

APPLICATIONS AND EXTENSIONS OF DEGRADATION MODELING*

F. Hsu, W.E. Vesely†, M. Subudhi, and P.K. Samanta

Department of Nuclear Energy
Brookhaven National Laboratory
Upton, New York 11973, USA

BNL-NUREG--46380

†Science Applications International Corporation, Ohio, USA DE92 010078

ABSTRACT

Component degradation modeling being developed to understand the aging process can have many applications with potential advantages. Previous work has focussed on developing the basic concepts and mathematical development of a simple degradation model. Using this simple model, times of degradations and failures occurrences were analyzed for standby components to detect indications of aging and to infer the effectiveness of maintenance in preventing age-related degradations from transforming to failures. Degradation modeling approaches can have broader applications in aging studies and in this paper, we discuss some of the extensions and applications of degradation modeling.

The application and extension of degradation modeling approaches, presented in this paper, cover two aspects: (a) application to a continuously operating component, and (b) extension of the approach to analyze degradation-failure rate relationship.

The application of the modeling approach to a continuously operating component (namely, air compressors) shows the usefulness of this approach in studying aging effects and the role of maintenance in this type component. In this case, aging effects in air compressors are demonstrated by the increase in both the degradation and failure rate and the faster increase in the failure rate compared to the degradation rate shows the ineffectiveness of the existing maintenance practices. Degradation-failure rate relationship was analyzed using data from residual heat removal system pumps. A simple linear model with a time-lag between these two parameters was studied. The application in this case showed a time-lag of 2 years for degradations to affect failure occurrences.

1. INTRODUCTION

Component degradation modeling includes modeling of occurrences of component degradations and analyses of these occurrences to understand the aging-degradation process and its implications. In this modeling approach, dividing the operational performance of a component into three states - normal operating state, degraded state, and failure state, we established relations among these states using rates of degradation and failure occurrences. The relations are used to define estimates of the effectiveness of maintenance in preventing degradation from becoming failures. In an earlier paper¹ we have focussed on basic concepts and mathematical development of simple degradation modeling as applicable to aging and maintenance effectiveness applications.

*This work was performed under the auspices of the U.S. Nuclear Regulatory Commission.

In this paper, we study further application and extensions of degradation modeling approaches focusing on two aspects:

- a) applications of degradation modeling approaches to a continuously operating component, and
- b) extension of degradation modeling approaches to analyze degradation-failure rate relationship.

Previously, we studied standby "active" components.¹ Here, we analyze degradation and failure data for air compressors to study the applicability of this modeling approach to a continuously operative component. Thus, the degradation modeling analysis of air compressors shows the applicability of the approach for an active component under different operating conditions. Also, because they are continuously operating component, air compressors are expected to suffer degradations which are detected and corrected; thus, making them ideal candidates for degradation modeling analysis.

Understanding the relationship between degradations and failures is important in aging studies and can result in significant benefits in defining maintenance strategies for controlling aging and in conducting aging reliability and risk studies particularly when aging failure data are sparse. In terms of maintenance strategies, if degradation-failure relationship is known, then effective maintenance/repair/refurbishment can be performed through monitoring of degradations, thus avoiding component failures. For aging reliability studies, relationship between degradations and failure is important since it can be used to estimate failure rates from degradation rates when failure data are sparse. In this paper, this important correlation between degradations and failures is statistically studied and the concept of a delayed effect of degradation on failures is explored.

2. DEGRADATION ANALYSIS USING AIR COMPRESSOR AGING DATA

Here, our objective is to explore the applicability of degradation modeling approaches for a continuously operating component, different from standby components studied previously. We selected an air compressor for this analysis. The analysis approach is similar to that followed for the components studied in our earlier work.¹

Definitions of Degradations

To analyze degradations, the degraded state of the component must first be defined so it can be identified and analyzed. Definitions of the degraded state can be at a gross level or at a detailed level. At a gross level, a component is described as degraded whenever any deterioration occurs which does not cause loss of function. The operational performance of the component is divided into three states: the normal operating state, the degraded state, and the failure state. An example of a gross definition of degradation is that a component degradation occurs whenever corrective maintenance is required, but the component has not failed.

More detailed modeling of degradations involves dividing the degradation space into multiple degraded states. A given degraded state is then associated with a given range of characteristics of the component or performances of the component. For example, detailed degraded states for circuit breakers can be defined based on defined ranges for the pick-up/drop-out voltage, inrush/holding current, and other measurable degradation characteristics.

The advantage of defining more detailed degradation states is that we can accurately predict impacts on the failure rate of the component. When aging occurs, the component generally progresses

through a series of degradation states before failure occurs. By analyzing and modeling this progression, we can more accurately predict when failure will occur. For initial work, the gross definition of degradation can be used, which basically equates the degradation state occurring whenever corrective maintenance is required.

Table 1 presents an example of data analyses for an air compressor identifying degraded states, along with failure states of the component. In this example, failure states and degraded states of air compressors are distinguished based on engineers' judgement using the information on failure effect and the identified effected subcomponent. In some situations, judgements were used to determine whether the degradation was of the magnitude to be defined as a failure. For example, in general, an oil leak at the piston rod seal can be a degraded state for an air compressor, but in the example in Table 1, the leak was of sufficient magnitude to be called a failure of the air compressor.

Table 1. Typical Examples of Compressor Degradation Levels and Failure Mode and Effect

Compressor Subcomponent	Failure Classification	Failure Effect	Failure Mode	Degradation Level
Bearings	D	Monthly preventive maintenance - bearings greased		Low D
Filter	D	Monthly P.M. - filter cleaned		Low D
Gasket	D	Oil leak by gasket	Gasket deterioration	Intermediate D
Jacket Heat Exchanger	D	Corrosion deposits built up by aftercooler	Mechanical debris; poor water chemistry	Intermediate D
Bolts and Fasteners	D	Fractured stud on spacer	Mechanical vibration	High D
Pistons	D	Brass filings in high and low pressure regions found during P.M.	Mechanical wear	High D
Piston	F	Oil leak at piston rod seal	Mechanical wear	F
Lube Oil System	F	Pump seized and became inoperable	High temperature, mechanical wear	F

Analysis Approach

The main objective of the analysis was to obtain the aging failure rate and degradation rate based on component age-related failure and degradation data, respectively. These two parameters are used to obtain the effectiveness of maintenance in preventing age-related failure.

For the analysis of air compressors, aging data from only one of two BWRs were used. Based on the statistical test, the aging data in the two available units were not compatible with each other. Therefore, the aging data from unit one was used to provide a data base from four similar compressors. Similarly, statistical tests were also conducted to justify the data pooling across the four components. Details of the analysis are presented in Reference 2.

The process of data collection provides specific degradation and failure times of four similar compressors from one BWR. The data for each of the compressors individually were insufficient to determine the parameters (degradation rate and aging failure rate). Therefore, we analyzed data from the group of components (i.e., four compressors). Similar to the analysis on RHR pumps¹, statistical tests were conducted to justify the use of data across components.

(1) Mann-Whitney U Test

The Mann-Whitney U test was used in the analysis to identify components belonging to the same population. The four components in unit studied showed statistically identical distributions of times between degradations (and failures). Thus, the aging data from across the four components in unit one is combined for the analysis.

(2) Trend Testing and Identification of Age-Group with Degradation and Failure Times

The data obtained by the "data combining" method¹ were tested for time trends before developing age-related degradation and failure rates. Statistical tests were used to define component age groups showing similar aging behavior. We observed that the first three years of the compressors life showed a decreasing trend, and the last five years showed a increasing trend on both degradation rate and failure rate.

Aging Effects on Degradation

We analyzed the degradation data for the compressors with the following objectives:

- (a) To identify age-groups where statistically significant time trends exist, and
- (b) To determine time trends and degradation rates, using regression analysis.

The results and the characteristics of estimated degradation rate are summarized in Figure 1, which shows both the degradation rate (λ_d) and the logarithm of the degradation rate ($\ln\lambda_d$) that characterized the air compressors over ten years (presented as 40 quarters). Statistical tests showed that the degradation behavior across these components are similar, and accordingly, a generic degradation characteristic was studied. The age-dependent degradation rate is based on approximately 240 degradation occurrences observed for four compressors over the ten years of operation.

DISCLAIMER

This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

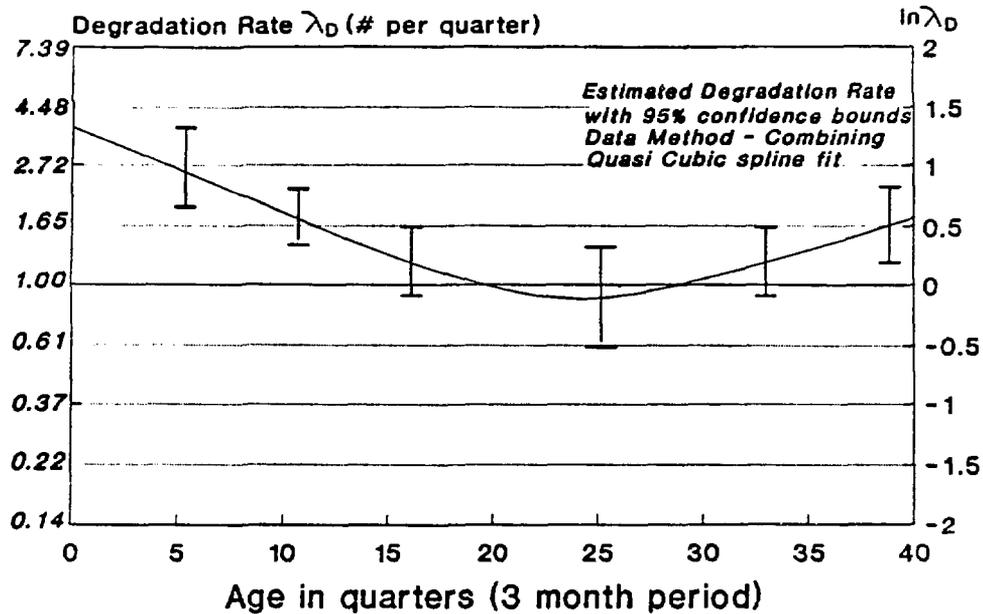


Figure 1. Age-dependent degradation rate (data on 4 air compressors)

The following observations can be made from the age-dependent degradation rate for the underlying air compressors.

- (a) The degradation rate shows significant age-dependence; the early life of the compressors (the first five years) shows a statistically significant decreasing trend, and the later life (last five years) shows a statistically significant increasing trend with the age of the compressors.
- (b) The increase in degradation rate, which is of interest in aging studies, is significant.
- (c) The 95% confidence bounds for the degradation rate show that the uncertainty in the estimation is reasonably small. The large number of degradations observed in the component contributed to this lower uncertainty.

Aging Effects on Failures

The aging-failure data for the compressors were also analyzed with the following objectives:

- (a) To identify age-groups where statistically significant time trends exist, and
- (b) To determine aging-failure rates in the age-groups where time trends exist.

Figure 2 shows both the failure rate (λ_f) and the logarithm of the failure rate ($\ln \lambda_f$) for the air compressors over ten years. The age-dependent failure rate presented is based on 25 failures observed for four compressors over ten years of operation.

The following observations can be made from the aging-failure rate obtained for the air compressors:

- (a) The aging-failure rate shows significant decreasing trend in the first two and a half years (in 10 quarters), and an increasing trend for the last five years of the component's ten-year life.
- (b) The behavior of aging-failure rate is similar to the degradation rate in the early two and one-half years, but differs after that. The aging-failure rate was generally lower (factor of 2 to 8) than the degradation rate and the difference decreased with increasing age. The aging failure rate reached about the same level as the degradation rate at the end of the component's ten years of operation.
- (c) The 95% confidence bounds associated with aging-failure rate show higher uncertainty compared to the degradation rate due to the lower number of failures observed.

Evaluation of Maintenance Effectiveness

As discussed in our earlier report¹, the degradation modeling approach estimates the effectiveness of maintenance in preventing age-related failures. The transition probability from a maintenance state to a failure state signifies the ineffectiveness of maintenance in the simplified model studied. The complement of maintenance ineffectiveness is maintenance effectiveness.

The maintenance effectiveness for the air compressors is obtained for each ten quarters of age. The maintenance effectiveness (1 = excellent maintenance, 0 = poor or no maintenance), as plotted in Figure 3, varies between 0.3 and 0.9 for the first 30 quarters, but is significantly lower (about 0.1) in the last 10 quarters, which signifies the small difference maintenances made in preventing degradations of components from transferring to failures.

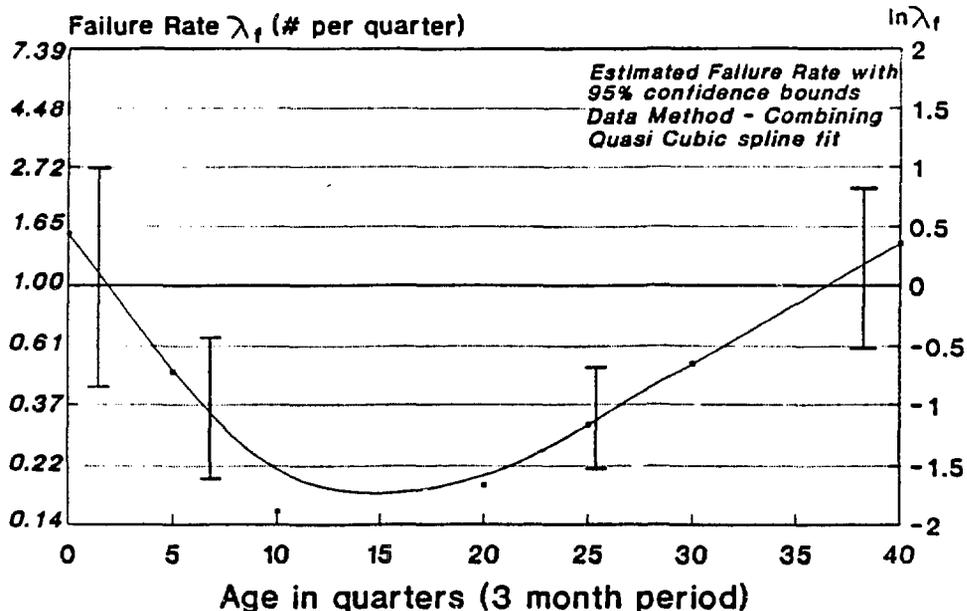


Figure 2. Age-dependent failure rate (component: 4 air compressors)

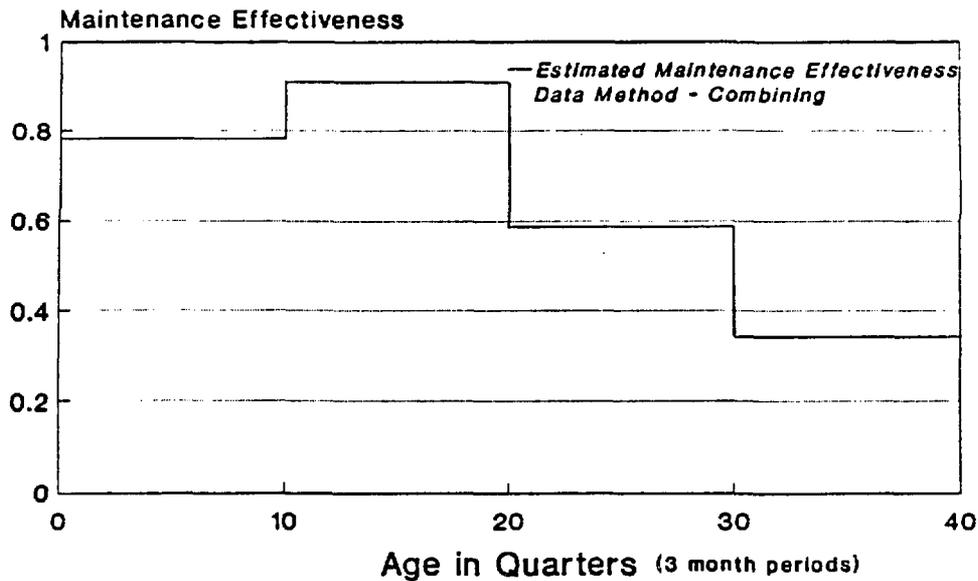


Figure 3. Estimated maintenance effectiveness (component: air compressors)

3. ANALYSIS OF DEGRADATION-FAILURE RELATIONSHIP

In this chapter, we present an event-count based approach for data analysis to study the relationship between degradations and failures. This approach uses non-parametric statistical methods to estimate and seek relations between degradation and failure rates based solely on the number of observed degradations and failures in each unit time or age interval.

This approach provides a simple framework for exploring the relationship between degradation and failure rate. Since aging-related failures, in general, pass through a degraded state first, the degradation rate serves as a precursor to the failure rate. Increasing aging trend in the degradation rate can signal future increasing aging trends in the failure rate. We study simple linear relationship between these two parameters considering any delayed effect that degradations may have on failure occurrences.

In general, disciplines that can be used to develop relationships between the degradation rate and the failure rate include engineering, reliability, and statistical disciplines. Engineering and reliability disciplines are required to develop the theoretical models between the degradation rate and failure rate. Statistical disciplines are required to estimate unknown parameters and to validate the theoretical models. The relationships between the degradation rate and failure rate, which are studied here, are among the simplest models to develop; they are consistent with reliability and engineering considerations. In the relationships which are developed, the degradation rate is related to the failure rate by appropriate transition probabilities. These transition probabilities are obtained by studying the correlations between occurrences of degradation and failures. They also include the effectiveness of maintenance in controlling the degradations before becoming failures.

Analysis of Correlation Between Degradation and Failure Frequencies - Time-Lag Considerations

As we stated, the objective of degradation modeling is to develop relationships between the component degradation rate and the component failure rate. These relationships involve predicting how the component failure rate will change based on observations of the component degradation rate. Of most interest is predicting aging trends in the failure rates based on observed aging trends and patterns in the degradation rate.

If λ_f denotes the failure rate, and λ_d denotes the degradation rate, then the objective of degradation modeling can be interpreted as developing relationships between λ_d and λ_f . If the symbol "R" denotes these relationships then we may write:

$$\lambda_f = R(\lambda_d) \quad (1)$$

Thus, the objective of degradation modeling is to find the relationship R.

This equation expresses the relationship between degradation and failure rate increasing aging trends in the degradation rate can signal future increasing aging trends in the failure rate. Also, by recording the characteristics of the degradations, the severity of the degradation rate can be determined. Increasing severities of the degradation rate can also signal future increases in the failure rate. We, however, focused on relating occurrence rates and did not study the impact of increased severity of the degradation to failure rate at this time. Effect of increased degradation severity can be studied by expanding the Markov modeling approach to multiple degraded states supported by engineering criteria and data to obtain the necessary information from tests on component, maintenance, and operability records.

For our study, the relationship (1) is expressed as:

$$\lambda_f(t+l) = C_{df} \lambda_d(t) \quad (2)$$

where,

$\lambda_d(t)$ is the degradation rate at time (t)

$\lambda_f(t+l)$ is the failure rate at time (t+l)

l is the time-lag at which degradations impact failure occurrences

C_{df} is the correlation coefficient between degradation occurrences and failure occurrences

The above expression assumes a linear relationship where C_{df} to be estimated from data analyses, is similar to the parameter of maintenance ineffectiveness. The parameter l represents the delayed effect because the component generally passes through a degraded state before experiencing failures, and is also estimated from data.

We used the event-count based data analysis to determine the correlation coefficient as well as the lagged time between degradation and failure frequencies. Using the data, the Kendall's Rank Correlation analysis method was employed to estimate the correlation coefficient for each individual plant data, as well as the combined data of the 3 plants. A statistical software package (STATGRAPH) was used to calculate the correlation coefficient for a large number of possible time-lag values. Among all

the calculated time-lag correlation coefficients, the correlation coefficient using a time-lag of 2 years reached the maximum value at a significance level of $\alpha=0.029$. The statistical results of Kendall's Rank Correlation coefficients are summarized in Table 2 and Table 3.

Table 2. Kendall's Rank Correlation Analysis Results for RHR Pumps at 3 Units

Correlation Analyses Between N_f and N_d .

Plant 1:	Correlation Coefficient:	0.3570
	Significance Level:	0.0139
Plant 2:	Correlation Coefficient:	0.5429
	Significance Level:	0.0005
Plant 3:	Correlation Coefficient:	-0.2067
	Significance Level:	0.5134
3 Plant Combined:		
N_f vs. N_d :	Correlation Coefficient:	0.3721
	Significance Level:	0.0692

N_f = number of failures

N_d = number of degradations

Table 3. Kendall's Rank Correlation Analysis Using Time-Lag Considerations (Data on RHR Pumps from 3 Units)

No Time-Lag

Correlation Coefficient:	0.3721
Significance Level:	0.0692

One-Year Time-Lag

Correlation Coefficient:	0.1826
Significance Level:	0.3966

Two-year Time-Lag

Correlation Coefficient:	0.505
Significance Level:	0.0294

Estimation of Failure Rate from Degradation Data - Time-Lag Regression

One of the applications of degradation modeling is to estimate the failure rate from the degradation rate of a component. Here, using the time-lag correlation coefficients obtained in the previous section, the failure counts are estimated from degradations counts. The lagged regression technique was used to estimate the failure frequency based on the correlation coefficient and estimated time-lag. A linear regression model was used, although time-lag regression methods can use exponential or other non-linear models depending on the data distribution properties.

Analysis of data on RHR pumps is presented as an example of this application. Figure 4 presents the estimated failure frequency from the degradation frequency.

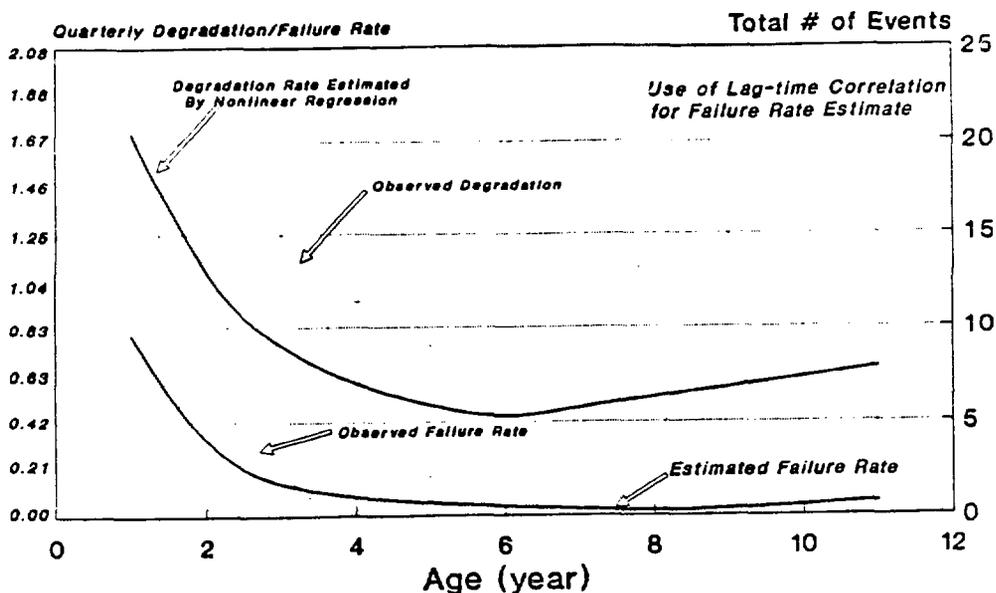


Figure 4. Degradation & failure rate estimation
(event-counts based approach - data on RHR pumps from 3 units)

In this figure, the estimated failure rate in the last two years (age 9 to 11) is obtained from the degradation rate. This estimated failure rate is obtained by using equation 2, where both the correlation between degradation and failures and the delayed effects are incorporated. The correlation coefficient and the 2-year time-lag were estimated using the first 9 years of data. The estimated failure rate shows the increasing trend similar to the degradation rate, but lagged by 2 years. This estimated failure rate is comparable to the failure rate obtained by assuming no failures during this period (age 9 to 11). However, because of the increasing trend, the estimated rate starts becoming larger than that obtained otherwise. As we discussed previously, estimating failure rate from degradation data can significantly help risk-evaluation of aging, but the results need to be validated further.

Applications of the Degradation Rate-Failure Rate Relationship

Once the relationship between the degradation rate and the failure rate is determined, it can be applied in several important ways. We studied one application (estimation of component failure rate from degradation rate), but other important applications can be studied with potential advantages. Some are summarized below.

1. The component failure rate can be estimated from degradation data. This estimation greatly increases the accuracy of the failure rate estimation for reliability and risk evaluations, and allows the failure rate to be estimated even if there is no failure data. If failure data exists, the estimate of the failure rate from the failure data can be optimally combined with the estimate from the degradation data.
2. Aging trends in the component failure rate can be estimated from aging trends in the degradation rate. This estimation is one of the most powerful applications of the degradation rate-failure rate relationship. Aging trends, which are identified in degradation data, can be input into the relationship to predict the aging trend in the failure rate. The determined aging-dependent failure rate in turn, can, be input to reliability and risk models to predict the resulting, impact on the reliability and risk.
3. Degradations can be monitored for their reliability and risk impacts. Alert levels and warning levels can be designed to monitor degradation to indicate when the failure rate is too high or is significantly increasing.
4. Maintenance can be monitored for its reliability and risk effectiveness. This again immediately follows from the degradation rate-failure rate relationship. The degradation rate-failure rate relationship which is determined through degradation modeling, is a function of the maintenance program. If the degradation rate as determined from the data on corrective maintenance and preventative maintenance implies that the failure rate is too high or is significantly increasing, then the maintenance is ineffective. If the failure rate is maintained at an acceptable level, then the maintenance is effective from a reliability and risk standpoint.

The accuracy and extent to which degradation rate-failure rate relationship can be determined are critical in demonstrating these applications. These applications can provide important inputs in maintenance decisions and aging evaluations, because in the past, degradations and maintenances have not been explicitly related to the failure rate, except in special cases.

4. SUMMARY

In this paper, we presented application of degradation modeling approaches to a continuously operating component, different from a standby component. In addition, the relationship between degradation and failure frequency was studied to predict failure rates based on degradations. The major findings are summarized below.

Application of Degradation Modeling to a Continuously Operating Component

The application of degradation modeling approaches to a continuously operating component (air compressors) shows the usefulness of this modeling approach in studying aging effects and the role of maintenance in this type of component. Analyses of degradation and failure data of air compressors using degradation modeling approaches show that aging effects are evident in both degradation and

failure occurrences. In this case, both rates show aging effects; however, the faster increase in the failure rate compared to the degradation rate indicates the ineffectiveness of maintenance, which is reflected in the evaluation of maintenance effectiveness. The decline in maintenance effectiveness with age signifies that maintenance is ineffective in preventing age-related degradations from failures.

Relation between Degradation and Failure Frequency

Understanding the relationship between degradations and failures is an important aspect in the degradation modeling approaches. Knowledge of relationships between degradations and failures will help define the maintenance activities necessary for preventing degradation-caused failures and can be used in risk-evaluations of aging. In this report, an event-count based approach to data analysis is presented to study correlations between degradation and failure frequencies. We used this approach to discover if there were delayed effects of degradations on failures. For the specific component studies (RHR pumps), a lag-time of 2 years was observed between degradation and failure occurrences. Existence of such lag-times, which are expected to be component specific, can be beneficial for deciding the maintenance activities that are necessary to mitigate the effects of aging. Additional applications will be needed to demonstrate the validity of the existence of time-lag between degradations and failures.

REFERENCES

1. P.K. Samanta, W.E. Vesely, F. Hsu, and M. Subudhi, "Degradation Modeling with Application to Aging and Maintenance Effectiveness Evaluations," NUREG/CR-5612, BNL-NUREG-52252, March 1991.
2. F. Hsu, W.E. Vesely, E. Grove, M. Subudhi, and P.K. Samanta, "Degradation Modeling: Extensions and Applications," BNL Technical Report A-3270 6-21-91, June 1991.