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Remaining Useful Life Estimation of Electric Cables in Nuclear Power Plants

Brent D. Shumaker*, Jonathan B. Ledlow, Ryan D. O'Hagan,Dan E. McCarter, Hashem M. Hashemian

Analysis and Measurement Services Corporation,
AMS Technology Center, 9119 Cross Park Drive, Knoxville, TN 37923
bshumaker@ams-corp.com

Electric cables help form the backbone of instrumentation and control (I&C) systems in nuclear power plants by providing power to electrical equipment and transmission paths for instrumentation signals used to perform safety functions and control plant operation. Operating experience in the existing fleet of nuclear reactors has shown that the number of cable failures increases with plant age resulting in plant transients, shutdowns, and in some cases, the loss of safety functions (NRC, 2012). As a result, cable condition monitoring and remaining useful life (RUL) estimation have become increasingly important in recent years, especially as many plants begin operation beyond their original licensing periods.
To facilitate the understanding of cable aging mechanisms and degradation detection, the United States Department of Energy (DOE) and the Electric Power Research Institute (EPRI) developed the Cable Polymer Aging Database (CPAD). The CPAD provides a repository of test results from cable aging experiments performed by a number of research institutions and represents one of the most comprehensive sources of cable degradation data that is publically available (EPRI, 2002).
This paper describes the process the authors used to select appropriate prognostic parameter(s), develop prognostic models, and estimate the RUL of nuclear power plant cables from the data contained in the CPAD.

1. Prognostic Model Development

The data in the CPAD consists of results from cable condition monitoring tests such as elongation-at-break (EAB), indenter modulus (IM), and insulation resistance (IR) that were performed as various cable polymer types were subjected to thermal aging. Figure 1 illustrates a simplified breakdown of the database records organized by polymer material and test type. As shown in Figure 1, cables with Chlorosulfonated Polyethylene (CSPE) and Ethylene-Propylene Rubber (EPR) insulation material were the most common contained in the database, while EAB and IM were the most common tests performed. This paper describes the development of a prognostic model to predict the RUL of CSPE jacketed cables from their EAB results in the CPAD as shown in Figure 2.

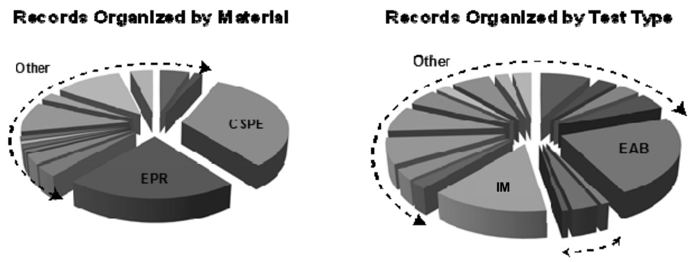

Figure 1: Cable Polymer Aging Database Records Organized by Material and Test Type

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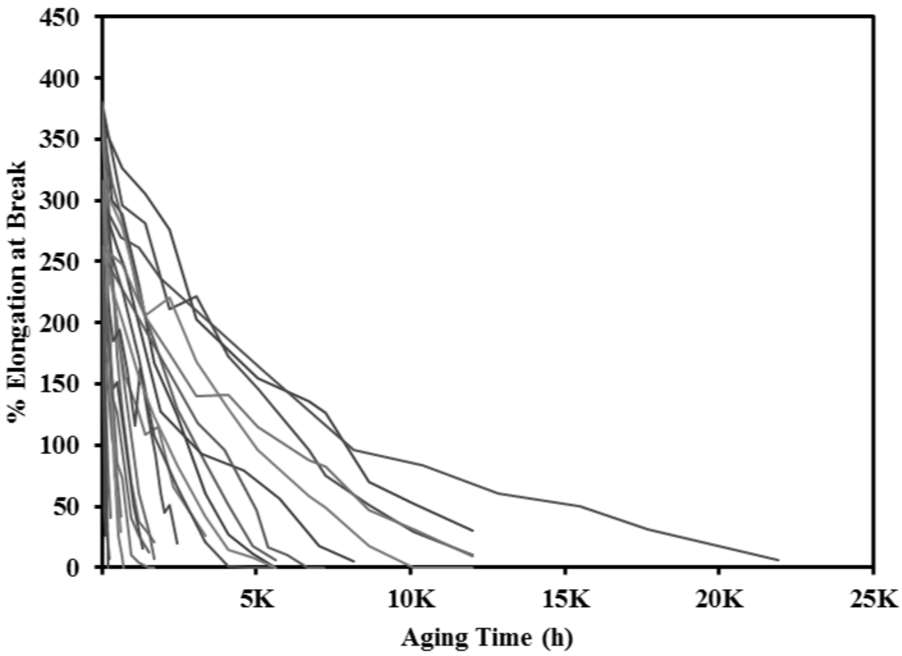

Figure 2: Elongation at Break (EAB) Data of CSPE Jacketed Cables Extracted from the CPAD

1.1 Prognostic Parameter Selection

A variety of measurements may be used to monitor the health and performance of nuclear power plant components. While these measurements are often useful in support of traditional maintenance programs, they cannot always be used with prognostic models. In practice, it is not always known a priori what measurements will be useful, and it is the selection of an appropriate prognostic parameter that is one of the first steps that must be performed when developing an RUL estimation for a given component (Lybeck et. al., 2011). To aid in this selection, 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 inclusion in a prognostic model: *monotonicity, trendability,* and *prognosability* (Coble and Hines, 2011). 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. The work described herein began by mining the CPAD data and evaluating potential prognostic parameters against these metrics. Table 1 shows the fitness as calculated using the described metrics for two parameters: EAB and Uptake Factor, which is a measure of the amount of solvent a polymer sample absorbs in a specified amount of time. The data for both parameters is shown in Figure 3. For the data in the CPAD, the EAB data had the highest fitness and was chosen to develop the prognostic models.

Table 1: Prognostic Parameter Metrics Values

Parameter	Monotonicity	Prognosability	Trendability	Fitness
EAB	0.54	0.92	0.88	**2.34**
Uptake	0.42	0.51	0.21	**1.14**

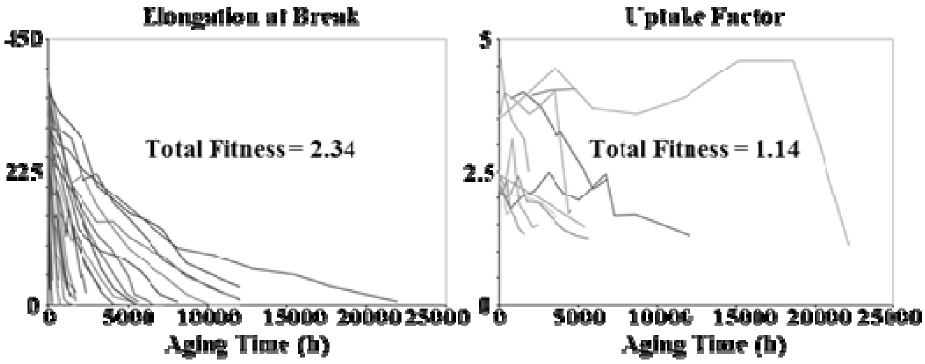

Figure 3: Examples of Prognostic Parameter Candidates from the CPAD

1.2 Data Normalization

Most of the data contained in the CPAD is a result of accelerated aging tests performed in a laboratory. Therefore, the cable samples were exposed to temperatures much greater than a normal operating temperature in a nuclear power plant. Additionally, the temperature used to age the samples was not constant across all tests (i.e. cable specimen 1 was thermally aged at 120 °C and cable specimen 2 was aged using 150 °C). This causes some samples to be aged much faster than others.

To properly develop a prognostic model, the aging data should be normalized to a single service temperature that is more representative of the typical operating conditions that the cables will experience in the plant. One of the most common methods for this is to use the Arrhenius Relationship, described in Equation 1, where t1 is the estimated age, t2 is the time the specimen was aged, T1 is the service temperature, T2 is the aging temperature, Ea is the activation energy, and k is the Boltzmann constant (Yang, 2007). This relationship was used to normalize the EAB data to a service temperature of 50 °C as shown in Figure 4. Figure 4 also shows the failure threshold of 50 % EAB (denoted by the dotted line) that was used to develop the prognostic models described herein.

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

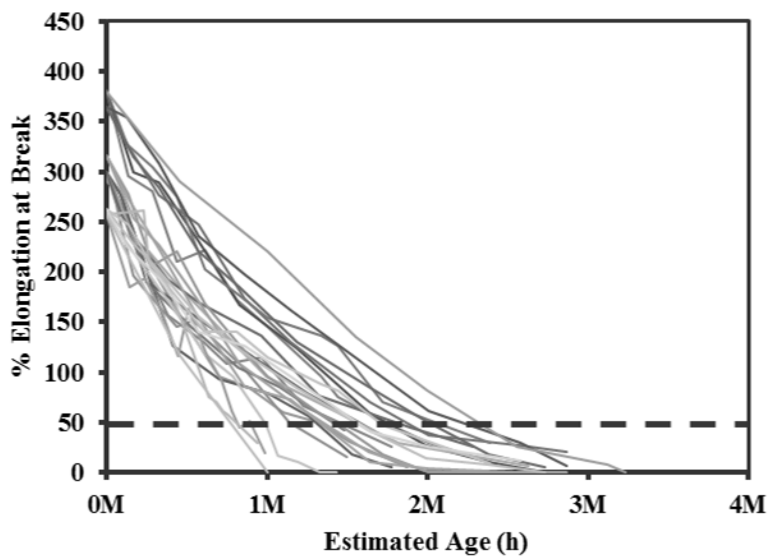

Figure 4: Normalized EAB data to a 50 °C Service Temperature

1.3 General Path Model Development

For the CPAD data, the General Path Model (GPM) approach was chosen to develop the RUL estimation. The GPM provides a versatile and robust method for modelling degradation for a wide array of systems and components (Lu and Meeker, 1993). An important aspect of GPM development is the selection of an appropriate functional form that will be used to establish the "general path" that a prognostic parameter will follow throughout a component's lifetime. In the simplest terms, a GPM can be thought of as a 'best fit' to an entire population of prognostic parameter data. Building a GPM consists of individually fitting the selected functional form to each curve and then calculating the average of each constant in the function. For example, building a quadratic-based GPM would involve fitting Eq 2 to each individual curve and then averaging each constant (*a, b,* and c). These average parameters would then be the parameters of the *general path.* Figure 5 shows both the quadratic and exponential GPMs overlaid with the normalized EAB data. For the CPAD data, the EAB data appeared to follow either a quadratic or exponential functional form described by equations 2 and 3, respectively. For this study, both functional forms were used for RUL estimation.

$$y = at^2 + bt + c \tag{2}$$

$$y = e^{mt+b} \tag{3}$$

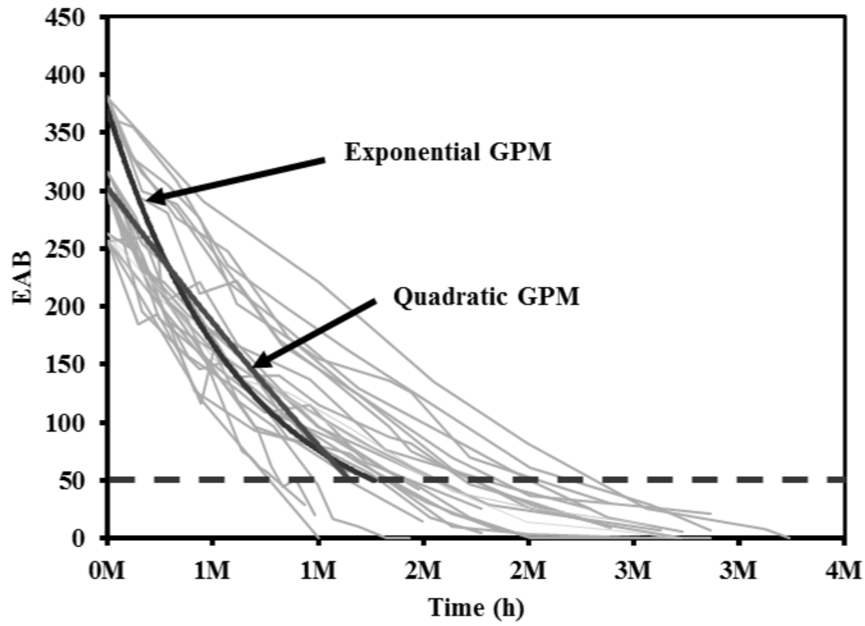

Figure 5: Exponential and Quadratic GPMs Overlaid with the Normalized EAB Data

2. Results

To test the performance of the GPM approach, each of the EAB data sets was censored, or removed, from the population prior to the model development and treated as an unknown data set. Then, the data points from the unknown data set were used one at a time to predict the RUL of the cable using GPMs and individual regressions with both exponential and quadratic functional forms. In contrast to the GPM, the individual regression uses only the data of the current set under inspection to predict failure. This consists of a best-fit of the selected function (Eq. 3) to only the data that is currently available for the element being tested – no historical data is used to predict failure. An example of each of these types of RUL predictions using 3 data points is shown in Figure 6. Table 2 shows the average error, or percentage difference, between the estimated RUL and the actual failure time, which was defined by an EAB value of 50 %. In each case, the prediction error decreases as more points are added. However, the GPM approach using an exponential functional form outperforms the other three methods. Additionally, these methods all provide better RUL estimates than a typical manufacturer's qualification of 40 y, which resulted in an RUL error of 75 % on average.

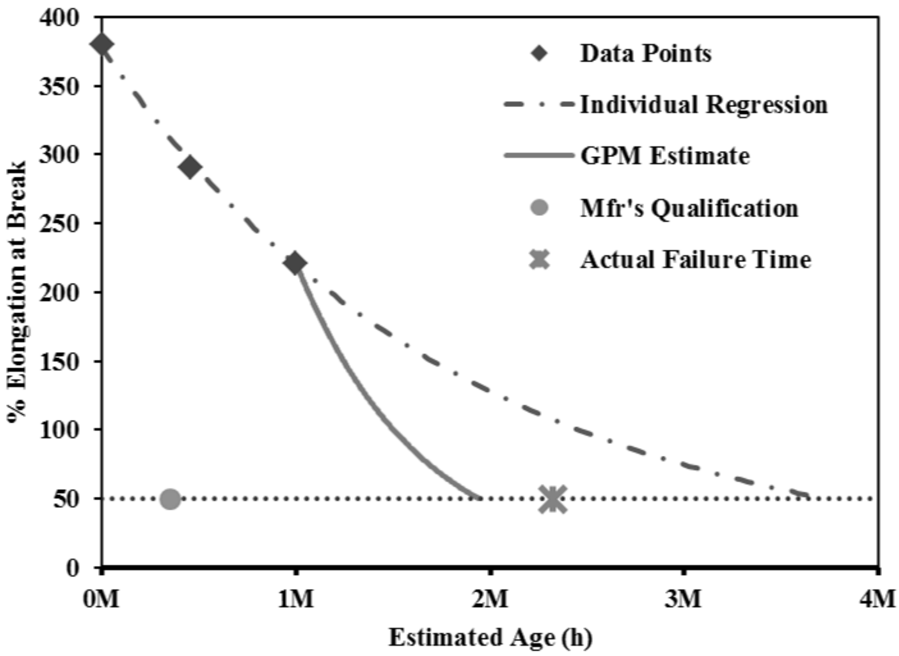

Figure 6: Example of RUL Estimation Techniques

Table 2: Example of RUL Predictions

Average RUL Estimate Errors - %				
Number of Points	**Exponential GPM**	**Exponential Individual**	**Quadratic GPM**	**Quadratic Individual**
1	27.0	NA	29.2	NA
2	25.9	166.0	27.6	75.4
3	21.9	40.0	25.4	73.7
4	18.7	27.8	26.1	61.0
5	13.6	18.5	23.3	48.1
6	9.3	17.9	17.0	40.9
7	7.6	15.1	12.8	34.8
8	4.9	14.8	8.9	34.3
9	3.8	14.8	5.9	36.4
10	7.3	15.0	4.5	30.8
11	0.2	8.7	0.6	40.5

3. Conclusions

The work herein describes an approach for developing prognostic models for RUL estimation of nuclear power plant cables. The existing data in the CPAD illustrates the applicability of cable condition monitoring data for prognostics. The results have shown that, with a collection of run-to-failure data, it is possible to build models for RUL prediction that provide estimations with reasonable accuracy. Additionally, as the cable nears the end of its operating life, a GPM estimate yields increasingly more accurate predictions. This will allow condition monitoring programs to better plan maintenance activities and avoid unplanned downtimes. While EAB measurements were used in this study, the framework proposed herein can be applied to many types of measurements, including those obtained through non-destructive testing.

4. Acknowledgments and Disclaimer

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