BNL

TECHNICAL REPORT
A-3270 6-21-91

DEGRADATION MODELING: EXTENSIONS AND APPLICATIONS

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June 1991

Prepared for

Nuclear Plant Aging Research (NPAR) Program

Under Contract No. DE-AC02-76CH00016
NRC FIN A-3270

EXECUTIVE SUMMARY

Component degradation modeling includes modeling of occurrences of component degradations and analyses of these occurrences to understand the degradation process and its implications. The degradation modeling that we discuss focuses on the analysis of times of degradation and failure occurrences to understand the aging degradation in components. Our previous paper[1] discusses the basic concepts and the mathematical development of a simple degradation model. Using the degradation modeling methodology, failure data on residual heat removal (RHR) pumps and service water (SW) pumps were analyzed to detect indications of aging and to infer the effectiveness of maintenance in preventing age-related degradations from transforming to failures. In this paper, further applications and extensions of degradation modeling are discussed.

Additional applications of degradation modeling are carried out for air compressors, a continuously operating component. We demonstrate that the analysis of degradation occurrences is useful in understanding the aging process and the role of maintenance in that process. For the air compressors, the failure rate and degradation rate show an early decreasing trend followed by a significant increasing trend that indicates effects of aging. The failure rate, which is significantly lower than the degradation rate in the first three years, increases faster in the later years, reaching approximately the same value as the degradation rate at the end of the ten years of operation. This behavior indicates the ineffectiveness of maintenance in preventing degradation from transforming into failures as the air compressors age.

Another important application of degradation modeling approaches is to predict aging-failure rate from degradation rate. Since aging-related failures, in general, pass through a degradation state first, the degradation rate serves as a precursor of the failure rate. Increasing aging trend in the degradation rate can signal future increasing aging trends in the failure rate. We study a simple linear relationship between these two parameters considering any delayed effect that degradations may have

on failure occurrences. An example of an application using the data on RHR pumps shows a time-lag of 2 years for degradation to affect failure occurrences.

For additional applications, extensions of degradation modeling are presented. The extended models, which we are developing, will explicitly show the reliability effects of different maintenance and test intervals, different maintenance and test efficiencies, and different repair times. Thus, the extended model will allow us to evaluate the reliability effects of different maintenance programs.

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ACKNOWLEDGEMENT

The authors wish to acknowledge Mr. Satish Aggarwal, NRC Technical Monitor for his technical support and encouragement in this project. The report also benefitted from reviews by J. Higgins, J. Taylor and R. Hall of BNL.

We are very thankful to Ms. Donna Storan for an excellent job in preparing this manuscript.

1. INTRODUCTION

This report presents the status of degradation modeling development in understanding the component aging process and the role of maintenance in mitigating that process. Component degradation modeling as defined here includes modeling of occurrences of component degradations and analyses of these occurrences to understand the degradation process and its implications.

Our earlier report[1] presents the basic concepts and the mathematical development of a simple degradation model. 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 were used to define estimates of the effectiveness of maintenance in preventing degradations from becoming failures. Specific applications of the theoretical model were performed which resulted in quantitative models of component degradation rates and component failure rates, all of them derived from plant-specific data. Degradation analyses were carried out for residual heat removal (RHR) pumps and emergency service water (SW) pumps - standby "active" components. Analyses of degradation data for both these pumps showed a "bathtub" curve for the degradation rate where a distinct, increasing aging trend was observed as time progressed. Interesting, pump failure rates did not show any increasing trend for the same time period, thus demonstrating the need to identify aging trends through analyses of component degradations. The applications also demonstrated how this modeling approach can be used to analyze and assess the effectiveness of maintenance.

To explore further the applicability of degradation modeling approaches, we analyzed a different component, air compressor, using the methodology defined in our earlier report[1]. Air compressors, continuously operating component, are different from standby active components studied in our previous applications. 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.

The degradation modeling approaches is an extension of standard reliability approaches where only two states, normal operating state and failure state, are considered. By including an additional state, degradation state, we obtain useful information on component aging and on the role of maintenance in preventing age-related failures. However, this modeling requires additional data which can have large associated uncertainties. In this report, sensitivity analyses are performed to address the uncertainties in the degradation modeling results due to inclusion of information on component degradations.

The promising results obtained from the application of simple degradation models to standby and continuously operating components (RHR pumps, SW pumps, and air compressors) encouraged us to expand this concept to study additional related aspects. The additional aspects studied here include:

a) relationship between degradation and failures,

b) extension of modeling to show effects of different maintenance and test intervals, and different repair times, and

c) extension of degradation modeling to include multiple degraded states.

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 report, this important correlation between degradations and failures is statistically studied and the concept of a delayed effect of degradation on failures is explored.

Finally, the simple degradation model studied and applied so far uses only degradation and failure occurrence times. The usefulness of the model can be enhanced by including additional relevant test and maintenance related information whereby the effect of test and maintenance strategies, in terms of test and maintenance frequencies, duration, and efficiencies, can be determined. Theoretical development which extends the basic degradation model to include different test and maintenance interval, different test and maintenance efficiencies, and different repair times is discussed. Basic framework for extending the model to multiple degraded states is also presented.

The report is organized as follows, Chapter 1 is the introduction. Analysis of air compressors is present in Chapter 2. Chapter 3 discusses the uncertainty issues brought in by including degradation information and the sensitivity analyses performed to study the impact of the issues on degradation modeling results. Chapter 4 explores the relationship between degradations and failures and the extension of the degradation modeling is presented in Chapter 5. The results and insights of this study are summarized in Chapter 6. Appendices present air compressor data used in the evaluations and the statistical evaluations conducted for the results presented in the main body of the report.

2. DEGRADATION ANALYSIS USING AIR COMPRESSOR AGING DATA

In this section, we present an application of age-related degradation and failure data analysis based on the component degradation modeling approach described in our earlier report[1]. 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 previous report[1].

2.1 Overview of Degradation Modeling Approaches

In this section, we a briefly summarize the degradation modeling approaches. Basically, we present the relationships to be used in applying degradation modeling to component degradation and failure data, the assumptions of degradation modeling, and basic formulations of the modeling approaches. Detailed mathematics of specific degradation modeling can be obtained from our earlier report[1].

To understand degradation modeling, we study a repairable component, i.e., a component that is being repaired and maintained. The "active" components, pumps, valves, circuit breakers, and compressors, are repairable components and are the focus of this study.

For the simple degradation model studied, we make the following assumptions:

1. Degradation always precedes failure.
2. When a component is repaired after a failure, the operational state of the component reflects more restoration than when on-line maintenance is performed.
3. When maintenance is performed following detection of a degraded condition, the component is restored to a maintained state, which reflects less restoration than when repair is performed after a failure.

We call the state after repair of a failure the "o" state; the state after failure the "f" state; and the one after maintenance the "m" state.

We use the Markov process approaches for degradation modeling, because with these approaches simple models can be constructed first and then expanded later to yield more complex models. Statistical analysis is coupled to the models to estimate unknown parameters from degradation data. The simplest model we present considers only one degraded state. Expanded modeling can include multiple-degraded states (Figure 2.1).

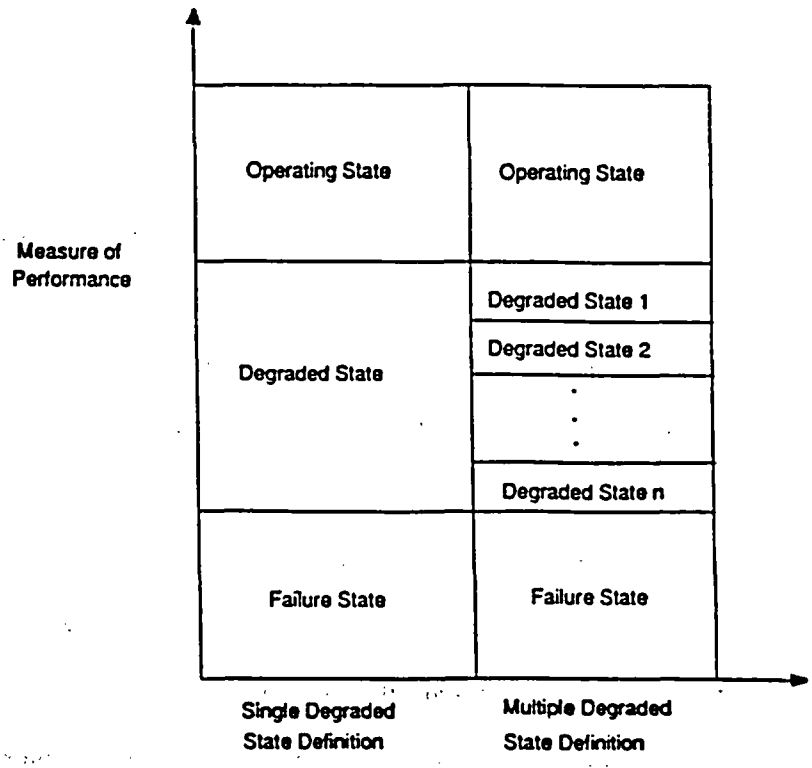


Figure 2.1. Alternatives for degraded state definitions

2.1.1 State Representation of Degradation Modeling

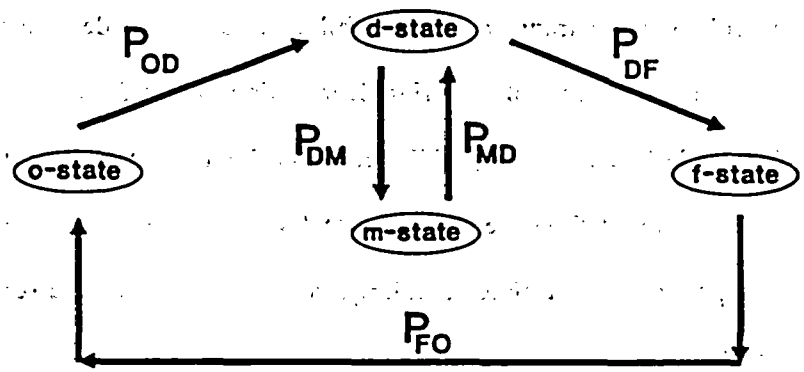
The Markov approaches of degradation modeling can be described by the state diagram for a component (Figure 2.2). Based on our assumptions, the component can be in a degraded state (d-state) through three processes:

a. the component reaches its first degraded state from a restored state (o-state),

b. the component undergoes recurring degradation with no intermediate failure (it is assumed that the component is in a maintained state (m-state) following a degradation), and

c. the component undergoes degradation following restoration resulting from a failure (f-state).

The component can fail only from a degraded state (d-state). However, it is assumed that maintenance is performed every time a degraded state is detected. Thus, a maintained state (m-state) is reached following a degraded state (d-state). For Markov modeling considerations, these two states are equivalent in this analysis.



o-state: restored state d-state: degraded state
m-state: maintained state f-state: failed state

P_{IJ} : transition probability from i-state to j-state

Figure 2.2. Markov state diagram component degradation modeling (single degraded state)

2.1.2 Transition Probabilities

The transition probabilities among the various states are as follows:

P_{OD} = probability that degradation occurs after the component is restored, with no failure before a degradation

$=$ 1 because we assume degradation always precedes failure

P_{DM} $=$ probability that maintenance is carried out once a degraded state is identified

P_{MD} $=$ probability that degradation occurs after maintenance before a failure occurs

$P_{DF} = P_{MF}$ $=$ probability that failure occurs after maintenance (performed following detection of a degraded state), with no intermediate degradation

P_{OF} $=$ probability that component is restored following failure

$=$ 1

Our interest lies in obtaining P_{MD} and P_{DF}. Principally, P_{DF} describes the effectiveness of maintenance and the probability of transferring to a failed state once a degraded state is reached. Similarly, P_{MD}, expresses the probability of recurring degradation before failure.

2.1.3 Frequency of Degradation, Frequency of Failure, and Transition Probabilities

Frequency of degradation defines the frequency of degraded state, i.e., the number of degraded states observed for a component per unit time. Similarly, the frequency of failure represents the failure states observed per unit time.

Let

$W_D(t)$ $=$ the degradation frequency at t

$W_F(t)$ $=$ the failure frequency at t

Developing balance equations from the renewal theory[2], one can obtain the steady-state solution that relates the frequency of degradation, the frequency of failure, and the transition probabilities. (Mathematical derivation is described in our earlier report[1].) W_D and W_F represent the steady state degradation and failure frequencies.

$$W_D = W_F + W_D P_{MD} \tag{2.1}$$

$$W_F = W_D P_{DF} \tag{2.2}$$

Expressed in terms of transition probabilities,

$$P_{DF} = W_F / W_D \tag{2.3}$$

$$P_{MD} = 1 - W_F / W_D = 1 - P_{DF} \tag{2.4}$$

These expressions define how the steady-state transition probabilities (P_{DF} and P_{MD}) can be obtained from the frequency of degradation and the frequency of failure. Using component reliability data bases such as the Nuclear Plant Reliability Data System (NPRDS) or a plant-specific data base, one can determine W_F and W_D, and hence, W_F / W_D for various components. These ratios can also be determined for various failure modes of a component to evaluate the type of maintenance carried out for a component.

The interpretations of the steady-state solutions are as follows:

1. The larger the ratio of frequency of failure and frequency of degradation (W_F / W_D) the larger is the probability that a failure will occur after degradation, P_{DF}.
2. For a given degradation frequency, W_D, the larger the probability, P_{DF}, the larger is the failure frequency, W_F.
3. The ratio W_F / W_D is a measure of ineffectiveness of maintenance in that it is equal to P_{DF}. However, smaller values of P_{DF} can result in larger values of W_F, if W_D is larger.
4. Another measure of effectiveness of maintenance is the failure frequency, W_F itself, which is equal to $W_D P_{DF}$.

The approaches presented above define how information on degradation can be used to obtain the characteristics of degradation (frequency, the transition probabilities from degraded to failure state and from maintained to degraded state), and how the frequency of component failure relates to such characteristics.

2.1.4 Aging Effects on Degradation Rate and Failure Rate

The effect of aging on component reliability may be manifested through either increased degradation or increased failures, or both. Generally, earlier studies have focussed on increased failures

due to aging. Here, the focus has been on degradations, along with an analysis of failures to seek a relationship between the two.

The degradation rate, λ_{MD}, is defined as the rate of degradation occurring after maintenance given that no previous degradation has occurred. Similarly, the failure rate, λ_{DF}, is the rate of a failure occurring after a degradation given that no previous failure has occurred.

The age-dependent λ_{MD} can be obtained by observing the times of degradation. The time of degradations, $t_1, t_2, \ldots, t_n$ is used to estimate the parametric form of $\lambda_{MD}(t)$. Similarly, time of failures is used to estimate the parametric form of $\lambda_{DF}(t)$.

When times of failure of the aged component are also present, along with the information on degradation, the former can be used to develop the age-dependent λ_{DF}, which can then be compared to λ_{MD}. The different behavior of $\lambda_{DF}(t)$ and $\lambda_{MD}(t)$ signify different types of effectiveness of maintenance in the component's aging process. If $\lambda_{MD}(t)$ shows a significant aging effect as opposed to $\lambda_{DF}(t)$, then the maintenance averts component failure. Conversely, maintenance is ineffective if the transition probability, P_{MD}, in the aging process is higher than the steady-state value.

2.1.5 Assumptions and Limitations in the Methodology

The degradation modeling presented in this section is the first step in developing the component aging reliability model using data on degradation. The specific analyses of examples presented in the next section also demonstrate the applicability of the methodology and show how useful insights can be derived from this approach. Nevertheless, at this time, several assumptions for this simple model are made, many of which will be dealt with as we make future extensions to the model and gain more experience with the analyses. In this section, we discuss the assumptions and limitations in the methodology and their implications in our results.

1. In the modeling presented, the component degradation is represented by a single-degradation state. Degradations are generally continuous and not discrete as treated in the model. For this simplest model, the assumption is that a degradation state occurs

when the degradation, which can be continuous, exceeds some threshold. Our objective is to demonstrate how important insights relating to aging and maintenance can be obtained by using degradation information in its simplest form. As we stated, more extended models can be developed that allow multiple states of degradation.

2. The model assumed that maintenance is performed every time a degraded state is detected. A degraded state as used in the model is a state in which degradation has exceeded a threshold requiring maintenance. Thus, a degraded state is associated with a requirement for maintenance. The data used in the analyses are delineated so that the identified degraded states are associated with maintenance. However, we recognize that component degradations can be identified where no maintenances are performed. Extended models with multiple degraded states will be able to distinctly treat degraded states which are not necessarily associated with maintenance requirements.

3. Maintenance as used in the model is corrective maintenance, not preventative maintenance. More frequent corrective maintenances are associated with more frequent degradation occurrences exceeding some threshold. Nondetected degradations and scheduled maintenances are not explicitly treated by the model.

4. Data requirements for applications of degradation modeling are more comprehensive because degradation data are required. However, degradation data are often unavailable, and if available, they are often incomplete. The interpretation of available data for degradation modeling application also needs to be systematized. Realizing the difficulty in obtaining comprehensive data, one of the objectives of this paper is to develop models which show how degradation data can be specifically used for maintenance. If these specific benefits and uses of degradation data are presented, then there will be more of an incentive to collect more accurate degradation data.

2.2 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. Figure 2.1 illustrates the basic alternative for defining the degradation state.

Table 2.1 presents an example of component data analyses identifying degraded states, along with failure states of the component. In this example, derived from the analyses of data for air compressors, 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 2.1, the leak was of sufficient magnitude to be called a failure of the air compressor.

Table 2.1. 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

2.3 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

(Appendix A). 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.

The process of data collection (Appendix A) 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 pumps[1], 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" method[1] 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.

2.4 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 details of the statistical analysis are presented in the appendices. The results and the characteristics of estimated degradation rate are summarized in Figure 2.3, 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 (Appendix A) 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.

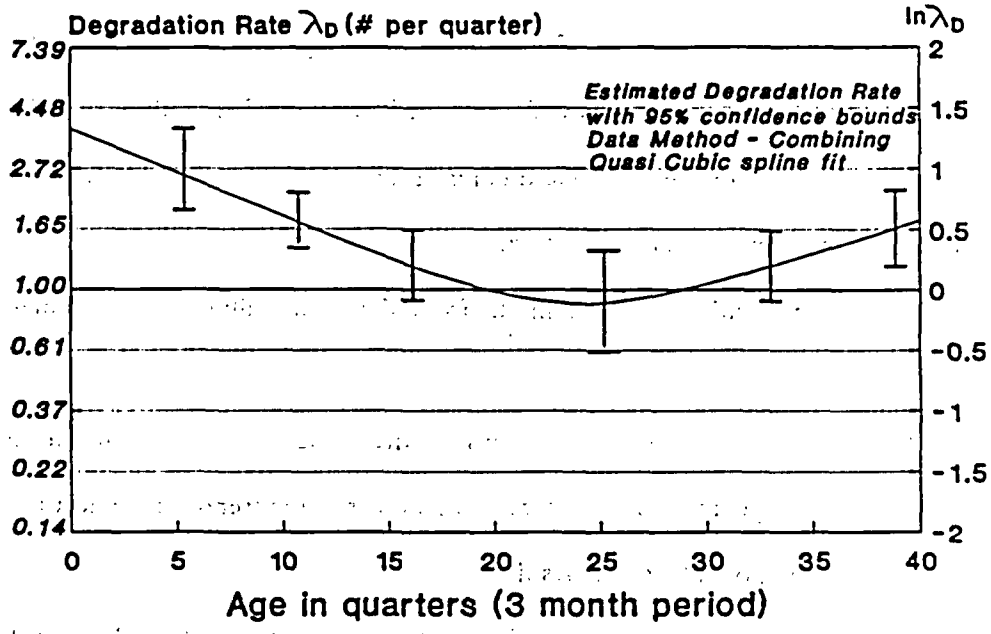


Figure 2.3. Age-dependent degradation rate (data on 4 air compressors)

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.

2.5 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 2.4 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-years 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.

2.6 Evaluation of Maintenance Effectiveness

As discussed in our earlier report[1], 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 2.5, 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.

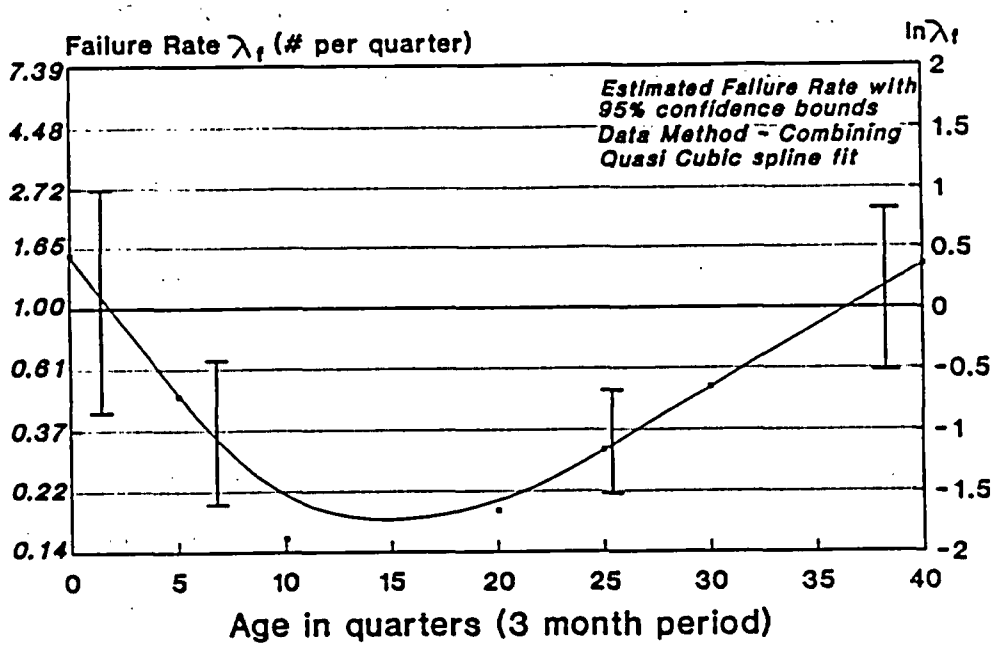


Figure 2.4. Age-dependent failure rate (component: 4 air compressors)

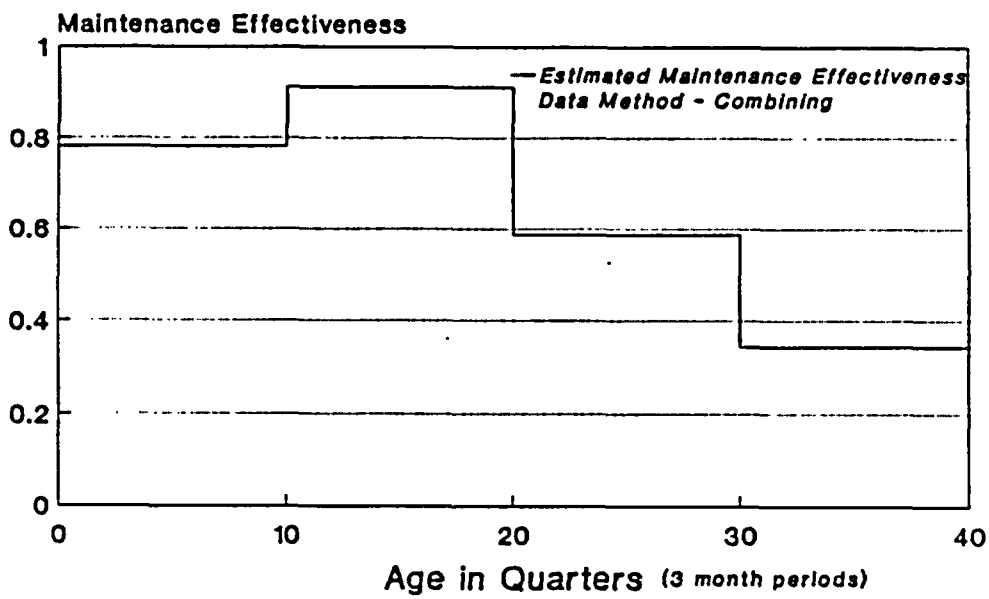


Figure 2.5. Estimated maintenance effectiveness (component: air compressors)

3. SENSITIVITY ANALYSES OF DEGRADATION MODELING RESULTS

The degradation modeling approach depends on the available data on component performance and the interpretation of the data for use in this approach. The limitations in obtaining the data and the subjectivity involved in interpreting it have the potential to affect the results used in judging aging effects. In this section, we present sensitivity analyses to study the impact of several issues on degradation modeling results. Sensitivity analyses were performed for three aspects:

i) partitioning of component reliability records (test and maintenance data) into degradation and failure states,

ii) uncertainty in degradation occurrence times, and

iii) impact of component test frequency to detect degradation and failure occurrences.

3.1 Sensitivity Analysis on the Partitioning of Aging-Failure Data

The partitioning of aging-failure data, from the engineering standpoint, is the fundamental issue of whether a component's state is classified as degraded or failed. Analysis of engineering data for defining component degradation state and failure state are discussed in Appendix A.

The main objective of this sensitivity analysis is to analyze the sensitivities of degradation modeling results to the uncertainties in aging-data partitioning into degradation or failure. As stated, because clear, detailed information is not always available to define the component state, subjectivity will be involved in defining the state. If this process for defining the component state can cause significant variation in the results obtained through degradation modeling analyses, then approaches should be defined to account for uncertainties in using the results of the analyses. Processes can also be defined to limit the uncertainties in defining the component state from the available data base. In the next section, aging data on air compressors are used as a case study for this issue.

3.1.1 Analysis Approach

Sensitivity analysis was performed by determining aging failure rate, degradation rate, and the maintenance effectiveness parameter for different data classifications obtained from the data evaluation process. The analysis was performed based on the initially obtained data set.

The partitions of existing aging-data obtained by redefining the degraded and failure states for sensitivity evaluations were somewhat judgmental. For instance, the gasket leaking problem of the air compressors was classified as a degraded state of the component in the original data base. Ambiguity exists, however, in the sense that the gasket leakage problem up to a certain degree of severity will not affect the required functional performance of the air compressor, but beyond that level of severity the component will not be able to perform the required function, i.e., the component is in a failed state. Due to lack of detailed information, clearly identifying the component states is difficult. Therefore, in this sensitivity study, component degraded states were re-evaluated and defined as failure state where clear judgement could not be made. The aging-data set obtained after this partitioning and the description of related partitioning criteria are presented in the Appendix B.

3.1.2 Analysis Results on Sensitivity Partitioning of Aging-Failure Data

The same statistical analysis method was used on the data set obtained by repartitioning the aging-data for sensitivity evaluation. The details of data analysis and statistical test results are presented in Appendix B. Since it was assumed that failure occurs through the process of degradations, the times between degradation occurrences remain unchanged regardless of the failure time partitions. Therefore, throughout this sensitivity study the degradation rate is not affected by this repartitioning of component states.

Results of the analysis and general findings on the sensitivity of data partitioning are summarized as follows:

(a) Statistical Test for Data Combining

The statistical test for data combining across components was conducted on the newly partitioned data set. The results showed no significant difference for the Mann-Whitney U-Test on the new data set compared to the initial data set. The statistical tests still justified using data from unit one across the four air compressors; Table B.3 in Appendix B gives the details of these results.

(b) Trend Test Results and Identification of Age-Groups with Failure Times

The data obtained for this sensitivity evaluation were tested for time trends. No significant differences in time trends between corresponding age-groups compared to the original evaluations were observed. Table 3.1 presents the comparison of statistical parameters representing the failure rate trends showing the effect of data partitioning.

Table 3.1. Sensitivity of Failure Time Trend on Data Partitioning

Partition Status	Age Group	Aging Rate $\hat{b}$			Constant $\ln\hat{a}$			Model	
		$\hat{b}$	P	uncertainty (5% error)	$\ln\hat{a}$	P	uncertainty (5% error)	P	standard error
Before	0-15	-0.233	0.024	CL:-0.409 CU:-0.055	0.435	0.386	CL:-0.934 CU: 1.804	0.025	0.584
	15-40	0.1012	0.035	CL:0.0078 CU:0.1964	-3.696	0.007	CL:-6.22 CU:-1.163	0.035	1.398
After	0-12	-0.349	0.005	CL:-0.551 CU:-0.147	1.079	0.07	CL:-0.118 CU: 2.276	0.005	0.878
	12-40	0.085	0.02	CL:0.015 CU:0.154	-2.842	0.005	CL:-4.743 CU:-0.939	0.02	1.322

P: Significance level

The results presented in Table 3.1 can be interpreted as follows. In the early age group (about 0-15 quarters), the component shows negative aging effects in both cases (before and after data partition). However, the component shows a slightly lower negative aging factor before data partitioning rather than after partitioning. In the later age group (around 15-40 quarters), the aging factor before data partitioning ($\hat{b}$ = 0.1012) is slightly higher than the factor after data partitioning ($\hat{b}$ = 0.085). This higher factor shows that the aging effect may be slightly over estimated due to subjectivity in data-partitioning.

(c) Aging Effect on Degradation

There were no changes found in aging effects over degradation rate due to data partitioning because the degradation state remained unchanged following repartitioning for sensitivity evaluations.

(d) Aging Effect on Failures

The following sensitivity observations can be made from the aging failure rate obtained for the air compressors, based on the newly partitioned data base:

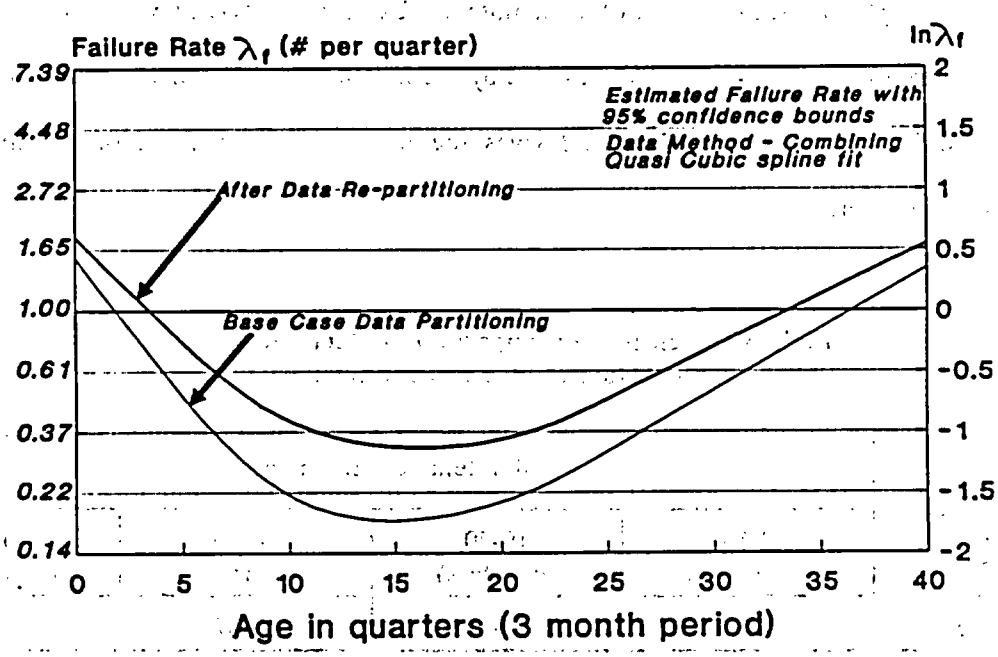
i. The aging-failure rate shows slightly different downward time trend in the first 10 quarters in that the failure rate obtained using the newly partitioned data shows a relatively smaller downward time trend (a factor of 4.5 decrease) compared to the previously obtained time-dependant failure rate (a factor of 7 decrease).

ii. In the last 15 to 20 quarters, no differences were found on the increasing time trends between the two data sets obtained by sensitivity failure time partitioning.

Figure 3.1 shows the sensitivity of aging failure rate to the subjectivity in data partitioning.

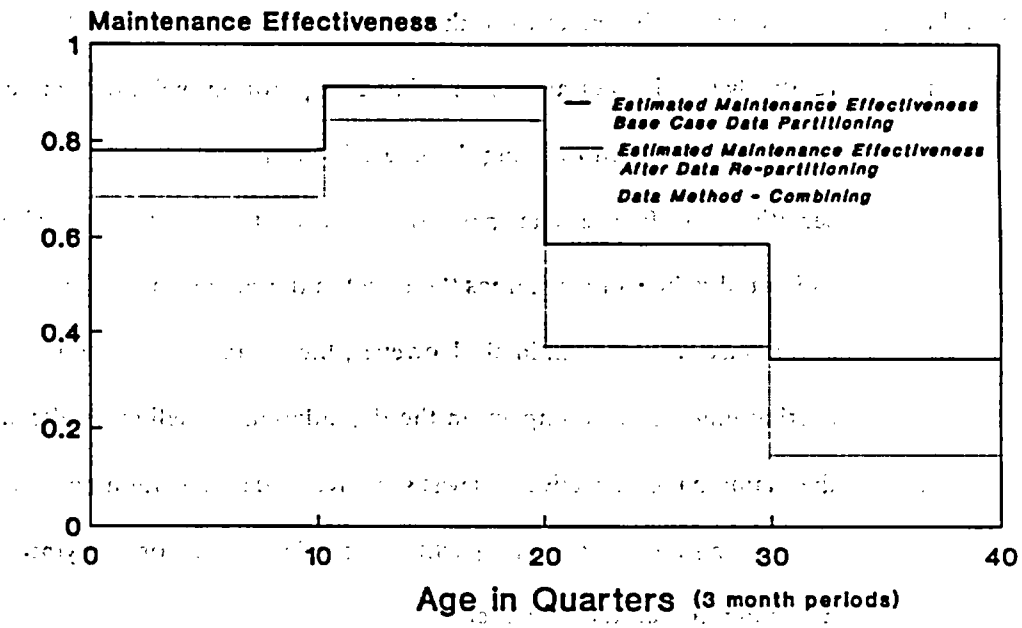
(e) Sensitivity Effects of Data Partitioning on Maintenance Effectiveness

The estimated maintenance effectiveness based on the newly partitioned aging data was obtained (Figure 3.2) by the same approach as before; the maintenance effectiveness varies between 0.7 to 0.85 for the first 20 quarters and then reaches approximately 0.1 in the last 10 quarters.



Data Source: 4 air compressors combined

Figure 3.1. Sensitivity of age dependent failure rate due to subjectivity in data partitioning



Data Source: 4 Air Compressors Combined

Figure 3.2. Sensitivity of estimated maintenance effectiveness in data partitioning

The maintenance effectiveness has almost the same time trend as the one obtained from the initial data set, except that the magnitude of the maintenance effectiveness (newly obtained) is decreased about 25%. Such a decrease is apparently caused by the increase in component failure rate obtained from repartitioning of the data. Table 3.2 gives the details of comparison of the maintenance effectiveness parameter.

Table 3.2. Sensitivity Comparison of Data Partitioning on Maintenance Effectiveness

Age Group/ Data Partitioning	Maintenance Effectiveness			
	0-10 (quarters)	10-20 (quarters)	20-30 (quarters)	30-40 (quarters)
Before	0.781	0.912	0.587	0.345
After	0.684	0.843	0.371	0.146

3.1.3 The General Conclusion on Sensitivity of Aging-Data Partitioning

The following conclusions can be made from the results of this sensitivity evaluation:

i. relatively small uncertainties on aging-data partitions will not significantly affect the results obtained by using the degradation modeling approach,

ii. sensitivity of failure-data partitions is reflected on the magnitude of the estimated failure rate, whereas the effect of the time trends on both degradation and failure rate was minimal. However, the engineering standard used in data partitioning can have impact on the degradation modeling results, and

iii. the maintenance effectiveness was sensitive to data partitioning. Thus, defining engineering criteria for data partitioning is important for applying degradation modeling in maintenance decisions.

3.2 Sensitivity Analysis on Uncertainty of Degradation Occurrence Times

In this section, we present a sensitivity study on the uncertainty of degradation occurrence times. The primary focus of this analysis is to incorporate the uncertainties present in the component degradation times used in the analysis. In practice, particularly for standby components where the component is tested at specified intervals to detect failures or degradation, there can be differences between the time at which degradation is detected and the time at which it actually occurred. This uncertainty was investigated by incorporating the undetected degradation occurrence times into data analysis of the degradation modeling method.

The sensitivity study was carried out based on the data on RHR pumps (as used in our earlier report[1]). The following assumptions were made to calculate undetected degradation occurrence times:

(a) On the average, the uncertainty in degradation occurrence time is one-half of the test interval.

(b) Degradation occurrence is a Poisson process in nature, and consequently, the undetected times between each degradation follow an exponential distribution with a constant mean, which is assumed to be the same as the distribution of test intervals.

(c) A Monte-Carlo simulation technique was used, and a computer program was written to generate the random sample for the undetected degradation occurrence time intervals.

3.2.1 Analysis Approach

In this sensitivity analysis, the time-dependent degradation rate was determined based on data, recalculated by incorporating the undetected degradation occurrence times. The data were modified according to the assumptions stated above, that is, the time intervals between degradation occurrences in the original data base were subtracted by the undetected times, which were generated randomly by a computer program using Monte-Carlo simulation techniques.

The statistical analysis method used in our earlier report[1] was applied on the new data set for RHR pumps [Appendix C, Table C.1], which was obtained by imposing the uncertainty in times of

degradation occurrences. The uncertainty times (undetected degradation occurrence times) were randomly generated by a computer program, which assumed an exponentially distributed random variable with a mean of (30/2=) 15 days, i.e., approximately 0.166 quarter, or half month. In other words, an average of 15 days (half of the test interval of one month) undetected time was imposed on the initial data set as the uncertainty in the degradation occurrence time. Details of data modification and statistical test results are presented in Appendix C.

Since this sensitivity analysis was primarily focused on degradation occurrence times, only the time-dependent degradation rate and its aging effect were analyzed and compared with the initial results, which do not include uncertainties in degradation occurrence times. Results of sensitivity analysis on the uncertainty of degradation occurrence for RHR pumps are summarized as follows:

(a) Trend Test Results and Identification Of Age-Group with Degradation Times

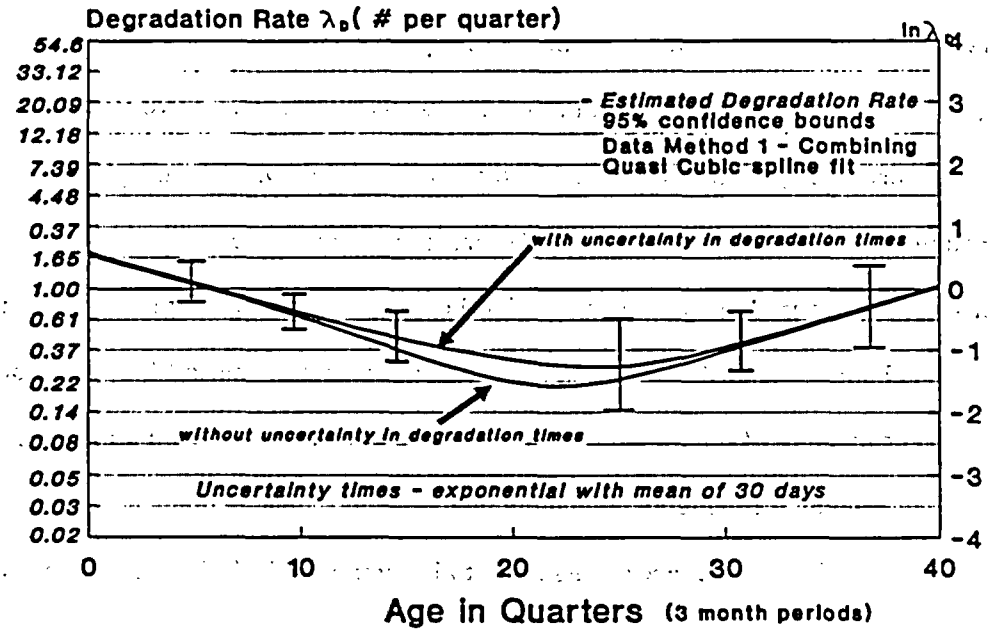
The data obtained by including of uncertainty in degradation occurrence times were tested for aging trends. We found no significant differences of time trends due to including uncertainty in degradation occurrence times. The comparison of statistical parameters showing the impact of uncertainty in degradation occurrence times is presented in Table 3.3.

The statistical parameters in Table 3.3 show almost the same time trending results in both cases which shows that the sensitivity of uncertainty in degradation occurrences is not statistically significant.

(b) Effect on Degradation Rate, Failure Rate, and Maintenance Effectiveness

No changes were found in aging effect over the time-dependent degradation rate, because of the imposition of uncertainty in degradation occurrence times. Figure 3.3 gives the time-dependent degradation rate over 10 years for RHR pumps in 3 plants. The imposed uncertainty on degradation occurrence times resulted in shifting the occurrence intervals which moved in the same direction (i.e., the original time intervals were all subtracted by a certain amount of uncertainty time, signifying that a degradation may have occurred before the detected time). However, this behavior, does not affect the time-dependent degradation rate.

Similarly, the aging effect as the failure rate remained unchanged, and thus, the maintenance effectiveness parameter was also insensitive to uncertainty in degradation occurrence times.



Data source: RHR pumps in 3 plants

Figure 3.3. Age-dependent degradation rate with uncertainty of degradation times

Table 3.3. Sensitivity of Degradation Time Trend on the Uncertainty of Degradation Occurrences

Data Status	Age Group (quarters)	Aging Rate $\hat{b}$			Constant $\ln\hat{a}$			Model	
		$\hat{b}$	P	uncertainty (5% error)	$\ln\hat{a}$	P	uncertainty (5% error)	P	standard error
Ignore Occurrence Uncertainty	0-20	-0.095	0.0006	CU:-0.0508 CL:-0.1395	0.541	0.025	CU: 1.015 CL: 0.066	0.0001	1.234
	20-40	0.105	0.046	CU: 0.207 CL: 0.0022	-4.161	0.012	CU:-7.325 CL:-0.997	0.045	1.287
Incorporate Occurrence Uncertainty	0-20	-0.098	0.0001	CU:-0.0508 CL:-0.144	0.586	0.018	CU: 0.1027 CL: 1.068	0.0001	1.259
	20-40	0.1037	0.05	CU: 0.204 CL: 0.0013	-4.091	0.015	CU:-7.132 CL:-0.913	0.053	1.327

P: Significance level

3.3 Sensitivity of Test Frequency to the Estimation of Degradation Frequency

The degradations observed in a time period is dependent on the number of surveillance tests performed on the component. However, certain degradations can also be observed via operating parameters. By conducting surveillance testing at a frequency lower than the occurrence of degradation frequency, occurrences of degradations can remain undetected. Therefore, we studied the correlations between the observed degradation frequency and the test frequency. The analysis presented focusses on investigating the sensitivity and functional relationship between these two parameters. The following assumptions were made in deriving the correlation between degradation rate and test rate.

i. The number of degradations observed in a given time period follows a poisson process.

ii. Probability of observing a number of degradations in a total number of N tests follows a binomial distribution.

iii. Degradation frequency is assumed to be time invariable in a fixed time period.

Let,

P_d: probability of observing a degradation in each test.

T: assumed test interval.

λ: time invariant degradation rate (piecewise constant).

N_d: number of times tested for degradation in time period (t_1, t_2).

ω_t: test frequency (or test rate).

L: total time period of observations.

D_n: number of degradations observed in time period of T.

Based on the above assumptions, the Cumulative Distribution Function (CDF) of N_d can be derived as follows:

Since,

$$\omega_t = \frac{1}{T} \tag{3.1}$$

so,

$$N = \mathrm{Int}\left(\frac{t_2 - t_1}{T}\right) = \mathrm{Int}\left\{(t_2 - t_1)\omega_t\right\}$$

$$= \mathrm{Int}(L \cdot \omega_t) \tag{3.2}$$

$$E(D_n) = P_d \cdot N_d = (1 - e^{-\lambda T})\frac{L}{T}$$

$$= (1 - e^{-\lambda T})\mathrm{Int}\left[\frac{t_2 - t_1}{T}\right] \tag{3.3}$$

or,

$$E(D_n) = (1 - e^{-\lambda T}) \cdot L \cdot \omega_t$$

$$= \left(1 - e^{-\frac{\lambda}{\omega_t}}\right)\mathrm{Int}\left[(t_2 - t_1)\omega_t\right] \tag{3.4}$$

Thus, the probability of observing number of D_n degradations given P_d, N_d, and L will be:

$$P_r(D_n | P_d, N_d, L)$$

$$= \binom{N}{D_n}(1 - e^{-\lambda T})^{D_n} \cdot e^{-\lambda T(N - D_n)} \tag{3.5}$$

Hence,

the cumulative distribution function (CDF) of D_n can be obtained as:

$$P_r(k \le D_n | P_d, N, L)$$

$$= \sum_{i=1}^{k} \binom{N}{k} (1-e^{-\lambda T})^k \, e^{-\lambda T(N-k)} \tag{3.6}$$

The above expression (3.6) shows the probability of observing the number of degradations less than and equal to D_n in the time interval T with given degradation rate λ; probability of observing a degradation in each test (p_d); and the test frequency (ω_t).

The results of the sensitivity correlations between λ and ω_t are plotted in Figure 3.4, where complementary cumulative distribution function (CCDF) for observing degradations are plotted for six different values of test frequencies. The figure shows that the estimated degradation frequency can be considerably affected by the test frequency, which indicates the need for incorporating the test frequency directly into our degradation modeling approach.

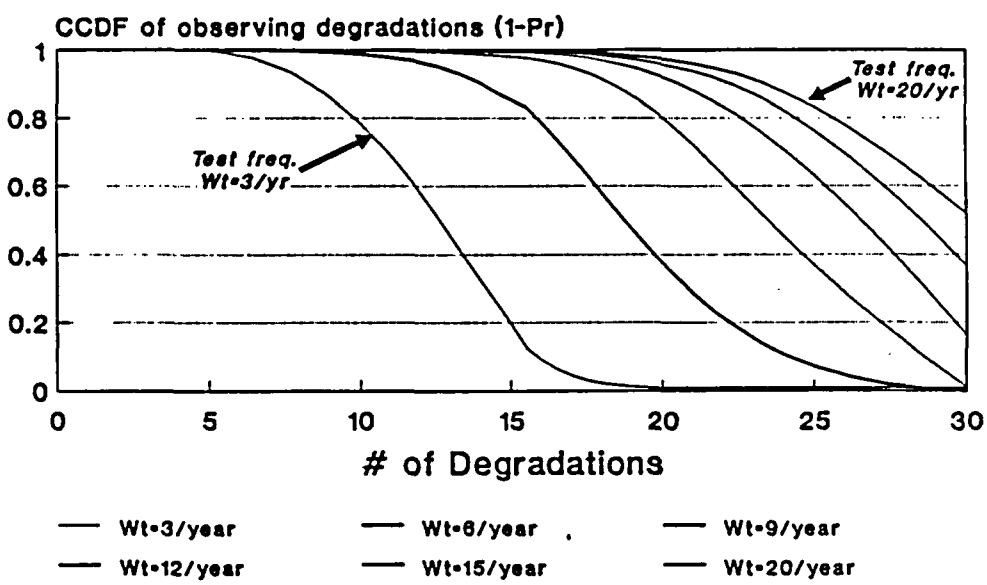


Figure 3.4. Sensitivity of test frequency to component degradation rate

4. ANALYSIS OF DEGRADATION-FAILURE RELATIONSHIP - EVENT-COUNT BASED APPROACH

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.

The data analysis is the first step in obtaining the necessary parameters for these relationships. The relationships can be applied in several different ways.

4.1 A Distribution-Free Statistical Test Approach for Data Combining

In this section, a distribution-free alternative of two-way Anova F test is demonstrated based on the event-count data analysis method. The analysis was carried out using the data on RHR pumps presented in our earlier report.[1]

Since the non-parametric statistical test is used to check the data discrepancy for data combining across the three plants, the original aging data set for the RHR pumps was reconstructed as given in Table 4.1 and 4.2, where the number of degradations for each plant within each year were counted and grouped into a plant-by-age contingency table.

Table 4.1. Degradation & Failure Data Based on Counts
(12 RHR pumps - 3 units)

Age (Years)	Plant 1		Plant 2		Plant 3		Total	
	nd1	nf1	nd2	nf2	nd3	nf3	Nd	Nf
1st	5	0	13	1	1	3	19	4
2nd	2	0	4	7	2	0	8	7
3rd	9	1	2	1	4	0	15	2
4th	4	0	3	0	0	0	7	0
5th	6	2	1	0	2	0	9	2
6th	4	0	3	1	0	0	7	1
7th	2	0	0	1	0	0	2	1
8th	1	1	0	0	2	0	3	1
9th	1	0	0	0	14	0	15	0
10th	0	0	0	0	2	0	2	0
11th	0	0	0	0	5	0	5	0

Table 4.2. Cross-tabulation of Age by Plants for Data on RHR Pumps
(A Distribution-Free Alternative of 2-Way Anova F Test)

	Plant / Age	Pl_j 1	2	3	Row Total
	1	1	5	13	19
	2	2	5	4	8
	3	4	2	2	15
	4	0	9	3	7
	5	2	4	1	9
t_i	6	0	6	3	7
	7	0	4	0	2
	8	2	2	0	3
	9	14	1	0	15
	10	2	0	0	2
	11	5	0	0	5
	Column Total	32	38	26	96

In Table 4.2, the variable Pl_j (j=1,2,3) for each column represents data from different plants, and the variable t_i (i = 1, 11) for each row represents data from different age groups. The effect of the time unit selected for the age group on the sample size depends on the sparsity of the data set. In this analysis, the aging data over the component life span of eleven years were divided into eleven groups, where data within the time unit of one year were combined.

To test the homogeneity of aging data in different plants, in order to combine them to increase the sample density, we used a chi-sqare test to check the following hypotheses:

(a) Do the plants (in terms of the number of events) appear to differ in the composition of their age groups?

(b) If differences exist between numbers in any one row, would they be only due to the random chances?

(c) Are the distributions of population from plants 1 through 3 identical?

The statistical hypothesis listed above, and the related test can be expressed mathematically as:

$$H_o: \; P_r(x = t_i | Pl_j) = P_r(x = t_i) \tag{4.1}$$

where,

H_o is the null hypothesis representing the homogeneity of aging behavior in different plants.

The test statistic:

$$Q = \sum_{i}^{r} \sum_{j}^{c} \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{4.2}$$

where,

E_{ij} is the expected frequency for the ijth cell in Table 4.2

O_{ij} is the observed number of degradations in the jth sample (i.e., jth plant) belonging to category i (i.e., age group i).

n_{i+} denotes the total number of items of age group i in the combined sample,

n_{+j} denotes the total number of items for plant j in the combined sample, and

n denotes the total number of observations.

$$n = \sum_{j=1}^{c} n_{+j} = \sum_{i=1}^{r} n_{i+} \tag{4.4}$$

where r and c represent the number of rows and columns in Table 4.2.

For a given type 1 error α, H_o will be rejected at significance level α if:

$$\sum_{i}^{r} \sum_{j}^{c} \frac{(O_{ij} - E_{ij})^2}{E_{ij}} > X^2_{(r-1)(c-1),\,\alpha} \tag{4.5}$$

Based on data in Table 4.2, the above test was conducted at a significance level of α=0.05, which gives:

$$X^2_{(r-1),\,(c-1),\,\alpha} = X^2_{10,2,0.05} = 81.41 > Q = 61.03 \tag{4.6}$$

that is,

H_o can not be rejected at α=0.05 level, which justifies combining data from RHR pumps from 3 plants for estimating degradation rate.

4.2 Estimation of Degradation and Failure Frequency Using Event Counts

Using the event-count based data set obtained by combining across the data from the 3 plants, a point estimate method was applied to obtain the estimation of degradation and failure rate over each year of the 10-year age period. We used a non-linear regression technique on the yearly point estimates to obtain the approximate time-dependent degradation and failure frequency. The estimated degradation and failure frequency are plotted on Figure 4.1. The degradation and failure rate estimates shown are consistent compared with the results obtained by the parametrical estimates given in our earlier report[1].

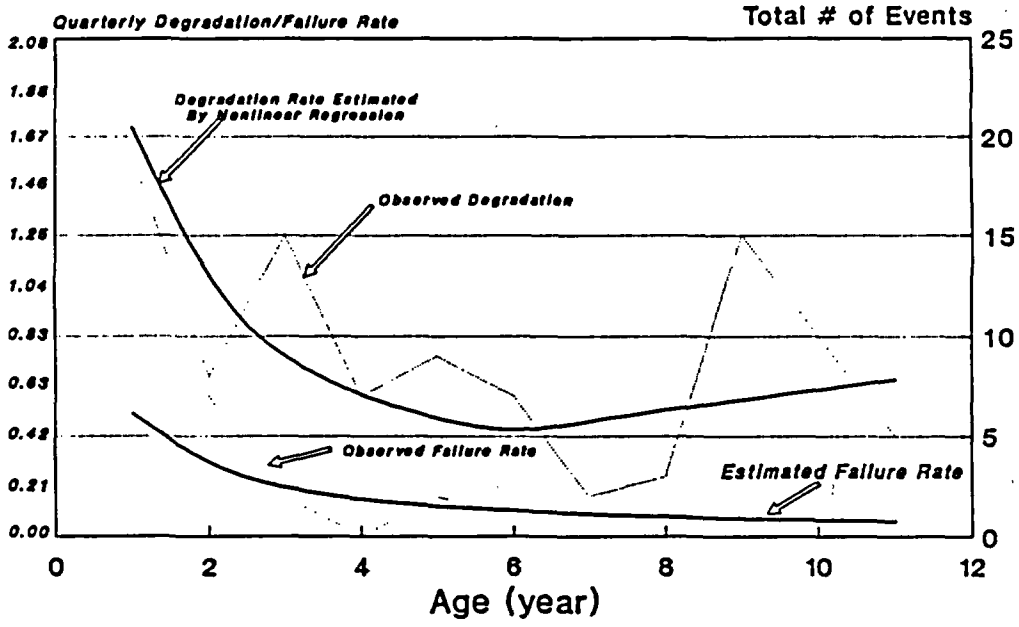


Figure 4.1. Degradation & failure rate estimation
(event-counts based approach - Data on RHR pumps from 3 plants)

4.3 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:

$$\lambda_f = R(\lambda_d) \tag{4.7}$$

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

Since aging-related failures, in general, pass through a degradation stage first, the degradation rate serves as a precursor to the 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 (5.7) is expressed as:

$$\lambda_f\,(t+l) = C_{df}\,\lambda_d(t) \tag{4.8}$$

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 in Table 4.1, 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 α=0.029. The statistical results of Kendall's Rank Correlation coefficients are summarized in Table 4.3 and Table 4.4.

Table 4.3. Kendall's Rank Correlation Analysis Results for RHR Pumps at 3 Plants

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 4.4. 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

4.4 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[1] is presented as an example of this application. Figure 4.2 presents the estimated failure frequency from the degradation frequency, and Table 4.5 shows estimated parameters from the data used in obtaining the failure frequency.

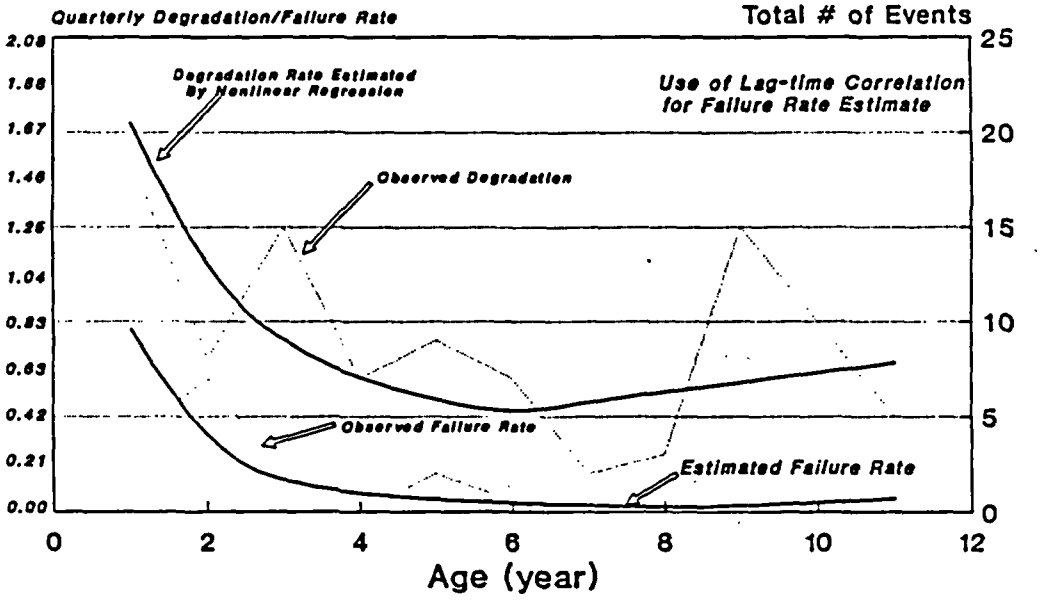


Figure 4.2. Degradation & failure rate estimation
(event-counts based approach - data on RHR pumps from 3 units)

In Figure 4.2, 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 4.8, 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.

Table 4.5. Estimated Parameters on Time-Lag Regression Analysis
(Combined Data of RHR Pumps from 3 Units)

Obtained Regression Model:	$N_f = -0.112 + 0.0942N_d$	
Coefficient:	0.0942 at significance level:	0.05
Constant:	-0.112 at significance level:	0.453
R Squared:	42.2% (indicates 42.2% of the total sample variation is explained by the model)	
Correlation Coefficient (N_f vs. N_d):	0.649	
Model is Significance at Level:	0.0582	
Standard Error of Estimation:	0.677	

4.5 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.

5. EXTENSIONS OF DEGRADATION MODELING: THE ANALYSIS OF PROGRESSIONS OF DEGRADED STATES

5.1 Background and Basic Concepts

The previous degradation models[1] that were developed involved integral equations. The integral equations expressed the degradation rate and failure rate (failure frequency) of a component at a given time in terms of the degradation rates and failure rates at earlier times multiplied by appropriate transition probabilities. These integral equations, which are basically balance equations, were used to obtain solutions for the degradation rate and failure rate for given cases. The degradation rate and failure rate were also used to define measures of maintenance effectiveness.

Our present work extends the previous degradation modeling by presenting models which explicitly show the reliability effects of different maintenance and test intervals, different maintenance and test efficiencies, and different repair times. This work also allows the reliability effects of different maintenance programs including minimal maintenance programs and comprehensive condition monitoring programs to be evaluated. The extended degradation models also allow multiple degraded states instead of a single degraded state. For example, the multiple degraded states can be associated with different degrees of degradation or a given degraded state can be associated with a particular piecepart of the component failing or degrading. A given degraded state can also be associated with a particular degradation mechanism or failure mechanism.

The extended degradation models, which are presented, include the previous models as special cases. However, the extended models are however presented in terms of differential equations. The previous models can also be presented in terms of differential equation models by simply differentiating the integral equations. The differential equation approach allows the models to be extended to cover multiple degraded states and to include detailed test, maintenance, and repair characteristics. The differential equation approach also allows standard and powerful Markov model approaches to be applied to obtain specific results when particular data are input.

5.2 Basic Approach

A straightforward, yet powerful approach for analyzing aging and degradation is to analyze degraded state progressions. This analysis consists of two steps: 1) classifying components' degraded states and 2) identifying transition rates between the individual states. The transition rates give the rate of transfer from one state to another. From the transition rates, component reliability characteristics as a function of age can then be determined by standard Markov state modeling techniques[2-4], but applied to degradation analyses. This report describes the approaches as applied to degradation analyses.

In the simplest case, which is generally modeled in probabilistic risk analyses (PRAs), the component is assumed to have only two states, a failed state and a successful operating state; intermediate degraded states are not explicitly modeled. Let 0 denote the operating state and 1 denote the failed state. The transition matrix, which contains the transition rates by which the component can transfer from 0 to 1 and vice versa, is then constructed.

For the two-state model (1=failed, 0=operating), the transition matrix is the following.

Initial State \ Final State	0	1
0	0	λ
1	μ	0

The quantity, λ, is the component failure rate, which is the rate for transferring from an operating state (0) to a failed state (1) in a given unit of time. The quantity, μ, is the repair rate, which is the rate for transferring from a failed state (1) back to an operating state (0) in a unit of time. The entries in the (0, 0) and (1, 1) positions of the transition matrix are zero since there is no change in state.

The failure rate, λ, and repair rate, μ, or their equivalents, are estimated to determine the associated component reliability characteristics. The failure rate, λ, can be estimated as one over the mean time to failure T_F,

$$\lambda = \frac{1}{T_F} \tag{5.1}$$

where T_F is estimated as the average of the observed times to failure. The repair rate, μ, can be estimated as one over the mean time to repair T_R,

$$\mu = \frac{1}{T_R} \tag{5.2}$$

where T_R is estimated as the average of the observed repair times.

Once the failure rate and repair rate are estimated, the component unavailability and other reliability quantities can be determined using state balance equations (which are termed Kolmogorov's equations). For example, the probability, p(t), that the component is in a failed state at time t+dt, which is the component unavailability, is given by the balance equation,

$$\begin{aligned} p(t+dt) &= p(t)(1-\mu dt) \\ &\quad + (1-p(t))\lambda\, dt \end{aligned} \tag{5.3}$$

This balance equation can be expressed in words as:

Probability that the component is down at t+dt	=	Probability that the component is down at t	.	Probability that repair is not completed in t to t+dt	
	+	Probability that the component is up at t	.	Probability that the component fails in t to t+dt	(5.4)

As observed in the above equation, the repair rate, μ, is such that when multiplied by a small increment of time, dt gives the probability of repair being completed in that increment of time when the component is down. One minus this quantity, i.e. $1-\mu dt$, gives the probability of the repair not being completed. The failure rate, λ, is such that when multiplied by a small increment of time, i.e., λdt, gives the probability of the component failing in the increment of time given the component is initially up.

Expanding p(t+dt) one then obtains:

$$p(t)+\frac{dp}{dt}dt=p(t)-p(t)\mu dt+\lambda dt-p(t)\lambda dt \tag{5.5}$$

or

$$\frac{dp}{dt}+(\mu+\lambda)p=\lambda \tag{5.6}$$

which is a standard first-order differential equation and can be solved by standard techniques to give:

$$p(t) = \frac{\lambda}{\mu+\lambda}(1-e^{-(\lambda+\mu)t}) \tag{5.7}$$

In PRAs, the steady-state or asymptotic value is used, where t goes to infinity (∞):

$$p(\infty) = \frac{\lambda}{\mu+\lambda} \cdot \tag{5.8}$$

5.3 Incorporation of a Component Degraded State

In addition to the success state and failed state, assume that one degraded stated also is considered for the component. Let the three states be denoted as 0,1,2:

0= operating state (good as new state) (5.9)

1= degraded state (a single degraded state) (5.10)

2= failed state (5.11)

The transition matrix can then be constructed as:

Initial State \ Final State	0	1	2
0	0	λ_{01}	λ_{02}
1	λ_{10}	λ_{11}	λ_{12}
2	λ_{20}	λ_{21}	0

The transition rates are defined by:

λ_{01}: the transition rate of going from an operating state (0) to a degraded state (1) (5.12)

λ_{02}: the transition rate of going from an operating state (0) to a failed state (2) without intermediate degradation being detected (5.13)

λ_{10}: the transition rate of maintenance correcting a degraded state (1) to an operating state (0) (5.14)

λ_{11}: the transition rate of going from a degraded state (1) to another degraded state (1) without intermediate failure (5.15)

λ_{12}: the transition rate of going from a degraded state (1) to a failed state (2) (5.16)

λ_{20}: the transition rate of repair from a failed state (2) to an operating state (0) (5.17)

λ_{21}: the transition rate of repair from a failed state (2) to a degraded state (1) (5.18)

Note that we included a transition rate, λ_{11}, which allows transitions from a degraded state to another degraded state; for example after maintenance has been performed.

For application, the transition rates need to be translated into quantities which can be interpreted by engineers and can be estimated from data or engineering experience. One such translation is to define the transition rates in times of average times of occurrences:

$\lambda_{01} = \frac{1}{T_{01}}; T_{01}$ = average time to a degraded state from an operational state (5.19)

$\lambda_{02} = \frac{1}{T_{02}}; T_{02}$ = average time to catastrophic failure from an operational state without intermediate degradation occurring (or being detected) (5.20)

$\lambda_{10} = \frac{1}{T_{10}}; T_{10}$ = average maintenance detection time plus duration time for restoring the degraded state (1) to as good as new state (0) (5.21)

$\lambda_{11} = \frac{1}{T_{11}}; T_{11}$ = average time from a degradation occurrence to another degradation occurrence (without an intervening catastrophic failure or replacement occurring) (5.22)

$\lambda_{12} = \frac{1}{T_{12}}; T_{12}$ = average time from a degradation occurrence to a catastrophic failure occurrence without the degradation being corrected (5.23)

$\lambda_{20} = \frac{1}{T_{20}}; T_{20}$ = average repair time in which as failed state is restored to as good as new state (5.24)

$\lambda_{21} = \frac{1}{T_{21}}; T_{21}$ = average repair time in which a failed state is restored to a degraded state. (5.25)

These average times, (T_{01}, T_{02}, etc.,) can then be estimated from data or from engineering experience. The above transition rate definitions can also be specialized for given situations, such as:

$\lambda_{02} = 0$: all catastrophic failures are preceded by a degradation (5.26)

$\lambda_{10} = 0$: maintenance restores the component only to a degraded state (as good as old) (5.27)

$\lambda_{11} = 0$: maintenance restores the component to as good as new (5.28)

$\lambda_{21} = 0$: repair restores the component to as good as new. (5.29)

Also, the average times (T_{01}, T_{02}, etc.,) can be expanded to identify more detailed factors and contributions:

$$\lambda_{10} = \frac{P_{MO}}{T_{1M} + T_M} \tag{5.30}$$

T_{1M} = average maintenance detection time

T_M = average maintenance duration

P_{MO} = the fraction of time that the maintenance restores the degraded state to as good as new

$$\lambda_{11} = \frac{1}{T_{1M} + T_M + T_{M1}} \tag{5.31}$$

T_{1M} = average time from a degradation occurrence to a maintenance action

T_M = average maintenance duration

T_{M1} = average time from a maintenance completion to a degradation occurrence without intervening catastrophic failure

$$\lambda_{12} = \frac{1}{T_{1M} + T_M + T_{M2}} \tag{5.32}$$

T_{M2} = average time from a maintenance to a catastrophic failure without another degradation occurring or being detected. (T_{1M} and T_M defined as above)

$$\lambda_{20} = \frac{P_{20}}{T_R} \tag{5.33}$$

T_R = average repair time

P_{20} = fraction of time that repair restores the component to as good as new

$$\lambda_{21} = \frac{P_{21}}{T_R} \tag{5.34}$$

P_{21} = fraction of time that the repair restores the component to a degraded state

The above quantities can be estimated from maintenance and failure data and from maintenance procedures. The reliability characteristics of the component, including the age

dependent failure rate and age-dependent unavailability, can then be determined using balance equations and standard differential equation techniques. These reliability characteristics, in turn, can be used in reliability and risk evaluations. Because the transition rates are expressed in terms of basic degradation and maintenance characteristics, there is a direct relationship between the degradation characteristics, the maintenance program characteristics, and the resulting reliability and risk implications.

5.4 Incorporation of a Maintenance State

To explicitly identify when the component is in maintenance, a maintenance state can be defined and can be added to the transition matrix. Let the maintenance state be denoted by M. The transition matrix is given below showing the added transition rates involving the maintenance state M.

Initial State \ Final State	0	1	M	2
0			λ_{0M}	
1			λ_{1M}	
M	λ_{M0}	λ_{M1}		λ_{M2}
2				

The additional maintenance transition rates are given by:

λ_{0M} = transition rate for an operational component being placed in maintenance (this could be considered as scheduled preventive maintenance, or can be set to zero if such occurrences are rare)

(5.35)

λ_{1M} = transition rate for going from a degraded state to a maintenance state (5.36)

$= \frac{1}{T_{1M}}$; T_{1M} = average time from a degradation occurrence to a maintenance action

λ_{M0} = transition rate for going from a maintenance state to an operational state (5.37)

$$= \frac{P_{M0}}{T_M} \quad (5.38)$$

P_{M0} = fraction of time the maintenance restores the component to as good as new

T_M = average maintenance duration

$$\lambda_{M1} = \frac{P_{M1}}{T_M} \quad (5.39)$$

P_{M1} = fraction of time that the maintenance restores the component to a degraded state

$$\lambda_{M2} = \frac{P_{M2}}{T_M} \quad (5.40)$$

P_{M2} = fraction of time the maintenance causes the component to be failed

5.5 Resolving Additional Degradation States

For additional degraded states 1, 2... k, one must now define the transition rates from the other states to 1, 2,...,k, the transition rates among 1, 2,...,k, and the transition rates to the other states. In terms of the transition matrix, this amounts to incorporating appropriate additional columns and rows for the degraded states:

Initial State \ Final State	0	1	2	....	k	k+1
0	0	λ_{01}	λ_{02}	....	λ_{0k}	λ_{0k+1}
1	λ_{10}	λ_{11}	λ_{12}	....	λ_{1k}	λ_{1k+1}
2	λ_{20}	λ_{21}	λ_{22}	....	λ_{2k}	λ_{2k+1}
.						
.						
.						
.						
k	λ_{k0}	λ_{k1}	λ_{k2}	....	λ_{kk}	λ_{kk+1}
k+1	$\lambda_{k+1}0$	λ_{k+11}	λ_{k+12}	....	λ_{k+1k}	0

In the above matrix, 0 is the operational state with no degradation, and k+1 is the failed state. The additional transition rates need to be estimated by expressing them in terms of average times of occurrences of events and fractions of times specific outcomes occur.

5.6 Incorporating Effects of Surveillance Tests

When failures are not detected until surveillance tests are performed, then the transition rate, λ_{20}, from a failed state (2) to an operational state (0) can explicitly account for surveillance tests

which are performed. If the transition rate, λ_{20}, is defined in terms of the average time from a failed state to an operation state then:

$$\lambda_{20} = \frac{1}{T_{20}}; T_{20} \quad = \text{the average time from a failed state to an operational state} \tag{5.41}$$

Now T_{20} can be expressed as

$$T_{20} = T_U + T_R \tag{5.42}$$

where,

$$T_U = \text{average time to detect the failure (the average undetected time)} \tag{5.43}$$

and

$$T_R = \text{average repair time} \tag{5.44}$$

For a constant failure rate (i.e. constant transition rate), when the component does fail, it is equally likely to fail in the interval, T, between tests. Then:

$$T_U = T/2 \tag{5.45}$$

Hence,

$$T_{20} = T/2 + T_R \tag{5.46}$$

and

$$\lambda_{20} = \frac{1}{T/2 + T_R} \tag{5.47}$$

Thus, the transition rate, λ_{20}, explicitly contains the surveillance test interval. Consequently, the component failure probabilities and component unavailabilities, which are determined from the transition rates, contain the effects of the surveillance test. It should be noted that the above formulas, including the test intervals, also apply to a general multistate model as described in the previous section, where λ_{20} is replaced by the more general transition rate, $\lambda_{k+1,0}$, and where k+1 is the failed state.

5.7 Calculation of Component Reliability Characteristics Including the Component Unavailability

As we indicated, using the transition matrix, the probability that the component is in any given state at a given time can be determined. These state probabilities allow all the component reliability characteristics to be determined including the component failure rate and the component unavailability. This section reviews the basic approaches that are used to determine the state. Let $p_i(t)$ be the probability that the component is in state i at a given time, where i is any state such as the operational state, a degraded state, or a failed state. Then, the general balance equation for $p_i(t+dt)$ is:

$$p_i(t+dt) = \sum_j p_j(t)\lambda_{ji}dt + p_i(t)(1-\lambda_i dt) \tag{5.48}$$

where λ_{ji} is the transition rate from state j to state i and the sum is over all states j that can transfer to i. The rate λ_i is the sum of all transition rates out of state i,

$$\lambda_i = \sum_k \lambda_{ik} \tag{5.49}$$

Expanding $p_i(t+dt)$ to first order, Equation (2.49) becomes the first order differential equation,

$$\frac{dp_i}{dt} + \lambda_i p_i = \sum p_j(t)\lambda_{ji} \tag{5.50}$$

This set of differential equations for all the states i can be solved by standard differential equation techniques. The results are the state probabilities $p_i(t)$ as a function of time t for all states.

The unavailability of the component, in particular, is the state probability $p_2(t)$ (or $p_{k+1}(t)$ in the more general case), which is the probability that the component is in a failed state at time t. The component failure frequency is the probability that the component is in an operational state and then fails per unit time. Hence, the failure frequency is given by $p_o(t)\lambda_{02}$, where $p_o(t)$ is the probability of being in an operation state, and λ_{02} is the transition rate of going to a failed state. The probability that the component is in a degraded state of time, t, is given by $q_d(t)$, where d is the degraded state identifier. Other reliability characteristics can be determined similarly and can then be used as inputs to reliability and risk evaluations.

5.8 Incorporation of Aging Effects

Whenever degraded states are identified and included in the transition matrix, the resulting component failure rate, which includes the transitions through the degraded states, is age-dependent.

The failure rate is age-dependent even when the individual transition rates are constant and time independent. Thus, by classifying degraded states and defining the associated transition rates, one has a straightforward way of analyzing aging effects on the component failure rate and other reliability characteristics. The transition rates also include degradation characteristics and test and maintenance program characteristics; thus, reliability is directly related to these characteristics.

The transition rates can also be modified to analyze the effects of different aging management programs. For example, if the test and maintenance program does not replace degraded parts, but only assures that the component is operational, then the transition rate for restoring the component to as good as new can be taken to be zero (i.e., $\lambda_{10} = 0$, where 1 is the degraded state, and 0 is the good as new, operational state). This situation represents a minimal maintenance policy and resulting component reliability characteristics can be determined for given degradation characteristics. Additional maintenance activities can be analyzed by modifying the maintenance characteristics and associated transition rates. The effects of maintenance can be modeled in more detail by classifying different degraded states and defining the transitions associated with the maintenance procedures. Furthermore, pieceparts of the component can furthermore be individually modeled by defining transition rates for each piece or part and obtaining the resulting state probabilities.

6. SUMMARY

Our previous report[1] describes the basic concepts and applications of degradation modeling for aging analysis of standby active components. This report presents more applications and extensions of degradation modeling approaches to study the effects of aging in components and the role of maintenance in controlling the effects of aging. Here, degradation modeling approaches are applied in studying the aging effects and maintenance effectiveness of continuously operating components (air compressors). Sensitivity evaluations are performed to study the effects of uncertainties on the degradation modeling results, and also, the mathematical modeling is extended for studying reliability effects of maintenance strategies and for interfacing with probabilistic risk assessment (PRA) evaluations.

a) 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 effective in preventing age-related degradations from failures.

b) Sensitivity Analyses of Degradation Modeling Results

Sensitivity evaluations were performed to evaluate the effect of three factors: a) engineering evaluation of failure data, i.e., subjectivity in classifying degraded vs. failure state of a component, b) uncertainty in degradation occurrence time available from plant records, and c) the effect of test frequency. Results of sensitivity evaluation show that the effects of data partitioning is not significant. The subjectivity involved in the data evaluation does not change the overall trend in the results.

Similarly, the effect of uncertainty in degradation occurrence time is also not significant. However, we observed that the estimated degradation rates can be influenced by the frequency at which tests are performed to detect degradations or failures. The effect of test frequency is probably pronounced because of the single degraded state in the modeling. The extensions of degradation modeling presented in this report includes test frequency and also, multiple degraded states.

c) 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.

d) Extensions of Degradation Modeling

Our present work extends the previous degradation modeling by presenting models which explicitly show the reliability effects of different maintenance and test intervals, different maintenance and test efficiencies, and different repair times. This extension will allow us to evaluate the reliability effects of different maintenance programs.

REFERENCES

1. P.K. Samanta et al., "Degradation Modeling with Application to Aging and Maintenance Effectiveness Evaluation," NUREG/CR-5612, BNL-NUREG-52252, March 1991.

2. A.T. Bharucha-Reid, Elements of the Theory of Markov Processes and Their Applications, McGraw Hill, New York, 1960.

3. H.L. Tijms, Stochastic Modeling and Analysis, John Wiley and Sons, New York, 1986.

4. L. Kleinrock, Queueing Systems, Vols 1 and 2, John Wiley and Sons, New York, 1975.

5. M. Villaran et al., "Aging Assessment of Instrument Air Systems in Nuclear Power Plants, NUREG/CR-5419, BNL-NUREG-52212, January 1990.

APPENDIX A: AGING DATA EVALUATION OF AIR COMPRESSORS

A.1 Brief Description of Air Compressors*

Air compressors used in instrument and service air systems in nuclear power plants are either positive displacement or nonpositive displacement types, called continuous flow and dynamic compressors. The reciprocating-piston compressor is the most common positive displacement type because of its high-pressure capability, ability to dissipate the heat of compression, and versatility. Air is compressed by the alternate filling and compression of a cylinder by the reciprocating motion of a piston. The rotary motion of the crankshaft, driven by and electric motor, diesel, or some other prime mover, is translated via the connecting rod into the reciprocating motion of the piston within the cylinder. On the intake stroke, the piston moving downward in the cylinder creates a negative pressure across the spring-loaded intake valve causing it to open. Intake air is drawn through the filter/silencer into the cylinder. When the piston reaches the bottom of its stroke, the differential pressure across the intake valve is less than the spring force pushing to close the valve. Therefore, the intake valve closes and the compression portion of the cycle begins. As the piston moves upward into the cylinder bore, reducing the volume as it travels, air pressure and temperature increase. When the pressure differential across the discharge valve exceeds the spring pressure holding it closed, the valve opens. The volume of hot compressed air is then driven into the system via the discharge manifold as the piston continues to the top of its stroke. Once the piston reaches the top of its stroke, the differential pressure across the discharge valve drops below the closing force of the spring and the valve closes, completing the cycle.

A.2 Engineering Evaluation of Air Compressor Aging Data

Testing and maintenance records on air compressors were analyzed to obtain the aging data for degradation modeling. In this evaluation, the first step was to identify whether the condition of the component indicated an age-related problem. Every test and maintenance record was inspected and

*The description of air compressors is reproduced from Villaran et al.[5].

categorized as defined in Table A.1. The age-related problems are classified as N, D, or F; non-aging problems include human errors in performing the maintenance or testings (H), affecting component performance (E). Table A.2 illustrates typical examples of each category for an instrument air compressor, and Table A.3 presents a typical failure mode and effect analysis defining various levels of degradation (low, intermediate, and high).

Table A.1. Categorization of Component Failure or Maintenance Data

Aging-Related Problems

N: No component degradation. No maintenance was performed.

D: Definite degradation in the component. Maintenance was performed to repair the degraded condition.

F: Severe degradation in the component. Immediate maintenance was required.

Non-Aging-Related Problems

H: Component degradation due to a human error.

E: Degradation of components other than the prime component being evaluated. Maintenance was performed to correct the degradation, which if not corrected, may have had a deleterious effect on the prime component.

Table A.2. Analysis of Maintenance Log for an Instrument Air Compressor

Equipment No.	Date	Description	Primary Subcomponent	Failure Classification
1K107A	4/07/80	Quarterly PM: outer bearings greased with EP #2	Bearings	D
1K107A	12/10/87	Inst. air cylinder leaking. Replaced worn oil wiper ring. The shaft was also worn.	Mechanical	F
1K107A	4/20/87	Semi-annual I.A. P.M. inspected and cleaned motor. No loose bolts, cracks, worn parts, or excessive grease. All satisfactory.	Motor	N
2K108B	5/6/85	Compressor has excessive oil leak. Removed and reassembled packing; it was installed backwards. Operates satisfactorily.	Mechanical	H
2K107B	5/4/83	Monthly P.M. Replaced intake filter.	Filter	E

Table A.3. Typical Examples of Degradation Levels and Failure Mode and Effect on Compressors

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

A.3 Aging Data on Air Compressors

Aging data on air compressors are obtained by analyzing plant maintenance records for two units. Since the units are different ages, data for each unit covered different periods: 36 quarters for unit one and 20 quarters for unit two (Table A.4). This table contains the observed dates for degradations and failures. Table A.5 presents the failure data where only the observed failure times are recorded. As these tables show, significantly more information on component aging is obtained by focussing on degradation data.

Table A.4. Air Compressor Aging Data: Degradation and Failure Times (2 Nuclear Units)

Mo	Dy	Yr	Plt	Comp	SEVTY	DSCP	Tij	Ti	Agp
1	24	80	1	1	D	BRGS	0.64	0.64	1
4	7	80	1	1	D	BRGS	0.81	1.46	1
7	25	80	1	1	D	BRGS	1.20	2.66	1
9	2	80	1	1	D	BRGS	0.41	3.07	1
12	3	80	1	1	D	MECH	1.01	4.08	1
12	30	80	1	1	D	BRGS	0.30	4.38	1
3	17	81	1	1	D	JKTHX	0.86	5.23	1
4	24	81	1	1	D	BRGS	0.41	5.64	1
6	22	81	1	1	D	BRGS	0.64	6.29	1
8	24	81	1	1	D	COMPR	0.69	6.98	1
9	29	81	1	1	D	BRGS	0.39	7.37	1
11	5	81	1	1	D	FLTR	0.40	7.77	1
1	4	82	1	1	D	BRGS	0.66	8.42	1
1	25	82	1	1	D	COMPR	0.23	8.66	1
4	14	82	1	1	D	MECH	0.88	9.53	1
1	20	83	1	1	F	COMPR	3.07	12.60	1
3	9	83	1	1	D	COMPR	0.54	13.14	1
1	19	84	1	1	F	COMPR	3.44	16.59	1
4	30	84	1	1	D	COMPR	1.12	17.71	1
11	16	84	1	1	D	MECH	2.18	19.89	1
1	17	85	1	1	F	COMPR	0.68	20.57	2
7	12	85	1	1	D	UNLOA	1.94	22.51	2
7	15	85	1	1	F	UNLOA	0.03	22.54	2
12	27	85	1	1	F	COMPR	1.80	24.34	2
4	17	86	1	1	D	MOTOR	1.22	25.57	2
11	24	86	1	1	D	MECH	2.41	27.98	2
1	5	87	1	1	D	LUBOIL	0.46	28.43	2
3	9	87	1	1	F	LUBOIL	0.71	29.14	2
7	2	87	1	1	D	COMPR	1.26	30.40	2
12	10	87	1	1	F	COMPR	1.76	32.16	2
12	17	87	1	1	D	COMPR	0.08	32.23	2
2	15	88	1	1	D	GASKE	0.64	32.88	2
4	1	88	1	1	D	GASKE	0.51	33.39	2
6	21	88	1	1	D	UNLOA	0.89	34.28	2
11	14	88	1	1	D	GASKE	1.59	35.87	2
11	26	79	1	2	D	COMPR	1.29	1.29	1
1	13	80	1	2	D	MECH	0.52	1.81	1
1	24	80	1	2	D	BRGS	0.12	1.93	1
1	31	80	1	2	D	COMPR	0.08	2.01	1
4	7	80	1	2	D	BRGS	0.73	2.74	1
7	25	80	1	2	D	BRGS	1.20	3.94	1
12	30	80	1	2	D	BRGS	1.72	5.67	1
1	27	81	1	2	F	LUBOIL	0.30	5.97	1
4	24	81	1	2	D	BRGS	0.97	6.93	1

Table A.4. (Cont'd)

Mo	Dy	Yr	Plt	Comp	SEVTY	DSCP	Tij	Ti	Agp
5	5	81	1	2	D	COMPR	0.12	7.06	1
6	22	81	1	2	D	BRGS	0.52	7.58	1
8	26	81	1	2	D	MECH	0.71	8.29	1
9	29	81	1	2	D	BRGS	0.37	8.66	1
11	5	81	1	2	D	FLTR	0.40	9.06	1
1	4	82	1	2	D	BRGS	0.66	9.71	1
2	12	82	1	2	F	MECH	0.42	10.13	1
2	24	82	1	2	D	COMPR	0.13	10.27	1
4	23	82	1	2	D	MOTOR	0.66	10.92	1
6	21	82	1	2	D	COMPR	0.64	11.57	1
4	25	84	1	2	D	COMPR	7.38	18.94	1
5	28	84	1	2	D	COMPR	0.37	19.31	1
7	25	84	1	2	F	JKTHX	0.63	19.94	1
10	17	85	1	2	D	COMPR	4.91	24.86	2
4	17	86	1	2	F	BRGS	2.00	26.86	2
8	18	86	1	2	D	MECH	1.34	28.20	2
11	24	86	1	2	D	MECH	1.07	29.27	2
6	11	87	1	2	D	LUBOIL	2.19	31.46	2
12	17	87	1	2	F	COMPR	2.07	33.52	2
9	8	88	1	2	D	COMPR	2.90	36.42	2
9	17	88	1	2	F	COMPR	0.10	36.52	2
10	2	88	1	2	F	UNLOA	0.17	36.69	2
10	6	88	1	2	F	COMPR	0.04	36.73	2
10	7	88	1	2	D	MECH	0.01	36.74	2
8	10	79	1	3	D	BRGS	0.10	0.10	1
8	14	79	1	3	D	COMPR	0.04	0.14	1
10	22	79	1	3	D	GASKE	0.76	0.90	1
2	27	80	1	3	D	BRGS	1.39	2.29	1
3	27	80	1	3	D	JKTHX	0.33	2.62	1
4	7	80	1	3	D	BRGS	0.11	2.73	1
6	27	80	1	3	D	BRGS	0.89	3.62	1
7	25	80	1	3	D	BRGS	0.31	3.93	1
8	1	80	1	3	D	COMPR	0.07	4.00	1
10	18	80	1	3	D	JKTHX	0.86	4.86	1
10	20	80	1	3	D	MECH	0.02	4.88	1
12	30	80	1	3	D	MOTOR	0.78	5.66	1
3	17	81	1	3	D	LUBOIL	0.86	6.51	1
3	27	81	1	3	D	FLTR	0.11	6.62	1
4	24	81	1	3	D	BRGS	0.30	6.92	1
6	22	81	1	3	D	MECH	0.64	7.57	1
9	29	81	1	3	D	BRGS	1.08	8.64	1
11	5	81	1	3	D	FLTR	0.40	9.04	1
1	4	82	1	3	D	BRGS	0.66	9.70	1
2	24	82	1	3	D	COMPR	0.56	10.26	1
7	21	82	1	3	D	BRGS	1.63	11.89	1
10	21	82	1	3	D	COMPR	1.00	12.89	1

Table A.4. (Cont'd)

Mo	Dy	Yr	Plt	Comp	SEVTY	DSCP	Tij	Ti	Agp
4	4	83	1	3	D	MECH	1.81	14.70	1
4	22	83	1	3	D	COMPR	0.20	14.90	1
10	21	83	1	3	F	COMPR	1.99	16.89	1
12	12	83	1	3	D	MECH	0.57	17.46	1
1	20	84	1	3	D	GASKE	0.42	17.88	1
1	26	84	1	3	D	MECH	0.07	17.94	1
11	16	84	1	3	D	FLTR	3.22	21.17	2
1	27	85	1	3	D	GASKE	0.79	21.96	2
2	27	85	1	3	D	MECH	0.33	22.29	2
4	30	85	1	3	D	COMPR	0.70	22.99	2
4	17	86	1	3	F	BRGS	3.86	26.84	2
4	27	87	1	3	D	UNLOA	4.11	30.96	2
7	23	87	1	3	D	COMPR	0.96	31.91	2
10	2	87	1	3	D	COMPR	0.77	32.68	2
3	31	88	1	3	D	MECH	1.99	34.67	2
10	6	88	1	3	D	MECH	2.06	36.72	2
7	31	79	1	4	F	COMPR	0.68	0.68	1
8	10	79	1	4	D	BRGS	0.10	0.78	1
10	2	79	1	4	F	LUBOIL	0.58	1.36	1
10	11	79	1	4	D	COMPR	0.10	1.46	1
2	2	80	1	4	D	COMPR	1.23	2.69	1
2	27	80	1	4	D	BRGS	0.28	2.97	1
3	27	80	1	4	D	JKTHX	0.33	3.30	1
4	7	80	1	4	D	BRGS	0.11	3.41	1
6	24	80	1	4	D	LUBOIL	0.86	4.27	1
6	27	80	1	4	D	BRGS	0.03	4.30	1
7	25	80	1	4	D	BRGS	0.31	4.61	1
11	6	80	1	4	D	MECH	1.12	5.73	1
12	30	80	1	4	D	BRGS	0.60	6.33	1
3	3	81	1	4	D	FLTR	0.70	7.03	1
3	17	81	1	4	D	LUBOIL	0.16	7.19	1
3	27	81	1	4	D	FLTR	0.11	7.30	1
4	24	81	1	4	D	BRGS	0.30	7.60	1
6	22	81	1	4	D	BRGS	0.64	8.24	1
7	28	81	1	4	D	GASKE	0.40	8.64	1
7	29	81	1	4	D	COMPR	0.01	8.66	1
8	14	81	1	4	D	COMPR	0.17	8.82	1
9	29	81	1	4	D	BRGS	0.50	9.32	1
10	6	81	1	4	D	MECH	0.08	9.40	1
11	5	81	1	4	D	FLTR	0.32	9.72	1
1	4	82	1	4	D	BRGS	0.66	10.38	1
1	25	82	1	4	D	COMPR	0.23	10.61	1
4	23	82	1	4	D	MOTOR	0.98	11.59	1
5	24	82	1	4	D	MECH	0.34	11.93	1
7	1	82	1	4	D	MECH	0.41	12.34	1
7	21	82	1	4	D	BRGS	0.22	12.57	1

Table A.4. (Cont'd)

Mo	Dy	Yr	Plt	Comp	SEVTY	DSCP	Tij	Ti	Agp
1	20	83	1	4	D	COMPR	1.99	14.56	1
3	15	83	1	4	F	BRGS	0.61	15.17	1
4	4	83	1	4	D	MECH	0.21	15.38	1
7	25	83	1	4	F	COMPR	1.23	16.61	1
7	20	84	1	4	D	COMPR	3.94	20.56	2
11	16	84	1	4	D	MECH	1.29	21.84	2
3	28	85	1	4	F	MECH	1.47	23.31	2
6	10	85	1	4	D	GASKE	0.80	24.11	2
12	1	85	1	4	D	GASKE	1.90	26.01	2
12	6	85	1	4	D	MECH	0.06	26.07	2
1	10	86	1	4	D	COMPR	0.38	26.44	2
3	29	86	1	4	F	MOTOR	0.88	27.32	2
4	21	86	1	4	F	UNLOA	0.24	27.57	2
1	5	87	1	4	D	COMPR	2.82	30.39	2
7	2	87	1	4	D	UNLOA	1.97	32.36	2
2	3	88	1	4	F	GASKE	2.34	34.70	2
7	1	88	1	4	D	UNLOA	1.64	36.34	2
7	15	88	1	4	D	COMPR	0.16	36.50	2
3	2	83	2	1	F	COMPR	0.56	0.56	
5	4	83	2	1	D	COMPR	0.69	1.24	
7	13	83	2	1	D	JKTHX	0.77	2.01	
8	16	83	2	1	D	JKTHX	0.37	2.38	
10	2	83	2	1	D	MECH	0.51	2.89	
4	25	84	2	1	D	MECH	2.26	5.14	
6	4	84	2	1	F	MECH	0.43	5.58	
6	27	84	2	1	F	MECH	0.26	5.83	
12	19	84	2	1	F	FLTR	1.91	7.74	
7	8	85	2	1	D	JKTHX	2.21	9.96	
1	7	86	2	1	D	COMPR	1.99	11.94	
10	27	86	2	1	D	UNLOA	3.22	15.17	
2	5	87	2	1	F	JKTHX	1.09	16.26	
2	12	87	2	1	D	MECH	0.08	16.33	
6	22	87	2	1	D	UNLOA	1.44	17.78	
11	29	87	2	1	D	JKTHX	1.74	19.52	
2	28	88	2	1	D	MECH	0.99	20.51	
3	31	88	2	1	D	UNLOA	0.37	20.88	
3	2	83	2	2	F	COMPR	0.56	0.56	
6	8	83	2	2	D	COMPR	1.07	1.62	
12	21	83	2	2	D	COMPR	2.14	3.77	
3	5	84	2	2	D	MECH	0.82	4.59	
5	30	84	2	2	F	COMPR	0.94	5.53	
10	22	84	2	2	D	COMPR	1.58	7.11	
2	6	85	2	2	D	MECH	1.16	8.27	
7	8	85	2	2	D	MECH	1.69	9.96	
11	1	85	2	2	D	GASKE	1.26	11.21	
5	27	86	2	2	F	GASKE	2.29	13.50	

Table A.4. (Cont'd)

Mo	Dy	Yr	Plt	Comp	SEVTY	DSCP	Tij	Ti	Agp
1	13	87	2	2	F	MECH	2.51	16.01	
2	12	87	2	2	D	COMPR	0.32	16.33	
3	31	87	2	2	D	MOTOR	0.54	16.88	
4	30	87	2	2	D	UNLOA	0.32	17.20	
7	6	87	2	2	D	COMPR	0.73	17.93	
4	14	88	2	2	D	UNLOA	3.09	21.02	
10	26	88	2	2	D	GASKE	2.13	23.16	
11	8	88	2	2	D	UNLOA	0.13	23.29	
11	14	88	2	2	D	COMPR	0.07	23.36	
2	29	84	2	3	D	COMPR	0.36	0.36	
4	16	84	2	3	D	COMPR	0.52	0.88	
7	20	84	2	3	D	MECH	1.04	1.92	
7	8	85	2	3	D	MECH	3.87	5.79	
1	9	88	2	3	D	GASKE	10.01	15.80	
6	4	88	2	3	D	GASKE	1.61	17.41	
11	26	88	2	3	D	MECH	1.91	19.32	
10	23	84	2	4	F	COMPR	2.72	2.72	
3	24	85	2	4	F	MOTOR	1.68	4.40	
4	19	85	2	4	D	UNLOA	0.28	4.68	
5	6	85	2	4	D	COMPR	0.19	4.87	
7	8	85	2	4	D	UNLOA	0.69	5.56	
1	9	86	2	4	D	GASKE	2.01	7.57	
1	14	86	2	4	D	UNLOA	0.06	7.62	
8	8	86	2	4	D	COMPR	2.27	9.89	
1	29	87	2	4	D	MOTOR	1.90	11.79	
10	3	87	2	4	D	UNLOA	2.71	14.50	
1	27	88	2	4	D	COMPR	1.27	15.77	
7	27	88	2	4	D	UNLOA	2.00	17.77	

NOTE:

BRGS - bearings
MECH - mechanical
JKTHX - jacket heat exchanger
COMPR - compressor
UNLOA - unloader
GASKE - gasket
LUBOIL - lubrication oil
FLTR - filter

T^{ij} - Time intervals of observed events

T^{i} - Age at which an event is observed

Y^{i} - Reciprocal of T^{ij}

Table A.5. Compressor Aging Failure Data (Unit 1; 4 air compressors)

Mo	Dy	Yr	Plt	Comp	SEVTY	DSCP	FTij	Fti	Yi	LgYi
7	31	79	1	4	F	COMPR	0.68	0.68	1.47	0.386
10	2	79	1	4	F	LUBOIL	0.68	1.36	1.47	0.386
1	27	81	1	2	F	LUBOIL	5.97	5.97	0.17	-1.787
2	12	82	1	2	F	MECH	4.16	10.13	0.24	-1.426
1	20	83	1	1	F	COMPR	12.6	12.6	0.08	-2.534
3	15	83	1	4	F	BRGS	13.81	15.17	0.07	-2.625
1	19	84	1	1	F	COMPR	3.99	16.59	0.25	-1.384
7	25	83	1	4	F	COMPR	1.44	16.61	0.69	-0.365
10	21	83	1	3	F	COMPR	16.89	16.89	0.06	-2.827
7	25	84	1	2	F	JKTHX	9.81	19.94	0.10	-2.283
1	17	85	1	1	F	COMPR	3.98	20.57	0.25	-1.381
7	15	85	1	1	F	UNLOA	1.97	22.54	0.51	-0.678
3	28	85	1	4	F	MECH	6.7	23.31	0.15	-1.902
12	27	85	1	1	F	COMPR	1.8	24.34	0.56	-0.588
4	17	86	1	3	F	BRGS	9.95	26.84	0.10	-2.298
4	17	86	1	2	F	BRGS	6.92	26.86	0.14	-1.934
3	29	86	1	4	F	MOTOR	4.01	27.32	0.25	-1.389
4	21	86	1	4	F	UNLOA	0.25	27.57	4.00	1.386
3	9	87	1	1	F	LUBOIL	4.8	29.14	0.21	-1.569
12	10	87	1	1	F	COMPR	3.02	32.16	0.33	-1.105
12	17	87	1	2	F	COMPR	6.66	33.52	0.15	-1.896
2	3	88	1	4	F	GASKE	7.13	34.7	0.14	-1.964
9	17	88	1	2	F	COMPR	3	36.52	0.33	-1.099
10	2	88	1	2	F	UNLOA	0.17	36.69	5.88	1.772
10	6	88	1	2	F	COMPR	0.04	36.73	25.00	3.219

FT_{ij} - Time intervals between observed failures

FT_{i} - Age at which an event (failure) is observed

FY_{i} - Reciprocal of FT^{ij}

A.4 Statistical Test Results for Combining of Air Compressors Aging Data

The Mann-Whitney test for the aging data of air compressors of two available nuclear units rejected the null hypothesis of identical samples (based on comparison of average ranks and significance level of 0.05). Table A.6 presents the results for the air compressors in the two nuclear units. Similarly, the test was carried out for the four air compressors within unit one, where the null hypothesis of identical samples was not rejected.

Therefore, the degradation behavior of the four air compressors in unit one belonged to the same population, and they were combined to build the data base for air compressors. Table A.7 presents the test results for combining the four components in unit one.

Table A.6. M-W Test Results for 2 Units
Air Compressor Aging Data

Comparison of Samples	Average Rank of 1st Samples	# of Valves of 1st Sample	Average Rank of 2nd Samples	# of Valves of 2nd Sample	Total obs	Test Statistic Z	P Value
plant 1 plant 2	97.617	154	127.18	56	210	3.116	0.00183

Table A.7. Statistical Test Results for Air Compressors in Unit 1

Comparison of Samples	Average Rank of 1st Sample	# of Valves of 1st Sample	Average Rank of 2nd Sample	# of Valves of 2nd Samples	Total obs	Test Statistics Z	α Value
component 1-component 2	36.89	35	31.97	33	68	-1.019	0.3083
component 1-component 3	39.21	35	34.96	38	73	-0.85	0.395
component 1-component 4	48.96	35	36.93	48	83	-1.241	0.25
component 2-component 3	35.73	33	36.24	38	71	0.098	0.92
component 2-component 4	43.89	33	39.01	48	81	-0913	0.361
component 3-component 4	46.71	38	40.96	48	86	-1.057	0.291

A.5 Regression Analysis to Obtain Aging Rates

For the age-groups showing significant trend with time, regression analysis are performed to obtain the aging rates. For degradation data, decreasing trend is defined for the 0-20 quarters, and increasing trend is defined for the remaining life: 20-40 quarters. The degradation and failure rate parameters, $\hat{a}$ and $\hat{b}$, are presented in Table A.8 and A.9, respectively.

Table A.8. Estimated Results for Degradation Rate Analysis
(4 compressors; data combined)

Data Use Method	Age Intervals	Aging Rate $\hat{b}$			Constant $\ell n\hat{a}$			Model	
		Estimated Parameter	Significant Level	Uncertainty (5% error)	Estimated Parameter	Significant Level	Uncertainty (5% error)	Significant Level	Standard Error of Estimate
Data Combining	0-20 (quarters)	-0.071	0.0003	CL: -0.107 CU: -0.0337	1.33	0.0001	CL: 0.986 CU: 1.679	0.0003	0.945
	20-40 (quarters)	0.06	0.073	CL: 0.005 CU: 0.115	-1.626	0.074	CL: -3.423 CU: 0.17	0.0735	1.046

Table A.9. Estimated Results for Failure Rate Analysis

Data Use Method	Age Intervals	Aging Rate $\hat{b}$			Constant $\ell n\hat{a}$			Model	
		Estimated Parameter	Significant Level	Uncertainty (5% error)	Estimated Parameter	Significant Level	Uncertainty (5% error)	Significant Level	Standard Error of Estimate
Data Combining	0-15 (quarters)	-0.233	0.024	CL: -0.409 CU: -0.055	0.435	0.386	CL: -0.934 CU: 1.804	0.025	0.584
	15-20 (quarters)	0.1012	0.035	CL: 0.0078 CU: 0.1946	-3.696	0.007	CL: -6.22 CU: -1.163	0.035	1.398

APPENDIX B: STATISTICAL RESULTS FOR SENSITIVITY ANALYSIS IN PARTITIONING OF AIR COMPRESSOR DATA

B.1 Database Obtained from Sensitivity Partitioning of Compressor Aging Data

Table B.1 presents the aging data on air compressors, based on the sensitivity data partitioning of failure severity. The failure data partitioned from degradations were expressed by a character variable "CRITC" (the "*" shows a partition from degradation to failure, and the "&" shows a partition from failure to degradation). Table B.2 gives the aging failure data set, obtained from the data in Table B.1.

B.2 Statistical Test Results for Data Combining Using partitioned Aging Failure Data

The Mann-Whitney test for the aging data of the four compressors in unit one was conducted using the data set obtained after the sensitivity data partitioning. The null hypothesis of identical samples (based on comparison of average ranks and significance level of 0.05) was not rejected. Table B.3 presents the results for the statistical tests.

Table B.1. Compressor Aging Data for Sensitivity Partitioning

Mo	Dy	Yr	Plt	Comp	SEVTY	CRTC	DSCP	Tij	Ti	FTij	Fti	
1	24	80	1	1	D		BRGS	0.64	0.64			
4	7	80	1	1	D		BRGS	0.81	1.46			
7	25	80	1	1	D		BRGS	1.20	2.66			
9	2	80	1	1	D		BRGS	0.41	3.07			
12	3	80	1	1	D		MECH	1.01	4.08			
12	30	80	1	1	D		BRGS	0.30	4.38			
3	17	81	1	1	D		JKTHX	0.86	5.23			
4	24	81	1	1	D		BRGS	0.41	5.64			
6	22	81	1	1	D		BRGS	0.64	6.29			
8	24	81	1	1	D		COMPR	0.69	6.98			
9	29	81	1	1	D		BRGS	0.39	7.37			
11	5	81	1	1	D		FLTR	0.40	7.77			
1	4	82	1	1	D		BRGS	0.66	8.42			
1	25	82	1	1	F	•	COMPR	0.23	8.66	8.66	8.66	•
4	14	82	1	1	D		MECH	0.88	9.53			
1	20	83	1	1	F		COMPR	3.07	12.60	3.94449	12.6	
3	9	83	1	1	D		COMPR	0.54	13.14			
1	19	84	1	1	F		COMPR	3.44	16.59	3.99	16.59	
4	30	84	1	1	D		COMPR	1.12	17.71			
11	16	84	1	1	D		MECH	2.18	19.89			
1	17	85	1	1	F		COMPR	0.68	20.57	3.98	20.57	
7	12	85	1	1	D		UNLOA	1.94	22.51			
7	15	85	1	1	F		UNLOA	0.03	22.54	1.97	22.54	
12	27	85	1	1	F		COMPR	1.80	24.34	1.8	24.34	
4	17	86	1	1	D		MOTOR	1.22	25.57			
11	24	86	1	1	D		MECH	2.41	27.98			
1	5	87	1	1	D		LUBOIL	0.46	28.43			
3	9	87	1	1	F		LUBOIL	0.71	29.14	4.8	29.14	
7	2	87	1	1	D		COMPR	1.26	30.40			
12	10	87	1	1	F		COMPR	1.76	32.16	3.02	32.16	
12	17	87	1	1	D		COMPR	0.08	32.23			
2	15	88	1	1	F	•	GASKE	0.64	32.88	0.72	32.88	•
4	1	88	1	1	D		GASKE	0.51	33.39			
6	21	88	1	1	D		UNLOA	0.89	34.28			
11	14	88	1	1	F	•	GASKE	1.59	35.87	2.99	35.87	•
11	26	79	1	2	D		COMPR	1.29	1.29			
1	13	80	1	2	D		MECH	0.52	1.81			
1	24	80	1	2	D		BRGS	0.12	1.93			
1	31	80	1	2	D		COMPR	0.08	2.01			
4	7	80	1	2	D		BRGS	0.73	2.74			
7	25	80	1	2	D		BRGS	1.20	3.94			
12	30	80	1	2	D		BRGS	1.72	5.67			
1	27	81	1	2	F		LUBOIL	0.30	5.97	5.97	5.97	
4	24	81	1	2	D		BRGS	0.97	6.93			
5	5	81	1	2	D		COMPR	0.12	7.06			

Table B.1. (Cont'd)

Mo	Dv	Yr	Plt	Comp	SEVTY	CRTC	DSCP	Tij	Ti	FTij	Fti	
6	22	81	1	2	D		BRGS	0.52	7.58			
8	26	81	1	2	F	•	MECH	0.71	8.29	2.32	8.29	•
9	29	81	1	2	D		BRGS	0.37	8.66			
11	5	81	1	2	D		FLTR	0.40	9.06			
1	4	82	1	2	D		BRGS	0.66	9.71			
2	12	82	1	2	F		MECH	0.42	10.13	4.16	10.13	
2	24	82	1	2	F	•	COMPR	0.13	10.27	0.14	10.27	•
4	23	82	1	2	D		MOTOR	0.66	10.92			
6	21	82	1	2	D		COMPR	0.64	11.57			
4	25	84	1	2	D		COMPR	7.38	18.94			
5	28	84	1	2	D		COMPR	0.37	19.31			
7	25	84	1	2	F		JKTHX	0.63	19.94	9.81	19.94	
10	17	85	1	2	D		COMPR	4.91	24.86			
4	17	86	1	2	D	&	BRGS	2.00	26.86			
8	18	86	1	2	D		MECH	1.34	28.20			
11	24	86	1	2	D		MECH	1.07	29.27			
6	11	87	1	2	D		LUBOIL	2.19	31.46			
12	17	87	1	2	F		COMPR	2.07	33.52	6.66	33.52	
9	8	88	1	2	F	•	COMPR	2.90	36.42	2.9	36.42	•
9	17	88	1	2	F		COMPR	0.10	36.52	0.1	36.52	
10	2	88	1	2	F		UNLOA	0.17	36.69	0.17	36.69	
10	6	88	1	2	F		COMPR	0.04	36.73	0.04	36.73	
10	7	88	1	2	D		MECH	0.01	36.74			
8	10	79	1	3	D		BRGS	0.10	0.10			
8	14	79	1	3	D		COMPR	0.04	0.14			
10	22	79	1	3	F	•	GASKE	0.76	0.90	0.9	0.90	•
2	27	80	1	3	D		BRGS	1.39	2.29			
3	27	80	1	3	D		JKTHX	0.33	2.62			
4	7	80	1	3	D		BRGS	0.11	2.73			
6	27	80	1	3	D		BRGS	0.89	3.62			
7	25	80	1	3	D		BRGS	0.31	3.93			
8	1	80	1	3	D		COMPR	0.07	4.00			
10	18	80	1	3	D		JKTHX	0.86	4.86			
10	20	80	1	3	D		MECH	0.02	4.88			
12	30	80	1	3	D		MOTOR	0.78	5.66			
3	17	81	1	3	D		LUBOIL	0.86	6.51			
3	27	81	1	3	D		FLTR	0.11	6.62			
4	24	81	1	3	D		BRGS	0.30	6.92			
6	22	81	1	3	F	•	MECH	0.64	7.57	6.67	7.57	•
9	29	81	1	3	D		BRGS	1.08	8.64			
11	5	81	1	3	D		FLTR	0.40	9.04			
1	4	82	1	3	D		BRGS	0.66	9.70			
2	24	82	1	3	D		COMPR	0.56	10.26			
7	21	82	1	3	D		BRGS	1.63	11.89			
10	21	82	1	3	D		COMPR	1.00	12.89			
4	4	83	1	3	F	•	MECH	1.81	14.70	7.13	14.70	•

Table B.1. (Cont'd)

Mo	Dy	Yr	Plt	Comp	SEVTY	CRTC	DSCP	Tij	Ti	FTij	Fti	
4	22	83	1	3	D		COMPR	0.20	14.90			
10	21	83	1	3	F		COMPR	1.99	16.89	2.19	16.89	
12	12	83	1	3	D		MECH	0.57	17.46			
1	20	84	1	3	D		GASKE	0.42	17.88			
1	26	84	1	3	D		MECH	0.07	17.94			
11	16	84	1	3	D		FLTR	3.22	21.17			
1	27	85	1	3	D		GASKE	0.79	21.96			
2	27	85	1	3	D		MECH	0.33	22.29			
4	30	85	1	3	D		COMPR	0.70	22.99			
4	17	86	1	3	D	&	BRGS	3.86	26.84			
4	27	87	1	3	D		UNLOA	4.11	30.96			
7	23	87	1	3	D		COMPR	0.96	31.91			
10	2	87	1	3	D		COMPR	0.77	32.68			
3	31	88	1	3	D		MECH	1.99	34.67			
10	6	88	1	3	D		MECH	2.06	36.72			
7	31	79	1	4	F		COMPR	0.68	0.68	0.68	0.68	
8	10	79	1	4	D		BRGS	0.10	0.78			
10	2	79	1	4	F		LUBOIL	0.58	1.36	0.68	1.36	
10	11	79	1	4	F	•	COMPR	0.10	1.46	0.1	1.46	•
2	2	80	1	4	D		COMPR	1.23	2.69			
2	27	80	1	4	D		BRGS	0.28	2.97			
3	27	80	1	4	D		JKTHX	0.33	3.30			
4	7	80	1	4	D		BRGS	0.11	3.41			
6	24	80	1	4	D		LUBOIL	0.86	4.27			
6	27	80	1	4	D		BRGS	0.03	4.30			
7	25	80	1	4	D		BRGS	0.31	4.61			
11	6	80	1	4	D		MECH	1.12	5.73			
12	30	80	1	4	D		BRGS	0.60	6.33			
3	3	81	1	4	D		FLTR	0.70	7.03			
3	17	81	1	4	D		LUBOIL	0.16	7.19			
3	27	81	1	4	D		FLTR	0.11	7.30			
4	24	81	1	4	D		BRGS	0.30	7.60			
6	22	81	1	4	D		BRGS	0.64	8.24			
7	28	81	1	4	F	•	GASKE	0.40	8.64	7.18	8.64	•
7	29	81	1	4	D		COMPR	0.01	8.66			
8	14	81	1	4	D		COMPR	0.17	8.82			
9	29	81	1	4	D		BRGS	0.50	9.32			
10	6	81	1	4	D		MECH	0.08	9.40			
11	5	81	1	4	D		FLTR	0.32	9.72			
1	4	82	1	4	D		BRGS	0.66	10.38			
1	25	82	1	4	D		COMPR	0.23	10.61			
4	23	82	1	4	D		MOTOR	0.98	11.59			
5	24	82	1	4	D		MECH	0.34	11.93			
7	1	82	1	4	D		MECH	0.41	12.34			
7	21	82	1	4	D		BRGS	0.22	12.57			
1	20	83	1	4	D		COMPR	1.99	14.56			

Table B.1. (Cont'd)

Mo	Dy	Yr	Plt	Comp	SEVTY	CRTC	DSCP	Tij	Ti	FTij	Fti
3	15	83	1	4	F		BRGS	0.61	15.17	6.53	15.17
4	4	83	1	4	D		MECH	0.21	15.38		
7	25	83	1	4	F		COMPR	1.23	16.61	1.44	16.61
7	20	84	1	4	D		COMPR	3.94	20.56		
11	16	84	1	4	D		MECH	1.29	21.84		
3	28	85	1	4	F		MECH	1.47	23.31	6.7	23.31
6	10	85	1	4	F		GASKE	0.80	24.11	0.8	24.11
12	1	85	1	4	D		GASKE	1.90	26.01		
12	6	85	1	4	D		MECH	0.06	26.07		
1	10	86	1	4	D		COMPR	0.38	26.44		
3	29	86	1	4	F		MOTOR	0.88	27.32	3.21	27.32
4	21	86	1	4	F		UNLOA	0.24	27.57	0.25	27.57
1	5	87	1	4	D		COMPR	2.82	30.39		
7	2	87	1	4	D		UNLOA	1.97	32.36		
2	3	88	1	4	F		GASKE	2.34	34.70	7.13	34.7
7	1	88	1	4	D		UNLOA	1.64	36.34		
7	15	88	1	4	D		COMPR	0.16	36.50		

Table B.2. Failure Data after Sensitivity Modification
(4 Components Combined)

Mo	Dy	Yr	Plt	Comp	SEVTY	DSCP	FTij	Fti	Agp	Md
1	25	82	1	1	F	COMPR	8.66	8.66	1	•
1	20	83	1	1	F	COMPR	3.94	12.60	1	
1	19	84	1	1	F	COMPR	3.99	16.59	1	
1	17	85	1	1	F	COMPR	3.98	20.57	2	
7	15	85	1	1	F	UNLOAD	1.97	22.54	2	
12	27	85	1	1	F	COMPR	1.80	24.34	2	
3	9	87	1	1	F	LUBOIL	4.80	29.14	2	
12	10	87	1	1	F	COMPR	3.02	32.16	2	
2	15	88	1	1	F	GASKET	0.72	32.88	2	•
11	14	88	1	1	F	GASKET	2.99	35.87	2	•
1	27	81	1	2	F	LUBOIL	5.97	5.97	1	
8	26	81	1	2	F	MECH	2.32	8.29	1	•
2	12	82	1	2	F	MECH	4.16	10.13	1	
2	24	82	1	2	F	COMPR	0.14	10.27	1	•
7	25	84	1	2	F	JKTHX	9.81	19.94	1	
12	17	87	1	2	F	COMPR	6.66	33.52	2	
9	8	88	1	2	F	COMPR	2.90	36.42	2	•
9	17	88	1	2	F	COMPR	0.10	36.52	2	
10	2	88	1	2	F	UNLOAD	0.17	36.69	2	
10	6	88	1	2	F	COMPR	0.04	36.73	2	
10	22	79	1	3	F	GASKET	0.90	0.90	1	•
6	22	81	1	3	F	MECH	6.67	7.57	1	•
4	4	83	1	3	F	MECH	7.13	14.70	1	•
10	21	83	1	3	F	COMPR	2.19	16.89	1	
7	31	79	1	4	F	COMPR	0.68	0.68	1	
10	2	79	1	4	F	LUBOIL	0.68	1.36	1	
10	11	79	1	4	F	COMPR	0.10	1.46	1	•
7	28	81	1	4	F	GASKET	7.18	8.64	1	•
3	15	83	1	4	F	BRGS	6.53	15.17	1	
7	25	83	1	4	F	COMPR	1.44	16.61	1	
3	28	85	1	4	F	MECH	6.70	23.31	2	
6	10	85	1	4	F	GASKET	0.80	24.11	2	•
3	29	86	1	4	F	MOTOR	3.21	27.32	2	
4	21	86	1	4	F	UNLOAD	0.25	27.57	2	
2	3	88	1	4	F	GASKET	7.13	34.70	2	

Table B.3. M-W Test Results for Data Counting of the Four Air Compressors (aging failure data was portioned)

Comparison of Samples	Average Rank of 1st Sample	# of Valves of 1st Sample	Average Rank of 2nd Sample	# of Valves of 2nd Sample	Total obs	Test Statistical Z	α Values
Component 1-Component 2	11.3	10	9.7	10	20	-0.566	0.571
Component 1-Component 3	7.3	10	8	4	14	0.212	0.8
Component 1-Component 4	12.2	10	9.91	11	-0.81	21	0.417
Component 2-Component 3	6.9	10	9	4	0.777	16	0.436
Component 2-Component 4	10.25	10	11.682	11	0.493	21	0.622
Component 3-Component 4	9.625	4	7.41	11	15	-0.784	0.433

APPENDIX C: STATISTICAL RESULTS FOR SENSITIVITY ANALYSIS ON UNCERTAINTY IN DEGRADATION OCCURRENCE TIMES

C.1 Database for the Sensitivity Analysis of Uncertainty in Degradation Occurrence Times

Table C.1 and C.2 present the aging data for the RHR pumps and air compressors. The data was obtained after imposing the uncertainty of degradation occurrence times. The uncertainty time intervals were assumed to be an exponentially distributed random variable with a mean of 15 days.

Table C.1. Units RHR Pump Data Combined with Uncertainty of Degradation Times

Mo	Dy	Yr	Plant	Comp	Svty	Tij	Ti	Uncrt	Ti'	Tij'
5	1	80	sas1	a	D	1.33	1.33	0.257	1.08	1.08
1	15	81	sas1	a	D	2.88	4.21	0.017	4.19	3.12
3	16	82	sas1	a	D	4.73	8.94	0.025	8.92	4.73
10	28	82	sas1	a	D	2.47	11.41	0.522	10.89	1.97
9	8	83	sas1	a	D	3.50	14.91	0.148	14.76	3.87
2	17	84	sas1	a	D	1.82	16.73	0.165	16.57	1.81
7	1	84	sas1	a	D	1.49	18.22	0.233	17.99	1.42
7	26	85	sas1	a	D	4.33	22.56	0.181	22.38	4.39
5	12	80	sas1	b	D	1.46	1.46	0.033	1.42	1.42
1	15	81	sas1	b	D	2.76	4.21	0.132	4.08	2.66
3	16	82	sas1	b	D	4.73	8.94	0.008	8.94	4.86
10	28	82	sas1	b	D	2.47	11.41	0.266	11.15	2.21
3	17	83	sas1	b	D	1.60	13.01	0.328	12.68	1.54
4	18	84	sas1	b	F	4.40	17.41	0.037	17.37	4.69
7	26	85	sas1	b	D	5.14	22.56	0.101	22.45	5.08
3	10	86	sas1	b	D	2.54	25.10	0.142	24.96	2.50
1	9	87	sas1	b	F	3.38	28.48	0.262	28.22	3.26
5	10	88	sas1	b	D	5.40	33.88	0.469	33.41	5.19
6	7	80	sas1	c	D	1.73	1.73	0.334	1.40	1.40
1	15	82	sas1	c	F	6.53	8.27	0.364	7.90	6.50
3	16	82	sas1	c	D	0.68	8.94	0.033	8.91	1.01
10	28	82	sas1	c	D	2.47	11.41	0.200	11.21	2.30
9	8	83	sas1	c	D	3.50	14.91	0.450	14.46	3.25
6	8	84	sas1	c	D	3.06	17.97	0.126	17.84	3.38
8	7	84	sas1	c	D	0.66	18.62	0.039	18.58	0.74
7	26	85	sas1	c	D	3.93	22.56	0.682	21.87	3.29
2	2	87	sas1	c	D	6.18	28.73	0.141	28.59	6.72
4	25	80	sas1	d	D	1.27	1.27	0.030	1.24	1.24
5	12	80	sas1	d	D	0.19	1.46	0.047	1.41	0.17
3	16	82	sas1	d	D	7.49	8.94	0.019	8.93	7.52
10	28	82	sas1	d	D	2.47	11.41	0.389	11.02	2.10
12	15	82	sas1	d	D	0.52	11.93	0.002	11.93	0.91
3	17	83	sas1	d	D	1.08	13.01	0.120	12.89	0.96
4	18	84	sas1	d	F	4.40	17.41	0.042	17.37	4.48
5	5	84	sas1	d	D	0.19	17.60	0.055	17.54	0.18
6	29	84	sas1	d	D	0.60	18.20	0.445	17.76	0.21
7	26	85	sas1	d	D	4.36	22.56	0.079	22.48	4.72
7	28	86	sas1	d	D	4.08	26.63	0.065	26.57	4.09
1	4	83	sas2	a	D	0.03	0.03	0.000	0.03	0.03
8	25	83	sas2	a	F	2.57	2.60	0.162	2.44	2.41
11	8	83	sas2	a	D	0.81	3.41	0.406	3.01	0.57
2	2	84	sas2	a	D	0.99	4.40	0.083	4.32	1.31
8	7	84	sas2	a	F	2.06	6.46	0.161	6.29	1.98
5	8	85	sas2	a	F	3.07	9.52	0.026	9.50	3.20
1	16	86	sas2	a	D	2.81	12.33	0.113	12.22	2.72
4	19	88	sas2	a	F	9.14	21.48	0.105	21.37	9.15
1	4	83	sas2	b	D	0.03	0.03	0.000	0.03	0.03
7	28	83	sas2	b	D	2.27	2.30	0.005	2.29	2.26
11	8	83	sas2	b	D	1.11	3.41	0.358	3.05	0.76
6	19	84	sas2	b	F	2.51	5.92	0.345	5.58	2.52
8	2	84	sas2	b	F	0.48	6.40	0.354	6.05	0.47

Table C.1. (Cont'd)

Mo	Dy	Yr	Plant	Comp	Svty	Tij	Ti	Uncrt	Ti'	Tij'
1	30	86	sas2	b	D	6.09	12.49	0.213	12.28	6.23
2	11	86	sas2	b	D	0.12	12.61	0.166	12.45	0.17
3	24	87	sas2	b	D	4.53	17.14	0.491	16.65	4.21
12	17	87	sas2	b	D	2.92	20.07	0.151	19.92	3.26
2	4	88	sas2	b	D	0.58	20.64	0.015	20.63	0.71
1	4	83	sas2	c	D	0.03	0.03	0.014	0.02	0.02
2	1	83	sas2	c	D	0.30	0.33	0.129	0.20	0.19
3	4	83	sas2	c	D	0.37	0.70	0.038	0.66	0.46
5	25	83	sas2	c	D	0.90	1.60	0.124	1.48	0.81
9	27	83	sas2	c	D	1.36	2.96	0.057	2.90	1.42
2	16	84	sas2	c	D	1.60	4.56	0.028	4.53	1.63
5	16	84	sas2	c	D	1.00	5.56	0.004	5.55	1.02
8	15	84	sas2	c	F	0.99	6.54	0.367	6.18	0.63
3	7	85	sas2	c	D	2.30	8.84	0.067	8.78	2.60
2	3	89	sas2	c	F	15.84	24.69	0.147	24.54	15.76
1	4	83	sas2	d	D	0.03	0.03	0.000	0.03	0.03
1	11	83	sas2	d	D	0.08	0.11	0.013	0.10	0.07
4	12	83	sas2	d	D	1.01	1.12	0.131	0.99	0.89
3	5	84	sas2	d	F	3.64	4.77	0.180	4.59	3.60
8	2	84	sas2	d	D	1.63	6.40	0.274	6.13	1.54
8	15	84	sas2	d	F	0.14	6.54	0.045	6.50	0.37
9	20	84	sas2	d	F	0.39	6.93	0.219	6.71	0.21
3	7	85	sas2	d	D	1.91	8.84	0.234	8.61	1.90
12	17	87	sas2	d	D	11.22	20.07	0.008	20.06	11.45
8	1	74	duan	a	D	1.00	1.00	0.268	0.73	0.73
12	5	74	duan	a	F	1.38	2.38	0.084	2.29	1.56
12	15	75	duan	a	D	4.17	6.54	0.013	6.53	4.24
9	20	76	duan	a	D	3.11	9.66	0.316	9.34	2.81
11	21	76	duan	a	D	0.68	10.33	0.096	10.24	0.90
12	26	76	duan	a	D	0.39	10.72	0.073	10.65	0.41
1	16	79	duan	a	D	8.39	19.11	0.005	19.11	8.46
3	16	82	duan	a	D	12.83	31.94	0.020	31.92	12.82
6	3	82	duan	a	D	0.86	32.80	0.623	32.18	0.25
10	23	82	duan	a	D	1.56	34.36	0.217	34.14	1.96
2	25	83	duan	a	D	1.41	35.77	0.299	35.47	1.33
3	3	85	duan	a	D	8.20	43.97	0.041	43.93	8.46
7	1	86	duan	a	D	5.37	49.33	0.150	49.18	5.26
4	23	75	duan	b	F	3.97	3.97	0.047	3.92	3.92
12	18	78	duan	b	D	14.78	18.74	0.019	18.73	14.81
3	10	82	duan	b	D	13.13	31.88	0.389	31.49	12.76
4	4	82	duan	b	D	0.27	32.14	0.002	32.14	0.65
5	1	82	duan	b	D	0.30	32.44	0.120	32.32	0.18
6	8	82	duan	b	D	0.41	32.86	0.042	32.81	0.49
8	1	82	duan	b	D	0.59	33.44	0.055	33.39	0.58
10	23	82	duan	b	D	0.91	34.36	0.445	33.91	0.52
2	9	83	duan	b	D	1.23	35.59	0.079	35.51	1.60
3	1	85	duan	b	D	8.36	43.94	0.065	43.88	8.37
4	23	82	duan	c	D	32.36	32.36	0.152	32.20	32.20
10	23	83	duan	c	D	6.06	38.41	0.162	38.25	6.05
3	1	85	duan	c	D	5.53	43.94	0.406	43.54	5.29
9	14	74	duan	d	F	1.48	1.48	0.161	1.32	1.32
3	18	76	duan	d	D	6.16	7.63	0.026	7.61	6.29

Table C.1. (Cont'd)

Mo	Dy	Yr	Plant	Comp	Svty	Tij	Ti	Uncrt	Ti'	Tij'
11	4	76	duan	d	D	2.51	10.14	0.113	10.03	2.42
5	1	82	duan	d	D	22.30	32.44	0.105	32.34	22.31
10	23	82	duan	d	D	1.91	34.36	0.170	34.19	1.85
12	1	82	duan	d	D	0.42	34.78	0.184	34.59	0.41
1	1	83	duan	d	D	0.39	35.17	0.005	35.16	0.57
1	1	84	duan	d	D	4.06	39.22	0.358	38.86	3.70
3	1	85	duan	d	D	4.72	43.94	0.345	43.60	4.73

Table C.2. Aging Data with Uncertainty Times of Degradation Occurrences
(4 Compressors Combined)

Mo	Dy	Yr	Plt	Comp	SEVTY	DSCP	Tij	Ti	Uncrt	Ti'	Tij'
1	24	80	1	1	D	BRGS	0.64	0.64	0.043	0.601	0.387
4	7	80	1	1	D	BRGS	0.81	1.46	0.003	1.453	0.851126
7	25	80	1	1	D	BRGS	1.20	2.66	0.004	2.651	1.198648
9	2	80	1	1	D	BRGS	0.41	3.07	0.087	2.900	0.248753
12	3	80	1	1	D	MECH	1.01	4.08	0.025	4.053	1.152969
12	30	80	1	1	D	BRGS	0.30	4.38	0.027	4.350	0.297311
3	17	81	1	1	D	JKTHX	0.86	5.23	0.039	5.194	0.844084
4	24	81	1	1	D	BRGS	0.41	5.64	0.030	5.614	0.419928
6	22	81	1	1	D	BRGS	0.64	6.29	0.024	6.265	0.650769
8	24	81	1	1	D	COMPR	0.69	6.98	0.005	6.972	0.707233
9	29	81	1	1	D	BRGS	0.39	7.37	0.022	7.345	0.372376
11	5	81	1	1	D	FLTR	0.40	7.77	0.001	7.765	0.420662
1	4	82	1	1	D	BRGS	0.66	8.42	0.044	8.378	0.612544
1	25	82	1	1	F	COMPR	0.23	8.66	0.055	8.601	0.222923
4	14	82	1	1	D	MECH	0.88	9.53	0.006	9.527	0.926321
1	20	83	1	1	F	COMPR	3.07	12.60	0.017	12.583	3.056038
3	9	83	1	1	D	COMPR	0.54	13.14	0.024	13.121	0.537528
1	19	84	1	1	F	COMPR	3.44	16.59	0.044	16.545	3.424386
4	30	84	1	1	D	COMPR	1.12	17.71	0.078	17.633	1.08788
11	16	84	1	1	D	MECH	2.18	19.89	0.013	19.876	2.24299
1	17	85	1	1	F	COMPR	0.68	20.57	0.056	20.511	0.63507
7	12	85	1	1	D	UNLOA	1.94	22.51	0.061	22.450	1.93941
7	15	85	1	1	F	UNLOA	0.03	22.54	0.005	22.539	0.088485
12	27	85	1	1	F	COMPR	1.80	24.34	0.033	24.311	1.77219
4	17	86	1	1	D	MOTOR	1.22	25.57	0.075	25.492	1.180518
11	24	86	1	1	D	MECH	2.41	27.98	0.021	27.957	2.465128
1	5	87	1	1	D	LUBOIL	0.46	28.43	0.007	28.427	0.469974
3	9	87	1	1	F	LUBOIL	0.71	29.14	0.114	29.031	0.604018
7	2	87	1	1	D	COMPR	1.26	30.40	0.023	30.377	1.34576
12	10	87	1	1	F	COMPR	1.76	32.16	0.019	32.137	1.76038
12	17	87	1	1	D	COMPR	0.08	32.23	0.005	32.228	0.091432
2	15	88	1	1	F	GASKE	0.64	32.88	0.008	32.870	0.64149
4	1	88	1	1	D	GASKE	0.51	33.39	0.003	33.386	0.515809
6	21	88	1	1	D	UNLOA	0.89	34.28	0.065	34.213	0.827231
11	14	88	1	1	F	GASKE	1.59	35.87	0.000	35.866	1.653388
11	26	79	1	2	D	COMPR	1.29	1.29	0.020	1.269	1.2689
1	13	80	1	2	D	MECH	0.52	1.81	0.007	1.804	0.535133
1	24	80	1	2	D	BRGS	0.12	1.93	0.009	1.924	0.120063
1	31	80	1	2	D	COMPR	0.08	2.01	0.014	1.928	0.003653
4	7	80	1	2	D	BRGS	0.73	2.74	0.013	2.731	0.803461
7	25	80	1	2	D	BRGS	1.20	3.94	0.011	3.934	1.202385
12	30	80	1	2	D	BRGS	1.72	5.67	0.007	5.660	1.726497
1	27	81	1	2	F	LUBOIL	0.30	5.97	0.025	5.941	0.281125
4	24	81	1	2	D	BRGS	0.97	6.93	0.027	6.906	0.965109
5	5	81	1	2	D	COMPR	0.12	7.06	0.028	6.889	-0.01743
6	22	81	1	2	D	BRGS	0.52	7.58	0.014	7.564	0.675057
8	26	81	1	2	F	MECH	0.71	8.29	0.027	8.262	0.69801
9	29	81	1	2	D	BRGS	0.37	8.66	0.004	8.651	0.389204
11	5	81	1	2	D	FLTR	0.40	9.06	0.019	9.037	0.385473
1	4	82	1	2	D	BRGS	0.66	9.71	0.018	9.694	0.656876

Table C.2. (Cont'd)

Mo	Dy	Yr	Plt	Comp	SEVTY	DSCP	Tij	Ti	Uncrt	Ti'	Tij'
2	12	82	1	2	F	MECH	0.42	10.13	0.028	10.105	0.411369
2	24	82	1	2	F	COMPR	0.13	10.27	0.031	10.236	0.131136
4	23	82	1	2	D	MOTOR	0.66	10.92	0.001	10.921	0.685238
6	21	82	1	2	D	COMPR	0.64	11.57	0.060	11.507	0.585759
4	25	84	1	2	D	COMPR	7.38	18.94	0.058	18.887	7.37981
5	28	84	1	2	D	COMPR	0.37	19.31	0.059	19.252	0.365176
7	25	84	1	2	F	JKTHX	0.63	19.94	0.036	19.909	0.656851
10	17	85	1	2	D	COMPR	4.91	24.86	0.136	24.719	4.810583
4	17	86	1	2	D	BRGS	2.00	26.86	0.082	26.774	2.054185
8	18	86	1	2	D	MECH	1.34	28.20	0.025	28.175	1.401126
11	24	86	1	2	D	MECH	1.07	29.27	0.002	29.264	1.089402
6	11	87	1	2	D	LUBOIL	2.19	31.46	0.002	31.453	2.189168
12	17	87	1	2	F	COMPR	2.07	33.52	0.002	33.520	2.066468
9	8	88	1	2	F	COMPR	2.90	36.42	0.021	36.401	2.880877
9	17	88	1	2	F	COMPR	0.10	36.52	0.006	36.516	0.115179
10	2	88	1	2	F	UNLOA	0.17	36.69	0.021	36.668	0.152238
10	6	88	1	2	F	COMPR	0.04	36.73	0.009	36.724	0.0557
10	7	88	1	2	D	MECH	0.01	36.74	0.005	36.740	0.015898
8	10	79	1	3	D	BRGS	0.10	0.10	0.001	0.099	0.0993
8	14	79	1	3	D	COMPR	0.04	0.14	0.061	0.144	0.045084
10	22	79	1	3	F	GASKE	0.76	0.90	0.011	0.889	0.744387
2	27	80	1	3	D	BRGS	1.39	2.29	0.025	2.264	1.375531
3	27	80	1	3	D	JKTHX	0.33	2.62	0.034	2.588	0.323765
4	7	80	1	3	D	BRGS	0.11	2.73	0.028	2.567	-0.02139
6	27	80	1	3	D	BRGS	0.89	3.62	0.002	3.620	1.053382
7	25	80	1	3	D	BRGS	0.31	3.93	0.022	3.911	0.291321
8	1	80	1	3	D	COMPR	0.07	4.00	0.030	3.970	0.058566
10	18	80	1	3	D	JKTHX	0.86	4.86	0.046	4.810	0.839903
10	20	80	1	3	D	MECH	0.02	4.88	0.008	4.870	0.060325
12	30	80	1	3	D	MOTOR	0.78	5.66	0.037	5.619	0.748785
3	17	81	1	3	D	LUBOIL	0.86	6.51	0.039	6.472	0.853134
3	27	81	1	3	D	FLTR	0.11	6.62	0.001	6.621	0.148775
4	24	81	1	3	D	BRGS	0.30	6.92	0.023	6.899	0.27817
6	22	81	1	3	F	MECH	0.64	7.57	0.045	7.522	0.622927
9	29	81	1	3	D	BRGS	1.08	8.64	0.014	8.630	1.108383
11	5	81	1	3	D	FLTR	0.40	9.04	0.002	9.042	0.411818
1	4	82	1	3	D	BRGS	0.66	9.70	0.053	9.647	0.605071
2	24	82	1	3	D	COMPR	0.56	10.26	0.016	10.240	0.592317
7	21	82	1	3	D	BRGS	1.63	11.89	0.012	11.877	1.637091
10	21	82	1	3	D	COMPR	1.00	12.89	0.001	12.888	1.011333
4	4	83	1	3	F	MECH	1.81	14.70	0.003	14.697	1.808582
4	22	83	1	3	D	COMPR	0.20	14.90	0.028	14.733	0.036787
10	21	83	1	3	F	COMPR	1.99	16.89	0.036	16.853	2.11924
12	12	83	1	3	D	MECH	0.57	17.46	0.050	17.406	0.553112
1	20	84	1	3	D	GASKE	0.42	17.88	0.007	17.871	0.465188
1	26	84	1	3	D	MECH	0.07	17.94	0.014	17.861	-0.0098
11	16	84	1	3	D	FLTR	3.22	21.17	0.005	21.162	3.300546
1	27	85	1	3	D	GASKE	0.79	21.96	0.008	21.948	0.785952
2	27	85	1	3	D	MECH	0.33	22.29	0.003	22.286	0.338031
4	30	85	1	3	D	COMPR	0.70	22.99	0.065	22.924	0.638342
4	17	86	1	3	D	BRGS	3.86	26.84	0.000	26.844	3.920055
4	27	87	1	3	D	UNLOA	4.11	30.96	0.020	30.936	4.091558

Table C.2. (Cont'd)

Mo	Dy	Yr	Plt	Comp	SEVTY	DSCP.	Tij	Ti	Uncrt	Ti'	Tij'
7	23	87	1	3	D	COMPR	0.96	31.91	0.007	31.904	0.968467
10	2	87	1	3	D	COMPR	0.77	32.68	0.009	32.669	0.764507
3	31	88	1	3	D	MECH	1.99	34.67	0.074	34.593	1.923948
10	6	88	1	3	D	MECH	2.06	36.72	0.013	36.709	2.116499
7	31	79	1	4	F	COMPR	0.68	0.68	0.011	0.667	0.6669
8	10	79	1	4	D	BRGS	0.10	0.78	0.007	0.771	0.104275
10	2	79	1	4	F	LUBOIL	0.58	1.36	0.025	1.330	0.558903
10	11	79	1	4	F	COMPR	0.10	1.46	0.027	1.429	0.098442
2	2	80	1	4	D	COMPR	1.23	2.69	0.068	2.621	1.192614
2	27	80	1	4	D	BRGS	0.28	2.97	0.014	2.953	0.331677
3	27	80	1	4	D	JKTHX	0.33	3.30	0.027	3.273	0.320232
4	7	80	1	4	D	BRGS	0.11	3.41	0.004	3.407	0.133649
6	24	80	1	4	D	LUBOIL	0.86	4.27	0.019	4.248	0.841029
6	27	80	1	4	D	BRGS	0.03	4.30	0.018	4.282	0.034654
7	25	80	1	4	D	BRGS	0.31	4.61	0.028	4.583	0.300258
11	6	80	1	4	D	MECH	1.12	5.73	0.031	5.703	1.120025
12	30	80	1	4	D	BRGS	0.60	6.33	0.001	6.332	0.629682
3	3	81	1	4	D	FLTR	0.70	7.03	0.060	6.974	0.641314
3	17	81	1	4	D	LUBOIL	0.16	7.19	0.058	7.131	0.157588
3	27	81	1	4	D	FLTR	0.11	7.30	0.059	7.241	0.109621
4	24	81	1	4	D	BRGS	0.30	7.60	0.036	7.564	0.323517
6	22	81	1	4	D	BRGS	0.64	8.24	0.136	8.108	0.543917
7	28	81	1	4	F	GASKE	0.40	8.64	0.082	8.563	0.454185
7	29	81	1	4	D	COMPR	0.01	8.66	0.025	8.630	0.067793
8	14	81	1	4	D	COMPR	0.17	8.82	0.002	8.820	0.189402
9	29	81	1	4	D	BRGS	0.50	9.32	0.002	9.320	0.500279
10	6	81	1	4	D	MECH	0.08	9.40	0.002	9.398	0.07758
11	5	81	1	4	D	FLTR	0.32	9.72	0.021	9.701	0.303099
1	4	82	1	4	D	BRGS	0.66	10.38	0.006	10.371	0.670734
1	25	82	1	4	D	COMPR	0.23	10.61	0.021	10.590	0.218904
4	23	82	1	4	D	MOTOR	0.98	11.59	0.009	11.579	0.989033
5	24	82	1	4	D	MECH	0.34	11.93	0.005	11.929	0.349231
7	1	82	1	4	D	MECH	0.41	12.34	0.001	12.344	0.415178
7	21	82	1	4	D	BRGS	0.22	12.57	0.028	12.400	0.056262
1	20	83	1	4	D	COMPR	1.99	14.56	0.011	14.544	2.144321
3	15	83	1	4	F	BRGS	0.61	15.17	0.025	15.142	0.597753
4	4	83	1	4	D	MECH	0.21	15.38	0.034	15.344	0.201542
7	25	83	1	4	F	COMPR	1.23	16.61	0.072	16.539	1.195037
7	20	84	1	4	D	COMPR	3.94	20.56	0.002	20.553	4.014729
11	16	84	1	4	D	MECH	1.29	21.84	0.022	21.823	1.269099
3	28	85	1	4	F	MECH	1.47	23.31	0.030	23.281	1.458566
6	10	85	1	4	F	GASKE	0.80	24.11	0.046	24.065	0.784347
12	1	85	1	4	D	GASKE	1.90	26.01	0.008	26.004	1.938102
12	6	85	1	4	D	MECH	0.06	26.07	0.014	25.983	-0.0202
1	10	86	1	4	D	COMPR	0.38	26.44	0.039	26.405	0.422115
3	29	86	1	4	F	MOTOR	0.88	27.32	0.001	27.321	0.915442
4	21	86	1	4	F	UNLOA	0.24	27.57	0.023	27.544	0.222614
1	5	87	1	4	D	COMPR	2.82	30.39	0.045	30.344	2.800704
7	2	87	1	4	D	UNLOA	1.97	32.36	0.014	32.342	1.997271
2	3	88	1	4	F	GASKE	2.34	34.70	0.002	34.698	2.356262
7	1	88	1	4	D	UNLOA	1.64	36.34	0.053	36.292	1.59396
7	15	88	1	4	D	COMPR	0.16	36.50	0.016	36.484	0.192317

C.2 Comparison of Statistical Test Results for Data Combining on RHR Pump Aging Data

The Mann-Whitney test for the aging data with uncertainty times incorporated were conducted for the RHR pumps and air compressors, respectively. Table C.3 and C.4 present the test results.

Table C.3. Comparison of Test Results on Data Combining for RHR Pumps

Uncertainty Times Considerations	Comparisons of Samples	Average Rank of 1st Sample	# of Valves of 1st Sample	Average Rank of 2nd Sample	# of Valves of 2nd Sample	Total obs	Test Statistical Z	R Value
Before	plant 1 - plant 3	36.30	38	37.75	35	73	0.287	0.77
	plant 2 - plant 3	31.14	37	42.17	35	72	2.23	0.03
	plant 1 - plant 2	36.13	38	37.94	35	73	0.359	0.71
After	plant 1 - plant 3	36.15	38	37.91	35	73	0.347	0.727
	plant 2 - plant 3	31.5	34	42.25	35	69	2.07	0.082
	plant 1 - plant 2	44.5	36	31.2	7	73	-1.63	0.07

Table C.4. Comparison of Test Results on Data Combining for Air Compressors

With Incorporation of Uncertainty Times

Kruskal-Wallis analysis of CMPUNCRT.T_{ij} by Comp

Level	Sample Size	Average Rank
1	35	88.2857
2	33	78.2727
3	38	78.0789
4	48	68.6458

Test statistic = 3.95496 Significance level = 0.266369

Without Incorporation of Uncertainty Times

Kruskal-Wallis analysis of CMPUNCRT.T_{ij} by Comp

Level	Sample Size	Average Rank
1	35	88.9571
2	33	77.2727
3	38	78.5921
4	48	67.5938

Test statistic = 1.54586 Significance level = 0.671726