function to each path in a population of degradation paths, then uses the average of each constant in the function to yield a 'general path.'

GPM development begins with the selection of an appropriate functional form that will be used to model the 'general path' that a prognostic parameter follows. Building a GPM consists of individually fitting the selected functional form to each degradation path and then calculating the average of each constant in the function. Ideally, selection of the functional form is done using a physics-based, first principles approach. For example, Lu and Meeker (1993) used Paris' Law to model crack growth propagation in the development of their GPM. Many times, however, the underlying physics may be unknown or the system too complicated to derive a first principles approach. In this case, empirical methods can be used (Hines et al., 2008).

Several techniques can then be used to apply the GPM to RUL estimation. One approach is to assume that each new component will always behave exactly as the general path. In other words, each new component will always have the same RUL as the general path. As expected, this approach has an appreciable amount of error as it ignores any current trends in data, although this technique does not suffer from the possible unreasonable estimations of the trend evaluation technique with new datasets.

For improved performance, it is desirable to combine the early strengths of the GPM-only approach and the late accuracy of the trend evaluation method. To accomplish this, a trade-off between the general path data and new data is needed. One simple method to accomplish this, referenced herein as the *Appended GPM* method, is to simply splice the general path onto the end of the new data. As shown in Figure 5, the general path is vertically shifted along the y-axis to intercept the final data point of the new dataset and the RUL. The difference between this time and the time at which the shifted GPM intercepts the failure threshold is the RUL.

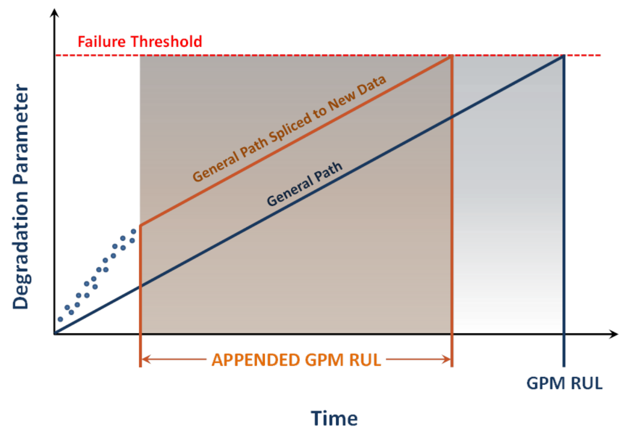

Figure 5. Example of RUL Estimation Using Appended GPM.E

The Bayes approach was developed to provide a statistical transition from an almost purely historical estimation in the beginning to an individual estimate towards the end of life as more data is collected. In this way, the RUL estimate typically converges on an accurate prediction faster than the two previous methods alone. This method uses a technique of Bayesian updating to gradually transition from the GPM-only estimation to the trend evaluation method as more and more data becomes available. Bayesian updating allows prior information about the general path model parameters to be combined with new data to generate a new estimation of model parameters for the current device (Coble and Hines, 2011). Essentially, as more data for the device is collected, the general path is weighted less in favor of the trend evaluation method.

A detailed mathematical analysis of this method is beyond the scope of this work and the interested reader is directed to Lindely and Smith (1972) for a more in-depth derivation. A brief review of this technique is provided here using the linear least-squares method. Equation 1 is a linear regression model and the model parameters b can be calculated using Eq. 2.

$$Y = bX \tag{1}$$

$$b = (X^T X)^{-1} X^T * Y \tag{2}$$

The vector Y is constructed using the degradation values of each degradation path, and the matrix X (Eq. 4) is constructed using the coefficients of the selected mathematical model (e.g., linear, quadratic, etc.).

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}; \; X = \begin{bmatrix} t_{11} & t_{12} & \dots & t_{1m} \\ t_{21} & t_{22} & \dots & t_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ t_{n1} & t_{n2} & \dots & t_{mn} \end{bmatrix} \tag{3,4}$$

The general path is then calculated as the average of each estimated model parameters determined from Eq. 2.

As new data is collected, Eqs. 3 and 4 are appended with the GPM model parameters and an identity matrix, respectively. To provide the transition between the GPM and the trend evaluation approach, the data is weighted using Eq. 5, which represents the accuracy of each entry in Eq. 3. To calculate the noise variance (σ_y^2), each model is subtracted from the corresponding measured values to normalize the error and enable a variance calculation. The individual variances will be averaged to obtain the population variance. The noise variance, σ_y^2, is typically very small compared to the model variances, σ_β^2, which are calculated from the distribution of GPM model parameters. Therefore, the historical model will be weighted more and have a greater influence. Finally, Eq. 6 is used to calculate the model parameters of the Bayesian-updated GPM.

$$\Sigma = \begin{bmatrix} \sigma_y^2 & 0 & \dots & 0 & 0 \\ 0 & \sigma_y^2 & & \vdots & 0 \\ 0 & & \ddots & 0 & \vdots \\ \vdots & & & \sigma_y^2 & 0 \\ 0 & 0 & \dots & 0 & \sigma_\beta^2 \end{bmatrix} \tag{5}$$

$$b = (X^T * \Sigma * X)^{-1} * X^T * \Sigma * Y \tag{6}$$

4. REMAINING USEFUL LIFE ESTIMATION WITH INDENTER MODULUS

4.1. Accelerated Aging of I&C Cables

Accelerated thermal aging of I&C cables was accomplished using the industrial furnaces shown in Figure 6. Several sample configurations were used to accommodate the collection of various types of electrical and mechanical measurements (Figure 7). For IM measurements, thirty two, 1-ft. cable samples were prepared. Sixteen of these samples consisted of complete sections of cable (i.e., jacket, insulation, and conductors) while the remaining sixteen consisted of only the insulation and conductor (Figure 8). To account for variation in local material composition and configuration of the complete cable sections, ten IM measurements were taken around the circumference of the outside of the jacket and averaged. For EAB measurements, tubular samples of the Ethylene Propylene Rubber (EPR) insulation material and dumbbell samples of the Chlorinated Polyethylene (CPE) jacket material were prepared in accordance with IEC/IEEE 62582 (IEEE, 2012) and a total of five EAB measurements were collected and averaged per test.

During thermal aging, all samples were subjected to a uniform temperature of 130°C, collecting various electrical and mechanical tests including IM and EAB at specific intervals throughout the accelerated aging period. The particular aging temperature selected for this work was based on aging experiments documented in a report investigating the qualification practices for low-voltage electric cables (Toman, 2005). The majority of these experiments were performed at temperatures between 120-150°C and these temperatures were selected based on qualifications performed by the original cable manufacturer.

It should be noted that because the physical configuration of the EAB samples is different than that of the samples used for IM testing, the EAB samples degrade faster, and thus provide a more conservative estimation of the cable's age. Further, although a direct one-to-one relation between IM and EAB could be established by collecting both measurements from the same sample, this is impossible since EAB is a destructive test. As discussed in Villaran, and Lofaro (2009), EAB measurements provide reliable and trendable measurements and can be directly correlated with material condition. Additionally, EAB is being used as a reference for the cable end-of-life, whereas the focus of this research is the general behavior of IM data as a function of cable age as well as its performance as a prognostic parameter for RUL estimation.

Figure 6. Industrial Furnaces Used for Accelerated Cable Aging

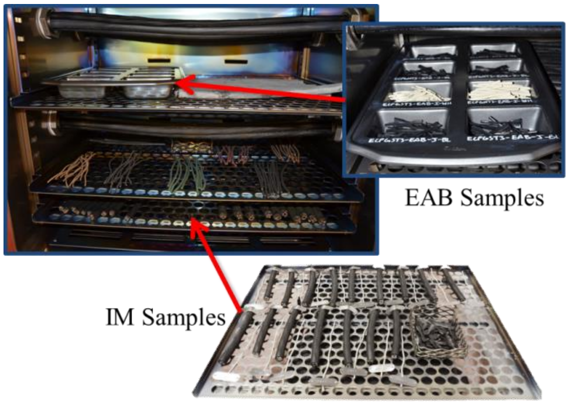

Figure 7. Cable Sample Configuration used for Accelerated Aging

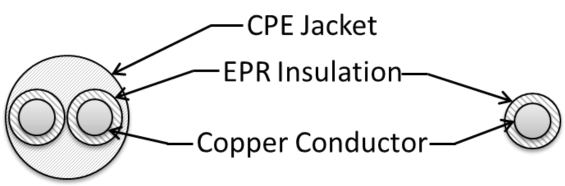

Figure 8. Sample Configuration Cross Sections for IM Measurements

4.2. Results of Accelerated Aging Experiment

Figure 9 and Figure 10 show the raw data results of EAB testing collected for the EPR insulation samples and the CPE jacket samples, respectively. Note that these figures represent the average of five individual EAB measurements per aging time, and the error bars represent the standard error. As indicated earlier, unlike the samples prepared for IM testing, the EAB samples consist of the polymer material *only*, prepared in accordance with IEC/IEEE standards. These results were used to guide the data collection of the aging experiment described herein, and determine the corresponding time of failure. Table 1 includes tabulated EAB averages and standard errors for reference.

Figure 11 and Figure 12 show the results of the IM testing In addition, the EAB results are overlaid with the IM data for reference. Referring back to Table 1, 3146 hours of aging would correspond to an EAB of approximately 168% and 89% for the EPR insulation/conductor and full cable sample, respectively, indicating that the IM cable samples have not yet reached end-of-life. Although the samples have not yet reached the benchmark 50% EAB, it is visually obvious that the IM measurements trend with time, and it is expected that this behavior will continue to end-of-life.

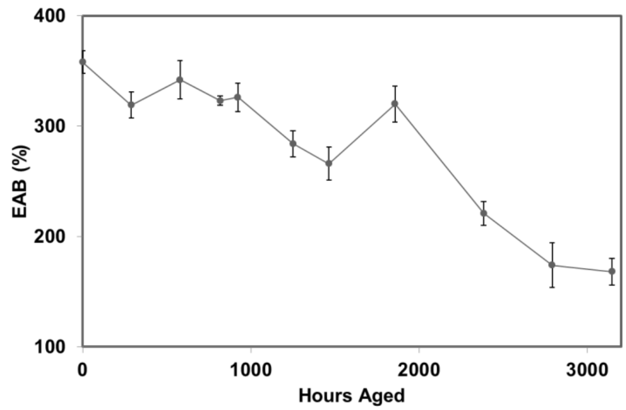

Figure 9. EAB Average of EPR Insulation. Error Bars Represent Standard Errors

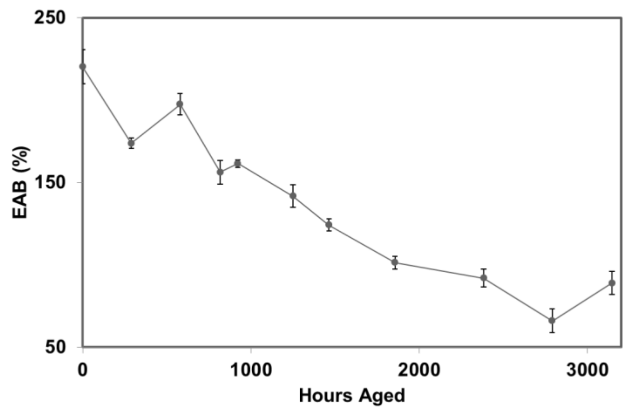

Figure 10. EAB Average of CPE Jacket. Error Bars Represent Standard Errors

Hours Aged	EPR Insulation		CPE Jacket	
	Average	Standard Error	Average	Standard Error
0	358	23.4	220	22.9
289	319	26.5	174	7.1
579	342	38.3	197	14.4
817	323	9.7	156	15.9
922	326	28.9	162	5.1
1250	284	26.3	142	15.2
1464	266	33.3	124	8.2
1856	320	36.7	101	8.8
2383	221	24.0	92	11.9
2790	174	45.4	66	16.2
3146	168	26.5	89	15.7

Table 1. EAB Results

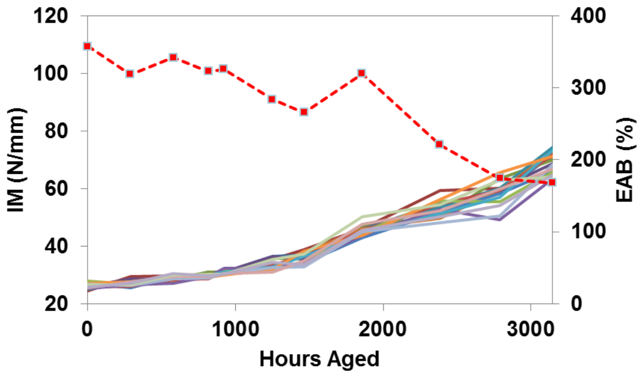

Figure 11. IM and EAB Measurements for EPR Insulation/Conductor Samples

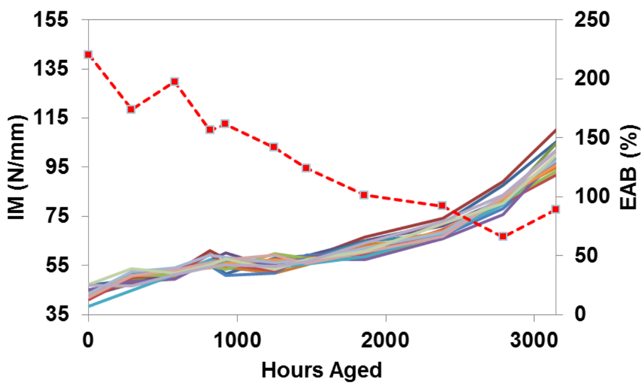

Figure 12. IM and EAB Measurements for Sections for Full Cable Samples

One important behavior to note is the apparent increase in variance of the IM measurement as a function of the cable's age. Figure 13 shows the standard deviation of the individual values for each measurement time. Here, the values appear somewhat constant until approximately 2000 hours where there is an increase with cable age. It is unknown if this increase as a function of age will continue. Further, the cause of this behavior is unknown, and could be a result of yet explained chemical changes in the polymer, thermal gradients in the cable aging oven, or limitations in the precision or accuracy of the measurement device.

4.3. Prognostics Model Development Using IM

Since the cable samples in the current accelerated aging experiment have not yet aged long enough to reach the corresponding 50% EAB, the failure threshold for these samples will be shifted to correspond to the current EAB values of 168% for the insulation/conductor configuration and 89% for the full cable configuration. Essentially, the final time value for each individual IM degradation path will correspond to the failure value for that cable sample.

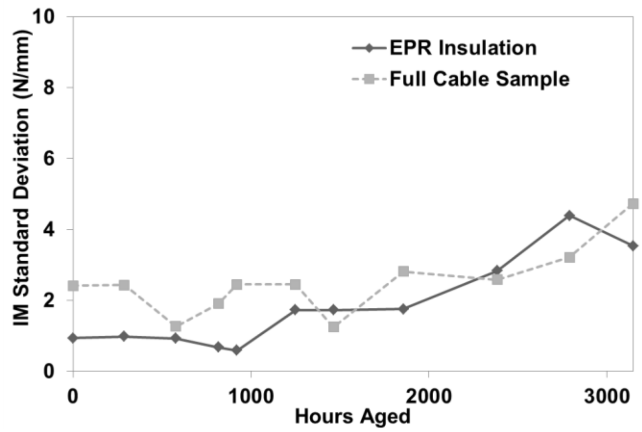

Figure 13. Standard Deviation of IM Data

Referring back to Section 3, now that a candidate prognostic parameter has been identified, its fitness should be quantified using the three metrics discussed (Coble, 2010). Performing these calculations results in the values shown in Table 2. Note that although the insulation/conductor IM parameter shows a higher fitness than that of the full cable sample (2.68 to 2.58), the full cable sample will be used for the GPM model development since this is the configuration that would be encountered in the field.

Metric	Insulation/ Conductor	Full Sample
Monotonicity	0.78	0.68
Trendability	0.98	0.98
Prognosability	0.92	0.92
Total Fitness	**2.68**	**2.58**

Table 2. Prognostic Fitness Metrics for IM

After quantifying the fitness of the candidate parameter, and confirming that it is a suitable prognostic parameter, the next step is to select the functional form for the GPM. Visual inspection of the full cable sample IM data (Figure 12) suggests that the data could be modeled using an exponential or polynomial function. Simple error analysis indicates that a 3rd order polynomial, of the form in Eq. (7), is well suited to model the data. Indeed, best-fit cubic functions to each individual path indicate R^2 values of greater than 0.97, suggesting that a 3rd order polynomial accounts for much of the variation in the data.

$$y(t) = at^3 + bt^2 + ct + d \tag{7}$$

The GPM is then calculated by performing a 3rd order polynomial fit to each individual degradation path and averaging the constants of each fit. This results in the general path shown in Figure 14. Here, the general path (dashed line) as well as the general path final value (dotted line) is superimposed on the individual IM degradation paths.

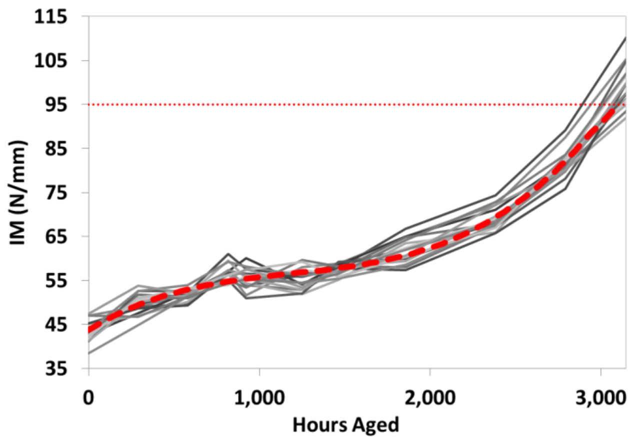

Figure 14. IM Data with Corresponding GPM (dashed) and GPM Failure Value (dotted).

It is important to note that the GPM developed from the aforementioned accelerated aging data is directly affected by the aging temperature. This means that any RUL estimations generated from this model are applicable only if the cable being tested is experiencing the same conditions as the cables used to build the model. For example, because the cables were aged at 130° C, a temperature significantly higher than would be typically encountered in a NPP, the accelerated aging data would need to be normalized to the temperature being experienced by the cable under test prior to GPM development. One of the most common methods for this is to use the Arrhenius Relationship (Yang, 2007), described in Eq. (8), where t_1 is the estimated age, t_2 is the time the specimen was aged, T_1 is the service temperature, T_2 is the aging temperature, E_a is the activation energy, and k is the Boltzmann constant.

$$\frac{t_1}{t_2} = e^{\frac{E_a}{k}*\left(\frac{1}{T_1}-\frac{1}{T_2}\right)} \tag{8}$$

Care should be taken when applying the Arrhenius relationship to note the assumptions of the underlying model, which include the assumption of a first-order relationship and constant activation energy. Normalization of the accelerated aging data and subsequent analysis is planned for future work.

5. RESULTS AND ANALYSIS

To test the performance of the GPM approach, an iterative technique was used to estimate the error of the GPM method and compare the GPM method to other types of RUL estimations. To start, each of the IM degradation paths was censored, or removed, from the population prior to the GPM development and treated as an unknown data set. Each of the data points in the censored, unknown data set was then treated as a simulated field measurement. RUL estimations were calculated from each data point of the censored degradation path using both types of GPM techniques (Bayes and appended) as well as a 3rd order trend evaluation.

Figure 15 shows the absolute percent error, calculated using Eq. 9, between the estimated RUL for all methods, averaged across all paths as a function of number of points. Note that at least 4 data points must be available in order to calculate a 3rd order polynomial fit for the individual method. Table 3 provides the numerical values of the average percent error along with the calculated standard errors. As expected, when estimating RUL using only a regression of the available data, the error tends to decrease as more data becomes available. Additionally, and more importantly, both GPM methods always outperform the individual fit method. This behavior is supported in other experiments performed by the authors to explore the use of Frequency Domain Reflectometry (FDR) as a prognostic parameter (Shumaker, McCarter, Hashemian, & O'Hagan, 2014).

$$\varepsilon = \left|\frac{RUL_{actual} - RUL_{calculated}}{RUL_{actual}} \cdot 100\right| \tag{9}$$

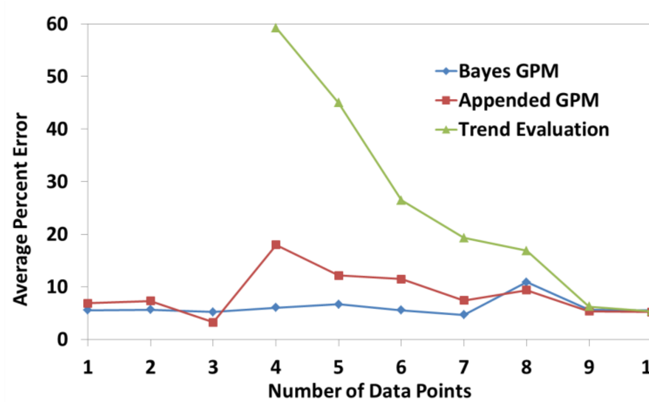

Figure 15. Absolute Percent Error in RUL Estimation as a Function of Number of Data Points.

No. of Pts.	GPM with Bayes		Appended GPM		Trend Evaluation	
	% Error	Std. Error	% Error	Std. Error	% Error	Std. Error
1	5.58	0.01	6.89	0.50	-	-
2	5.63	0.09	7.33	1.27	-	-
3	5.19	0.24	3.24	0.65	-	-
4	6.05	0.43	18.00	2.75	59.25	1.64
5	6.70	0.74	12.14	2.38	45.01	5.05
6	5.57	0.79	11.46	1.77	26.43	6.71
7	4.66	0.64	7.41	0.93	19.31	4.69
8	10.88	5.35	9.35	1.35	16.87	1.69
9	5.60	0.62	5.34	0.85	6.25	0.88
10	5.50	0.59	5.19	0.63	5.34	0.60

Table 3. Absolute Average Percent Errors and Standard Error of RUL Estimation Population.

Although this method performs well in laboratory conditions for CPE/EPR polymer cables, more experiments with different polymer materials subjected to a range of temperatures are needed to help establish the accuracy of the IM technique as a predictor of cable age. Additionally, the authors will soon begin investigating the relationship between the mechanical measurements of EAB and IM to other thermal and chemical measurements such as percent-crystallinity, melting temperature, or glass transition temperature changes.

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