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Degradation Modeling with Application to Aging and Maintenance Effectiveness Evaluations

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ABSTRACT

This report describes a modeling approach to analyze component degradation and failure data to understand the aging process of components. As used here, degradation modeling is the analysis of information on component degradation in order to develop models of the process and its implications. This particular modeling focuses on the analysis of the times of component degradations, to model how the rate of degradation changes with the age of the component. The methodology presented also discusses the effectiveness of maintenance as applicable to aging evaluations.

The specific applications which are performed show quantitative models of component degradation rates and component failure rates from plant-specific data. The statistical techniques which were developed and applied allow aging trends to be effectively identified in the degradation data, and in the failure data. Initial estimates of the effectiveness of maintenance in limiting degradations from becoming failures also were developed. These results are important first steps in degradation modeling, and show that degradation can be modeled to identify aging trends.

EXECUTIVE SUMMARY

The assessment of risk associated with aging in nuclear power plants encompasses many facets, an important element of which is the understanding of the aging phenomena associated with components of safety systems. In this report, the aging phenomena at the component level were studied to develop an aging reliability model representing the aging process experienced by components in nuclear power plants under presently existing test and maintenance practices. A new model was developed to process information on component degradation in order to analyze the degradation process and its implications. The focus was on modeling the degradation rate, i.e., the rate at which degradations occur, and failure rate, i.e., the rate at which failures occur, with the specific objective of developing explicit relationships between degradation characteristics and the component failure rate.

The research program goes beyond an analysis of times of degradation and failure. First, theoretical models that relate the degradation rate of the component to its failure rate are developed. With the relationships derived, information on component degradation can be used to predict the component failure rate and its significance. Specifically, this methodology can use aging trends in the component degradation rate to predict future aging trends in the component failure rate.

The capability of making such a prediction is important because the knowledge (or estimate) of related component aging failure rates is required to quantify the effects of aging on core damage frequency and risk. This knowledge is also needed to quantify the effectiveness of a given maintenance program in controlling the effects of aging on the core damage frequency and risk. However, failure data are often sparse. On the other hand, degradation data are more abundant because degradations occur at a higher rate than failures. Thus the methodology developed in this report allows component failure rates due to aging to be estimated from component degradation rates. This has the potential to greatly increase the accuracy and availability of component aging failure rates made available to the user in risk evaluations of aging effects.

It is important that, in addition to the identification of aging trends in degradation and failure data, the methodology allows maintenance indicators to be selected in such a way that component degradations are related to reliability and risk impacts. When the degradation indicators show significant impacts of degradation on the component failure rate and the resulting risk, maintenance should be performed to correct the degradations. Also, initial estimates of the effectiveness of maintenance in preventing degradations from becoming failures were developed. Thus the degradation indicators can provide a practical and effective means of monitoring component condition and signal for the correction of degradations before they have significant impacts on reliability and risk.

The specific applications of the developed theoretical approach were performed, which resulted in quantitative models of component degradation rates and component failure rates, all of them derived from plant-specific data. As part of the data analysis, statistical techniques that identify aging trends in failure and degradation data were developed. The aging trends can be of any kind and can exist in any segment of the data. Specifically, an analysis of residual heat removal (RHR) system pump data shows a "bathtub" curve for the degradation rate where a distinct, increasing aging trend is observed as time progresses. Interestingly, the pump failure rate does not show any increasing trend for the same time period, thus demonstrating the need to identify aging trends through analyses of component degradations.

In summary, these results reported are important first steps in showing that degradations can be modeled to identify aging effects. The theoretical methodology that is developed represents an advancement, demonstrating that degradation characteristics are explicitly related to failure-rate effects and hence ultimately to risk effects. Also, the effectiveness of maintenance can be analyzed and assessed. The next step would be to use the methodology and statistical techniques to develop and validate practical procedures for predicting aging failure rates from degradation data. This ability would provide powerful tools for analyzing aging effects in degradation data and for predicting their implications for reliability and risk.

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ACKNOWLEDGMENTS

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1. INTRODUCTION

The assessment of risk associated with aging in nuclear power plants encompasses many facets, of which an important element is the understanding of the aging phenomena associated with components of safety systems. We study the aging phenomena at the component or sub-component level so that we can develop an aging reliability model representing the aging process experienced by components in nuclear plants under existing test and maintenance practices. In this report, we present an approach to analyze component degradation and failure data to understand the aging process, and also to evaluate the effectiveness of maintenance in preventing age-related failures.

The study of aging at the component level can be broadly divided between two types of components – active components (e.g., pumps, valves, and circuit breakers), and passive components (e.g., structures and pipes). In this report, the primary focus is on active components, although the approaches that are presented can also be explored for application to passive components.

Study of aging characteristics at the component level is an assessment of the deterioration of component reliability with time, and an identification of the activities or processes that could mitigate such deterioration. Reliability analyses are typically focused on determining aging failure rate with time. Analyses of data on plant experience indicate that components experience various forms of degradation that are detected and corrected through testing and maintenance. This report presents an approach to using information on component degradation to understand aging reliability characteristics of components. Incorporation of component degradation characteristics in an aging reliability model (which has not been done before) will improve our understanding of the aging process, and also help determine activities to mitigate such deterioration.

The degradation information evaluated in this study includes the times of 1) degraded failures, and 2) corrective maintenances. The data may also include the component's condition in terms of the parameter values recorded at times of corrective maintenances. The degradation modeling approaches presented can use this information to study the aging effects evident in degradations to relate reliability characteristics to the effectiveness of maintenance in mitigating aging effects. At present, we study degradation modeling using degradation times, and do not directly use component condition in terms of engineering conditions. The degradation modeling approach also is directly tied to the component reliability study, as such information can be used to predict the component's failure rate and unavailability which can be used as input into risk and reliability models.

This report develops the concept of using degradation information in an aging reliability study. An application of this concept is presented for (two) specific safety system components, namely Residual Heat Removal (RHR) system pumps and service water (SW) system pumps. This analysis forms the basis for developing a component aging reliability model using degradation information. Such models will significantly improve studies of aging risk.

The degradation modeling in this report focuses on the following aspects:

a. consideration of the degraded state before an age-related failure in studying component aging,

b. evaluation of maintenance effectiveness parameter in preventing age-related failure,

c. modeling of degradation and aging-failure rates using exponential rate models,

d. employing statistical approaches to use data across similar components and across nuclear power plants in component aging study,

e. testing statistical trends to define aging intervals showing (increasing/decreasing) trends in aging failure or degradation times, and calculating the corresponding rates using regression analysis, and

f. interpretation of information on degradation and aging-failure rate in evaluations of aging and maintenance effectiveness.

This report is organized as follows: Chapter 1 is introduction. Chapter 2 presents the basic concepts of degradation modeling; the methodology, with the mathematical formulations, is presented in Chapter 3. The regression analysis approach to obtain degradation and aging-failure rates is presented in Chapter 4, which also discusses Cox's exponential rate model used to define aging rates. Chapter 5 presents the results obtained for the RHR pumps and their interpretation. A summary of the insights obtained from the application is presented in Chapter 6. Appendix A gives the details of the degradation modeling approach. The analysis of aging failure data (degradation times and failure times) is presented in Appendix B. Appendices C and D provide details of the statistical analyses for the RHR pumps. Appendix E presents analyses of degradation and failure data for SW pumps. Definitions of the terms used in the report are presented in Appendix F.

2. CONCEPT AND OBJECTIVES OF DEGRADATION MODELING

Analyses of component reliability records show that besides data on component failure, significant information exists on component degraded conditions, including times at which such degraded conditions are observed, and also values of observed parameters indicating degradation. Often, a component reliability record contains much more information on degradations than on failure. The concept of degradation modeling is to use degradation data to develop component reliability characteristics and to understand aging effects.

The objectives of degradation modeling are:

1. To quantify and characterize the frequency of degradation,
2. To model and quantify the effects of aging on the frequency of component degradation and degradation characteristics,
3. To model and quantify the frequency of component failure and aging effects on such frequency,
4. To establish the use of information on component degradation in aging evaluations such that operational activities can be defined to mitigate such deteriorations,
5. To establish relations between component degradations and failures so that frequency of component failure can be estimated from the frequency of component degradation frequency and degradation characteristics, and
6. To develop a reliability model for component aging using information on degradation and failure as an input to aging reliability and risk studies.

This study attempts to develop degradation modeling approaches to accomplish the above objectives. At this time, we primarily address the first four objectives and briefly discuss the insights on the last two. The development of a degradation model for aging evaluation studies requires investigation of all the above aspects.

The concepts and steps of degradation modeling are as follows. degradation data is collected, consisting of the times and characteristics of degradations. The times of degradations can include times of incipient failures, of degraded failures, and of corrective maintenances (based on different definitions of component states, certain incipient failures may not be applicable). The characteristics of degradations can include the values observed for various operational parameters and material properties. The use of operational parameters and material properties in defining degraded states has not been attempted at this time.

Such data are used to quantify the component degradation frequency versus time and age. The times of component aging failure are also studied to quantify the aging failure frequency versus time. The degradation frequency and aging-failure frequency provide an evaluation of the aging process, and can also be used to evaluate the effectiveness of maintenances in preventing age-related failures.

Data on degradation- and aging-failure can also be used to establish the relationships between the two. Based on such relationships, which are strongly influenced by operational practices, such as maintenance, aging failure rates can be estimated from degradation rates. As is evident in component reliability data bases, there are more data on degradation than on aging failures: therefore, such relationships can provide an estimate of aging-failure rate where there is insufficient data. However, the relationship among degradations, failures, and maintenances is complex, and in this report, we attempt to define such a relationship.

Reliability models can also be constructed which relate the frequency of degradation to the frequency of component failure and to component reliability. The models use component operating characteristics, maintenance considerations, and engineering considerations. The age-dependent frequency of degradation is used as input into the models to predict the age-dependent frequency of failure. In such an approach, the key point is that failures do not necessarily have to be observed, rather only degradations, to predict the component's failure and reliability behavior, including the failure rate and unavailability of the components.

The degradation modeling approach studied in this report assumes that components pass through a degraded state before experiencing failures: this may be a simplified model. In reality, a component may experience multiple degraded states in its path to failure (Figure 1, on page 6). The Markov modeling approach presented in this report can be expanded to include multiple states, and it can provide a better explanation of the aging process and the influence of maintenances in that process. Further development of this approach will consider multiple states incorporating effects of tests and maintenance.

Degradation models have many potential applications. As discussed, the times of corrective maintenances, that signify degraded states, can be used to predict future times of failures. The aging effect on degradation rates can be indicative of future growth in aging failures rates which may necessitate appropriate corrective actions, e.g., maintenance, overhauls, or replacements. Time-dependent degradation rates can be used to estimate time-dependent failures rates for use in aging intervals where failure data do not support the development of aging-failure rates. Component reliability models can be developed that incorporate information on degradation, and can be input to aging risk and reliability studies. Thus degradation models can be a valuable tool for aging evaluation applications, license renewal applications, and reliability-centered maintenance applications.

3. METHODOLOGY: DEGRADATION MODELING APPROACHES

In this chapter, a brief summary of the degradation modeling approaches is presented. 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. Appendix A provides the detailed mathematics of specific degradation modeling.

To understand degradation modeling, we study a repairable component, i.e., a component that is being repaired and maintained. The "active" components, as defined in the NPAR program, are repairable components, and are the focus of this study.

For one of the simplest models, 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, the degraded state the "d" state and the one after maintenance is performed the "m" state.

We use Markov process approaches for degradation modeling; they have the advantage that simple models can first be constructed and then expanded 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 will include multiple degraded states (Figure 1). For the simplest model using single degraded state definitions, approaches are developed that can be applied to current data, and to obtain significant insights, as demonstrated in Chapter 5.

3.1 State Representation of Degradation Modeling

The Markov approaches of degradation modeling can be described by the state diagram for a component (Figure 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

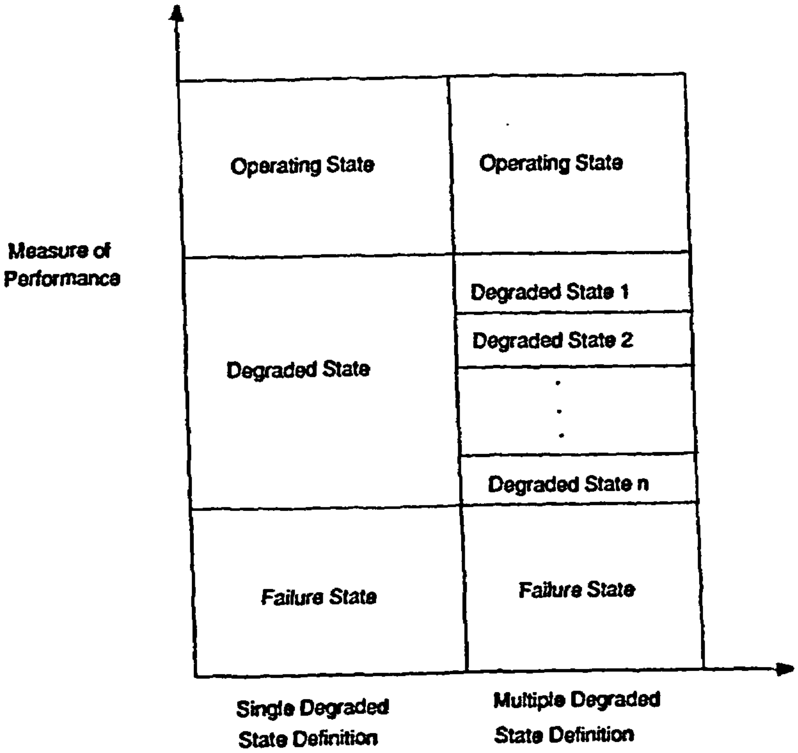

Figure 1. Alternatives for degraded state definitions

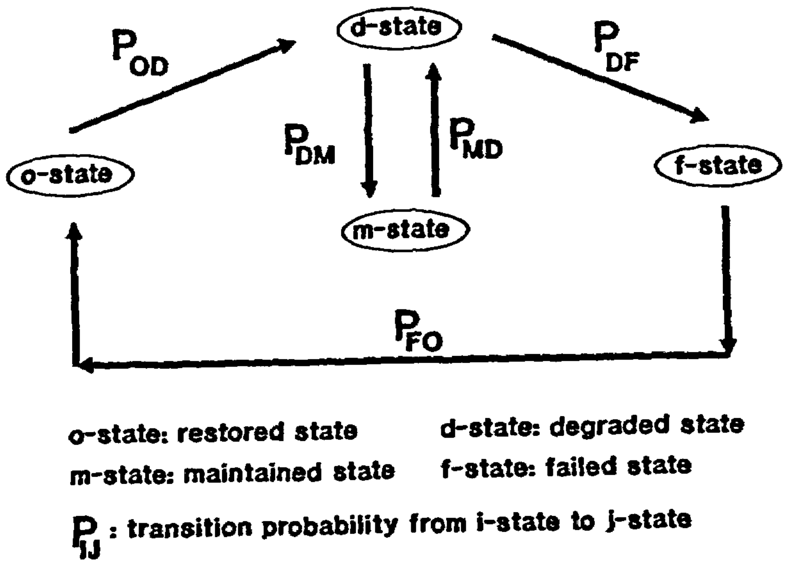

Figure 2. Markov state diagram for component degradation modelling (single degraded state)

(m-state) is reached following a degraded state (d-state). For Markov modeling considerations, these two states are equivalent in this analysis.

3.2 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 since we assume degradation always precedes failure

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

= 1 since maintenance will be performed to remedy the degraded state.

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

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

P_{FO} = probability that component is restored following failure

= 1

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

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

Degradation frequency defines the frequency of degraded state, i.e., the number of degraded states observed for a component per unit time. Similarly, the failure frequency 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 (Ref. 1), one can obtain the steady state solution that relates the degradation frequency, failure frequency, and the transition probabilities. (Mathematical derivation is presented in Appendix A.) W_D and W_F represent the steady state degradation and failure frequencies.

$$W_D = W_F + W_D P_{MD} \tag{3-1}$$

$$W_F = W_D P_{DF} \tag{3-2}$$

Expressed in terms of transition probabilities,

$$P_{DF} = W_F / W_D \tag{3-3}$$

$$P_{MD} = 1 - W_F / W_D = 1 - P_{DF} \tag{3-4}$$

The above expressions define how the steady state transition probabilities (P_{DF} and P_{MD}) can be obtained from the degradation frequency and failure frequency. Using component reliability data bases like NPRDS or plant-specific data bases, 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 determine the effectiveness of various maintenances carried out for a type of component.

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

1. The larger the ratio of failure frequency and degradation frequency (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 maintenance effectiveness 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 component failure frequency relates to such characteristics.

3.4 Incorporation of Aging Effects in Degradation Modeling

To develop a model for component reliability using information on degradation in our study of aging effects, we need to develop the age-dependence of the degradation parameters. Thus, for aging, at some threshold time (age t_0) the failure frequency W_F and degradation frequency, W_D will begin to increase. On the other hand, degradation frequency may show a significant aging effect (increase in degradation frequency with age) whereas the failure frequency may not (constant with age), indicating a reduced probability of transition from the degraded to the failure state. This may signify that maintenance is effective enough to maintain a constant failure frequency, and that aging degradation is manifested through age-dependency of degradation frequency.

The time dependent representation of W_F and W_D are presented in the appendix. From the relation one can obtain the frequency of failure in terms of the degradation frequency,

$$W_F(x) = \int_{t_0}^{t} W_D(x) f_{DF}(t - x)\, dx \tag{3-5}$$

where $f_{DF}(t - x)$ is the probability density that the failure occurs at t with no intermediate observed degradation, given the component was maintained at x. The probability density function is assumed to depend only on the interval $(t - x)$.

A prediction of the aging effect on the frequency of component failure can be obtained from the aging effect in degradation frequency using the above equation. However, this requires information obtained from the steady state process and as such, introduces the following assumptions:

1. That aging begins at some threshold time, and that both $W_F(t)$ and $W_D(t)$ increase from that same time.
2. The transition probability density, for example, $f_{DF}(x)$, depends only on the interval, and the steady-state probability density, obtained from steady-state data, can be applied for aging-dependent evaluation of $W_F(t)$ and $W_D(t)$.
3. The same transition probabilities, P_{DF} and P_{MD} , as developed from the steady-state case, also apply to the aging case.

The justification for using these assumptions and how the relationship expressed in Eqn. (3-5) can be obtained under these constraints are presented in Appendix A. The assumptions are both reasonable and necessary if we are to predict the aging effect on failure frequency, based on the observed frequency of degradation with a paucity of data on failure.

3.5 Aging Effects on Degradation 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, with an attempt to predict the corresponding characteristics of failure under appropriate constraints.

The degradation rate, λ_{MD} , is defined as the rate of degradation occurring after maintenance (given no previous degradation has occurred). Similarly, the failure rate, λ_{DF}, is the rate of a failure occurring after a degradation (given 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,...,t_n from some threshhold time is used to estimate the parametric form of $\lambda_{MD}(t)$. The process of estimation is briefly discussed in the next chapter.

a) Availability of Data on Failure

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 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 is effective in averting component failure. Conversely, maintenance is ineffective if the transition probability P_{MD} in the aging process is higher than the steady state value.

b) Insufficient Data on Failure

In the absence of data on failure, the degradation rate can be used to develop failure rate in the age-dependent scenario. One approach is to assume that both the failure rate and degradation rate have the same time dependence.

$$\lambda_{DF}(t) = k_{DF}g(t) \tag{3-6}$$

$$\lambda_{MD}(t) = k_{MD}g(t) \tag{3-7}$$

where g(t) is a general time-dependent or age-dependent function, possibly with a threshold time t_0 , i.e.,

$$g(t) = 1 \qquad t < t_0$$

$$= h(t) \qquad t > t_0 .$$

and k_{DF} , k_{MD} are constants. $\lambda_{DF}(t)$ can be obtained from $\lambda_{MD}(t)$ using the ratio $k_{DF} / (k_{DF} + k_{MD})$. Under this scenario, the ratio $k_{DF} / (k_{DF} + k_{MD})$ is a constant and is given by the transition probability P_{DF} obtained for the steady-state solution. In this situation, any available failure data can be used to check the assumption used in obtaining $\lambda_{DF}(t)$ from $\lambda_{MD}(t)$.

3.6 Basic Steps in Degradation Modeling

1. The data base on component reliability is evaluated to obtain the time of degradations (when maintenance is performed) and times of aging failures.
2. Degradation relationships are developed, based on the observed times at which degraded states occur.
3. The degradation relationships give the rate of transition from one degradation state to another.
4. Using information on failure time, an aging failure rate is developed.
5. The aging failure rate, the degradation rate, and transition probabilities are used to evaluate the aging process and the effectiveness of maintenance in component aging.
6. The degradation relationships are used to predict the time (age) of future failure of the component from the rate of occurrence of degradations.
7. The predicted time (age) of future failure can be used to produce a component failure rate, which can be used in probabilistic risk analysis (PRAs).

In Chapter 5, we present analyses of degradation and failure data for RHR pumps following the steps defined. Degradation modeling is applied up to Step 5. Additional evaluations and further developments of degradation modeling methodology are necessary to conduct Steps 6 and 7.

3.7 Assumptions and Limitations in the Methodology

The degradation modeling presented in this chapter is the first step in the component aging reliability model development using degradation information. The specific example analyses presented in the next chapter are also to demonstrate the applicability of the methodology and to show how useful insights can be derived from this approach. Nevertheless, at this time, for this simple model a number of assumptions are made, many of which are expected to 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 limitation in the methodology and their implications in the results presented.

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. The objective here is to demonstrate how important insights relating to aging and maintenance effectiveness can be obtained by using degradation information in its simplest form. As stated, more extended models can be developed that allow multiple states of degradation.

2. The model assumed that maintenance is performed everytime 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 maintenance requirement. The data used in the analyses are delineated such that the identified degraded states are associated with maintenance. It is, however, recognized 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 and not preventative maintenance. More frequent corrective maintenances are associated with more frequent degradation occurrances exceeding some threshold. Nondetected degradations and scheduled maintenances are not explicitly treated by the model. Extensions to multiple degraded state modeling can treat both nondetected degradations and effect of scheduled maintenances.

4. Test frequency to detect component degradation is not explicitly treated in the model. It is conceivable that degradation conditions may remain undetected, for longer durations because of low frequency of testing. This is because component testing intervals are defined to detect failure rather than degradations. Further extension of the model will include test interval times.

5. In the theoretical model development which relate degradation rate of the component to its failure rate, the failure rate and degradation rate are assumed to have the same time-dependence. This is one model for time-dependence relationship. Data analyses and sensitivity evaluations will be conducted to understand this relationship. The applications presented in this report do not require this assumption.

6. Data requirements for applications of degradation modeling are more comprehensive since degradation data are required. Degradation data are often unavailable and if available, 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 objective of this report is to develop models which show how degradation data can be specifically used in for maintenance decisions. If these specific benefits and uses of degradation data are recognized, then there would be more incentive to collect accurate degradation data.

4. REGRESSION ANALYSIS USING COX'S MODEL TO ESTIMATE AGING RATES (DEGRADATION AND FAILURE RATES)

4.1 Introduction

The degradation modeling approach presented in the previous chapter focuses on estimating two aging parameters—degradation rate and failure rate. The parameters are to be estimated from the degradation and failure times observed in components as they age. In this chapter, we discuss Cox's model (a form of exponential rate model) for developing aging rate parameters and the regression analysis used to estimate the model parameters.

4.2 Cox's Model to Develop Aging Rates

As described in Cox's model (Ref. 2), the age-dependent failure rate or degradation rate $\Lambda(t)$ for a component is given by:

$$\Lambda(t) = ae^{bt} . \tag{4-1}$$

Cox's model is also termed the exponential rate model, because aging behavior is modeled as being exponential with age. In Eqn. (4-1), t is the time or age variable, and a and b are parameters characterizing the aging behavior. The parameter a defines the baseline constant (failure or degradation) rate and the parameter b defines the relative aging effect. These parameters are discussed further below. If degradations are evaluated, then $\Lambda(t)$ is the degradation rate instead of the failure rate. In the following discussions, we shall focus on failure rates; however, the discussions equally apply to degradation rates.

When $\Lambda(t)$ is a failure rate, then $\Lambda(t)$ can represent the rate at which first failures occur given no previous failure rate. $\Lambda(t)$ can also represent the rate at which any failure occurs, first or otherwise. In this application, $\Lambda(t)$ is also called the failure frequency or failure intensity. This later case, where $\Lambda(t)$ represents the rate for any failure, is particularly applicable for repairable components.

Cox's model can accommodate constant failure rates, aging failure rates, and burn-in failure rates. If b is zero, then there is no aging effect and the failure rate is constant:

$$\Lambda(t) = a \text{ for } b = 0 . \tag{4-2}$$

If b is positive, $b > 0$, then there is an aging effect, with the failure rate increasing as the age increases. If b is negative, $b < 0$, then there is a burn-in or learning effect with the failure rate decreasing as the age increases. We shall be particularly concerned with aging effects or constant failure rates, i.e., $b \geq 0$. However, if data indicates there is a burn-in or learning effect, then this also will be identified by the analysis.

If b is small such that $bt \ll 1$, then the exponential that can be expanded by a first-order Taylor expansion and $\Lambda(t)$ becomes:

$$\Lambda(t) = a(1 + bt) \tag{4-3}$$

$$= a + abt \tag{4-4}$$

$$= a + ct \tag{4-5}$$

where,

$$c = ab \ . \tag{4-6}$$

Thus, Cox's model includes the linear aging failure-rate model, Eqn. (4-5), for parameter values b and ages t such that $bt << 1$.

In addition to accommodating different failure rates and including the linear aging model, Cox's model has other features. If the parameter a is treated as a baseline failure are Λ_0 , i.e.,

$$a = \Lambda_0 \ , \tag{4-7}$$

then, Cox's model can be written as:

$$\Lambda(t) = \Lambda_0 e^{bt} \ . \tag{4-8}$$

Thus, the factor e^{bt} can be interpreted as a relative aging factor which modifies the baseline, constant failure rate Λ_0 to account for aging behavior.

Cox's model allows standard statistical techniques to be applied to estimate the parameters a and b. Taking the natural logarithms of Eqn. (4-1) gives:

$$\ln \Lambda(t) = \ln a + bt \ . \tag{4-9}$$

Thus, $\ln \Lambda(t)$ is a linear function of the time or age variable t with slope b and intercept ln a. Consequently, linear regression analysis can be used to estimate the unknown parameters a and b from observed time or ages of failures. Because of its capabilities, the regression analysis approach for estimating the parameters of Cox's model is described in more detail in the next section.

The times (or ages) of failures can also be used to estimate the aging rate parameter b independent of the baseline parameter a. This approach can be useful if relative aging effects only are to be estimated. The relative times of failure are described by the relative failure distribution f(t), where:

$$f(t) = \frac{e^{bt}}{\int_{T_1}^{T_2} e^{bt} \, dt} \tag{4-10}$$

or

$$f(t) = \frac{be^{bt}}{e^{bT_2} - e^{bT_1}} \ . \tag{4-11}$$

In the above formulas, T_1 and T_2 are the initial and final times, respectively, of the observation period: the relative distribution f(t) only involves the aging parameter b. Standard statistical techniques, such as maximum likelihood, can then be applied to f(t) to estimate the aging parameter b.

Finally, by constructing the appropriate likelihood functions describing the observed times of failures, standard statistical techniques can estimate both parameters a and b. Classical statistical techniques and Bayesian techniques, which incorporate prior information, can be used.

4.3 The Regression Approach

The regression approach for estimating the parameters a and b is described in more detail here. Since most standard statistical packages and PC codes contain regression analysis, the approach can be a powerful tool.

Cox applies regression approach to estimate the parameters for the mean time between failures. We will show how regression can also be applied to data-based estimates of the failure rate. Such estimates are described in Ref. 3, and are called cycle-based failure rates. Our application also defines a framework for regression analysis using data-based failure rate estimates as the observed, dependent variables.

Cox describes the regression approach only for independent observations, or independent estimates; we have extended it to correlated estimates. This is important, since it allows cycle-based failure rates to be used which consist of overlapping times between failures.

Let t_1, t_2,...t_n be the observed times (or ages) of failure. As discussed previously, even though failure rate modeling is discussed, Cox's model can model degradation occurrences versus time or age for any definition of degradation states. For degradation modeling, t_1, t_2,...t_n are the observed times or ages at which the degradation occurs.

A data-based estimate of the failure rate at an observed time (or age) of failure t_i is simply one over the time between failures. If we let r_i be the empirical or data-based failure rate estimate, then:

$$r_i = \frac{1}{t_i - t_{i-1}} \qquad i = 2,...n \ . \tag{4-12}$$

This is a standard empirical estimate of the failure rate (see for example, Ref. 4). More generally, an estimate $r_i^{(k)}$ of the failure rate at time t_i considering k times between failure is:

$$r_i^{(k)} = \frac{k}{t_i - t_{i-k}} \qquad i = k+1,...n \tag{4-13}$$

In Ref. 3, the failure rate estimate $r_i^{(k)}$ is termed the k-cycle-based failure rate since it encompasses k cycles (i.e, times between failure).

Now, in describing the regression approach, Cox focuses on the length L of k times between failure, where $L = t_i - t_{i-k}$. The length of k times between failures are used, where k is generally 3 to 5, to smooth the failure behavior. Cox shows that the expected value of the log of L is a simple function of the parameters. Specifically,

$$E(\ln L) = -\ln a - bt + c , \quad (4\text{-}14)$$

where "E( )" denotes the expectation and "ln" denotes the natural logarithm. The time t is a time at the midpoint of the k times between failure L. The constant c is a normalizing constant which is a function of k, the number of times between failure. Specifically,

$$c = \ln k . \quad (4\text{-}15)$$

If we let:

$$d = \ln a , \quad (4\text{-}16)$$

then Eqn. (4-14) becomes:

$$E(\ln L) = -d - bt + c . \quad (4\text{-}17)$$

Thus, if we let:

$$y = \ln L , \quad (4\text{-}18)$$

we obtain a linear equation for the expected value of y

$$E(y) = f - bt , \quad (4\text{-}19)$$

where,

$$f = c - d . \quad (4\text{-}20)$$

Cox also shows that if we partition the times of failures into disjoint groups, each containing k failures, then the different times between k failures L_1, L_2,... are independent. The variance of the times between k failures L_i is also independent of the failure rate. Specifically,

$$V(\ln L) = \frac{1}{k - \frac{1}{2}} . \quad (4\text{-}21)$$

Again letting y = ln L we have,

$$V(y) = \frac{1}{k - \frac{1}{2}} . \quad (4\text{-}22)$$

Equations (4-19) and (4-22) show that a standard linear regression can estimate the parameters of Cox's model. The steps in applying the regression are as follows:

1. Divide the times of failure t_1, t_2,...t_n into disjoint groups, each containing k times between failure. Thus, the first group would be t_1, t_2,...t_{k+1} (to obtain k times

between failures). The second group would start at t_{k+1} and would contain the next k + 1 time points. This grouping would proceed until all observations are used or there are fewer than k + 1 observations to group. The last group of observations which is smaller than k+1 observations is truncated and not used. Thus, it is optimal if k is selected such that all observations are used, i.e., such that n+1 is a multiple of k.

2. Assign an associated time or age for each group of failures. The assigned time or age is a value at a midpoint of the k failures. Any centrally located value will generally be sufficient, such as the median of the times of failures.

3. Apply standard linear regression to the observations (y_i, t_i) where t_i is the midpoint time or age, and y_i is the log of the k times between failure $y_i = \ln L_i$.

The slope of the regression line will give –b [See Equation (4-19)]. Equations (4-15), (4-16), and (4-20) can be used to determine the parameter a from the regression line intercept.

To show how we can apply the regression approach in terms of the empirical failure rate, we start with the basic regression equation, Equation (4-14).

$$E(\ln L) = \ln a - bt + \ln k , \tag{4-23}$$

where we substitute c = ln k into the equation [as given by Eqn (4-15)].

Transposing ln k to the left hand side of the equation, we have:

$$E(\ln L) - \ln k = -\ln a - bt , \tag{4-24}$$

or,

$$E\left(\ln \frac{L}{k}\right) = -\ln a - bt . \tag{4-25}$$

Multiplying both sides of the equation by –1 we have:

$$E\left(\ln \frac{k}{L}\right) = \ln a + bt . \tag{4-26}$$

Now k / L is the k-cycle failure rate estimate as defined by Eqn. (4-13), i.e.,

$$\frac{k}{L} = \frac{k}{t_i - t_{i-k}} \tag{4-27}$$

$$= r_i^{(k)} \tag{4-28}$$

Hence, Eqn. (4-26) becomes

$$E\left(\ln r_i^{(k)}\right) = \ln a + bt . \tag{4-29}$$

Defining again

$$d = \ln a \tag{4-30}$$

we thus have

$$E\left(\ln r_i^{(k)}\right) = d + bt \; . \tag{4-31}$$

From Eqn. (4-31) we thus see that under Cox's model the expected value of the k-cycle failure rate estimate is also a linear function of the time (or age) t.

To find the expression for the variance of $r_i^{(k)}$ we use the relationship between $r_i^{(k)}$ and L given by Eqn. (4-28), i.e.,

$$r_i^{(k)} = \frac{k}{L} \tag{4-32}$$

Therefore,

$$\ln r_i^{(k)} = \ln k - \ln L \; . \tag{4-33}$$

Taking the variance of both sides, we have, using standard variance operator properties,

$$V\left(\ln r_i^{(k)}\right) = V(\ln L) \; . \tag{4-34}$$

where V( ) again denotes the variance of the variable in the parentheses. Substituting the expression for V(ln L) given by Eqn. (4-21) we have

$$V\left(\ln r_i^{(k)}\right) = \frac{1}{k - \frac{1}{2}} \; . \tag{4-35}$$

Thus we have our re-defined regression equations, given by Eqn. (4-31) and (4-35), now reformulated in terms of the empirical estimates of cycle-based failure rate. (Note that Eqn. (4-35) which gives the variance is used for regression purposes to identify that all estimates $r_i^{(k)}$, i.e., all observations, have equal variance and no weighting is needed in the regression analyses.)* The previous steps defined for the regression application can still be used where now $y_i = \ln r_i^{(k)}$ is the dependent variable (instead of ln L). The midpoint time or age t_i is still the independent variable which is substituted for the variable t in Eqn. (4-31). The regression slope gives the parameter b and the regression intercept given ln a, from which a is determined. In the analysis presented for RHR pump, k = 1. We use standard regression analyses (using STATGRAPH statistical package, Ref. 4) to obtain the parameters a and b for the degradation or failure rate using the respective degradation or failure times.

*Knowledge of the variance allows different size groupings k with the weight for each group equal to the square root of one over the variance.

5. RESULTS AND INTERPRETATION OF AGE-RELATED DEGRADATION AND FAILURE DATA

In this section, we present an analyses of age-related degradation and failure data for selected components, namely RHR pumps and SW pumps. The primary focus of the analysis is to use the concept of degradation modeling, which is intended to provide an understanding of the aging process in the active components. Based on the data analyses, we discuss

1. behavior of degradation rate and aging failure rate with age of a standby safety system component and a continuously operating component (i.e., the RHR pump and SW pump).
2. interpretation of aging process through degradation and failure rate behavior, i.e., how meaningful information can be obtained by studying these parameters, and
3. derivation of effectiveness of maintenance in preventing age-related failures.

In addition to these items which focus on the interpretation of aging and evaluation of maintenance effectiveness, the analyses address the following aspects:

1. combining data from similar components in a plant and across plants,
2. data pooling across components, based on statistical tests of similar characteristics,
3. statistical trend testing to determine aging effect in failure and degradation data, and
4. regression analysis to obtain degradation rate and aging failure rate.

5.1 Analysis Approach

The primary objective of the analyses 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 failures.

The process of data collection provides specific degradation and failure times of several similar components (Appendix B). Focusing on the RHR pumps, data are obtained for a group of components from different plants. In this case, the data covered three different BWR units, each having four RHR pumps. The age of the plants differed, and the data did not cover the entire life of the component in all cases.

Individually, the data for each of the pumps were insufficient to determine the parameters (degradation rate and aging failure rate). Accordingly, we studied a component type (the RHR pump) using data from the group of components (in this case, 12 RHR pumps). Statistical tests were conducted to justify the use of data across components and across plants.

For SW pumps, data from seven BWR units out of twelve units were used in the analysis. Based on the statistical tests, the SW pump aging data in the remaining five units were not compatible with the data from the seven units used in the analysis. Each of these units has three or more SW pumps, thus providing a data base from about forty three pumps.

Similar to the analysis approach in RHR pumps, statistical tests were conducted to justify the use of data across components and across plants.

Statistical tests for use of data across components and across plants

The statistical tests were conducted with the following objectives:

1. to demonstrate that times between degradations (or between failures) across components within a plant are identically distributed, i.e., the components belong to the same population for analysis of degradation and failure rate characteristics, and

2. to demonstrate that components across the plants belong to the same population.

The tests were conducted separately for degradation and failure data. Mann-Whitney U-tests and Kruskal-Wallis (K-U) tests were used, details of which are presented in Appendix C. The results showed that components could be grouped together: for the RHR pumps, the statistical tests justified using data from twelve pumps across three different power plants. In the case of SW pumps, the test results justified use of data across seven units out of twelve units.

Data were combined in two ways. In Method 1, the data on time to degradation or time to failure were combined from different RHR pumps, i.e., separate data from each component were used to develop the data base. In Method 2, data from different components were "pooled", i.e., degradation and failure times obtained from each component were plotted on a single time-line to obtain new degradation and failure times for the analysis. In our terminology, we describe Method 1 as "data combining" and Method 2 is called "data pooling".

Trend testing and identification of age-groups with degradation and failure time

The data obtained by either of the methods ("data combining" or "data pooling") 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 early life showed a decreasing trend, and later life showed either increasing or constant trends with time. Using regression analysis, data from age-groups were appropriately partitioned that showed statistically significant time trends for developing aging rates.

5.2 Aging Effect on Degradation

The analysis of degradation data for the RHR pumps and SW pumps was conducted with the following objectives:

1. identification of age-groups where statistically significant time trends exist, and

2. determination of the time-trends, and degradation rates, using regression analysis.

The details of the statistical analyses are presented in Appendices C and D. Here, we discuss the results and the characteristics of degradation rate.

Figure 3 shows the degradation rate and the logarithm of the rate that characterized the RHR pumps over ten years (presented as 40 quarters). On the vertical axis, $\ln\lambda_D$ of 2, presented on the right side, implies λ_D equal to 7.39, presented on the left side. The degradation times were obtained from plant-specific data bases of twelve RHR pumps, four from each of three units (Appendix B). Statistical tests (in Appendix C) showed that the degradation behavior across these components are similar, and accordingly, a generic degradation characteristic was studied. Data combining and data pooling were studied: both showed similar results. The results obtained by data combining are discussed.

The following observations can be made from the age-dependent degradation rate for the RHR pumps:

1. The degradation rate shows significant age-dependence; the early life of the component (i.e., first five years) shows a decreasing trend (significance level: 0.001), and the later five years show an increasing trend (significance level: 0.05), with the age of the component.

2. The increase in degradation rate, which is of interest in aging studies, is significant: the degradation rate increased by almost an order of magnitude at the end of ten years.

3. The 95% confidence bounds for the degradation rate show that the uncertainty in the estimation is not large. The increased number of degradations observed in a component (compared to failure data) and the statistical approach taken for using data across similar components exhibiting similar degradation behavior contribute to lower range of uncertainty. This signifies that statistical methods can be used to estimate degradation rates.

Figure 4 shows the logarithm of the degradation rate that characterized the SW pumps over twelve years (presented as 50 quarters). The method of data combining was studied for SW pumps. The generic degradation characteristic was obtained by combining data across seven units consisting of forty-three pumps. Appendix E presents detailed results.

The observations on the age-dependent degradation rate for the SW pumps are as follows:

1. The degradation rate shows age-dependence: the early life of the component (i.e., first five years) shows a decreasing trend and the remaining seven years show an increasing trend with the age of the component.

2. The increase in the degradation rate as the component ages is not as significant as in the case of RHR pumps; nevertheless, the degradation rate is showing aging effect on the component. During the later seven year period the rate increased by about a factor of 3.

5.3 Aging Effect on Failures

The aging-failure data for the RHR pumps and SW pumps were also analyzed with the following objectives:

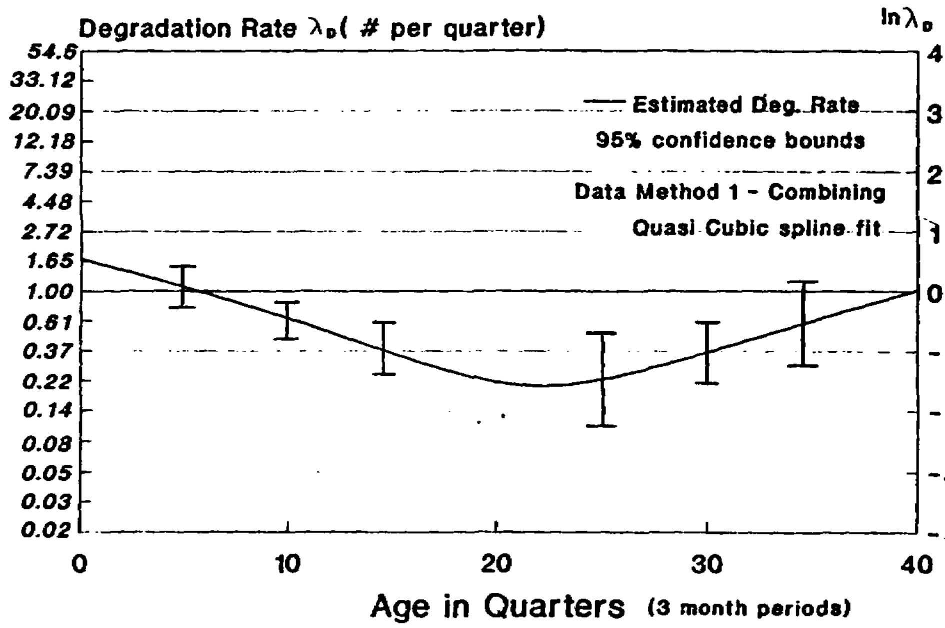

Figure 3. Age dependent degradation rate for RHR pumps
(3 plant data)

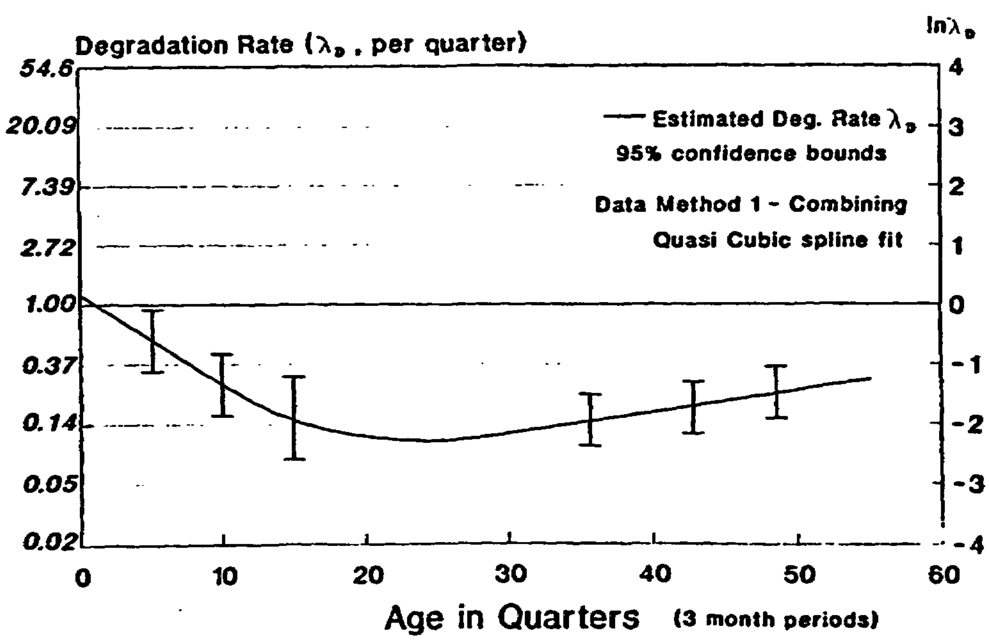

Figure 4. Age dependent degradation rate for SW pumps
(7 plant data)

1. identification of age-groups where statistically significant time trends exist, and
2. determination of aging-failure rates where time trends exist, and estimation of time-independent failure rate where time-trends cannot be established.

Again we discuss the results and the characteristics observed in the aging failure rate and give details of the analysis in the appendices. Appendices C and D present the detailed results for the RHR pumps and Appendix E describes SW pump study. Figure 5 gives the logarithm of the age-dependent failure for RHR pumps. The data base used covered the same components as for the degradation rate. The statistical tests justifying the use of data across twelve RHR pumps were the same, but the sparsity of data on aging failure required a slightly different analysis.

The aging-failure data for the RHR pumps show only a few failures during the later five years of the components (age 5–10 years) and, in general, the number of failures was small. The statistical trend testing, based on both data combining and pooling, showed a decreasing trend in the early life, but no trend in aging-failure could be established in the later five years. Because of the sparsity of the data, isotonic regression analysis was used to estimate failure rate for the first five years of RHR pumps where decreasing trend was observed. For the later five years, due to a lack of any trends, a constant, time-independent, failure rate was estimated.

The following observations can be made from the aging-failure rate obtained for the RHR pumps:

1. The aging-failure rate shows decreasing trend in the first five years, but a constant failure rate can only be estimated for later five years of the overall ten years. In other words, there was no trend of increasing failure with age for the ten-year operating period of the RHR pumps.
2. The aging failure rate shows a behavior similar to the degradation rate in the early five years, but differs after that. The aging-failure rate was significantly lower than the degradation rate and the difference increased with increasing age. The degradation rate was about a factor of 30 higher than the aging failure rate at the end of 10 years.
3. The 95% confidence bounds associated with aging-failure rate show higher uncertainty compared to the degradation rate, due to the few observations of failures.

Figure 6 gives the logarithm of the failure rate for SW pumps. For the SW pumps, only a few failure data points were available for analysis. The sparsity of this data base is partly attributable to the data source which is considered incomplete for the early life of the components. Appendix B discusses the SW pump data evaluation and the associated limitations.

The available SW pump data were not adequate to detect any statistical trend with confidence. Accordingly, no aging effect of the SW pump failures is established: a constant failure for the study period (approximately 12 yrs.) is estimated.

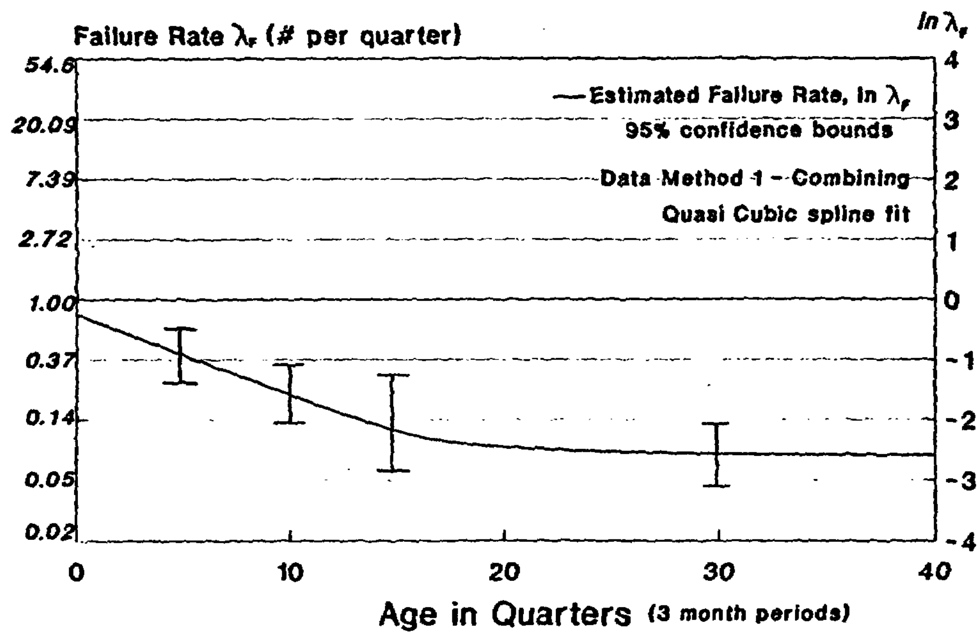

Figure 5. Age dependent failure rate for RHR pumps (3 plant data)

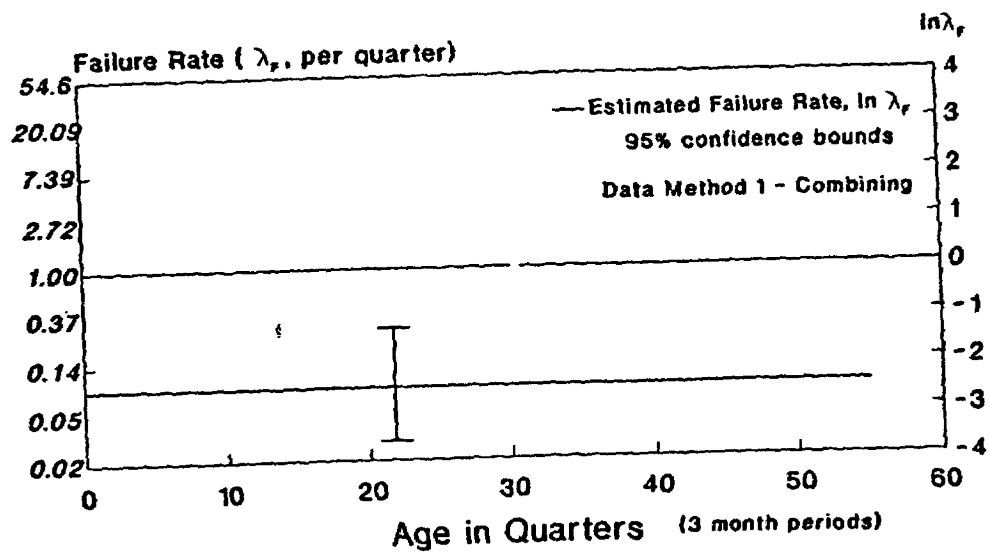

Figure 6. Age dependent failure rate for SW pumps (7 plant data)

5.4 Aging Evaluation Using Degradation and Aging-Failure Rate

The analysis of the degradation rate and the aging-failure rate provides a comprehensive picture of the aging process in the components studied (RHR and SW pumps) and provides interesting insights on component aging.

1. The use of information on degradation and failure not only increases significantly the information base for adequate analysis, but provides interpretations of the aging process that cannot be obtained by analyses of failure data alone. For both of these pumps, degradation data indicate aging whereas failure data are yet to indicate aging trends.

2. The aging trend in the degradation during the later 5 to 10 year period shows a significant effect on component degradation as the RHR pump ages, but a simultaneous lack of aging trend in the failure rate signifies that degradation has not been manifested in an increasing failure rate. Similarly, for the SW pumps, there is no aging effect on failures corresponding to the aging effect on degradations observed during the later seven years of operation. In the degradation modeling approach this finding signifies that maintenance is effective in preventing age-related failures, and that aging is represented through an increase in the degradation rate.

3. The relation between degradation and aging-failure rate in the first five years of the RHR pumps remained the same, i.e., both curves were similar and the degradation rate was steadily and consistently higher than the aging-failure rate. In the case of SW pumps, the degradation rate was consistently higher than the failure rate, but these rates show different behavior. However, failure data in the early life of SW pumps are considered incomplete.

4. The decreasing trend in the degradation rate for both pumps ends after the first five years, and the rates show differences with the corresponding failure rates, starting at this point.

5. Because there is more information on degradations, degradation rates are probably better indicators of aging than failure rates. Also, uncertainties in estimates of degradation rates are lower than those for aging-failure rates. Therefore, degradation rates can be effectively used to understand aging effects.

6. The relation between degradations and failures needs to be investigated further. The increase in degradation rate may be followed, after a time-lag, by an increased failure rate. The degradation rate, once it reaches a threshold value, may relate to failure. Investigation of these aspects through degradation modeling may suggest when maintenances or overhauls of components should be performed to prevent age-related increase in failure rates.

5.5 Evaluation of Maintenance Effectiveness

As discussed in Chapter 3, the degradation modeling approach provides an estimate of the effectiveness of maintenance in preventing age-related failures. The transition probability from a maintenance state to failure state signifies the ineffectiveness of maintenance in the simplified model studied. The complement of maintenance ineffectiveness is maintenance effectiveness.

For the RHR pumps, the maintenance effectiveness is obtained (Figure 7) for each 10 quarters of age. Effectiveness varies between 0.6 to 0.7 for the first 30 quarters, but significantly increases in the last 10 quarters. It is possible that effect of degradation on failures is delayed and data beyond 40 quarters might provide better estimates of maintenance effectiveness in the last ten quarters. The maintenance effectiveness for the SW pump (Figure 8) shows slightly different behavior. It declines in the early life and then shows increase in the later life. As discussed, the relationship among degradations, failures, and maintenances is complex but extremely useful for studying aging in repairable components. A better understanding of this parameter will allow estimation of aging-failure rate based on degradation rate estimates.

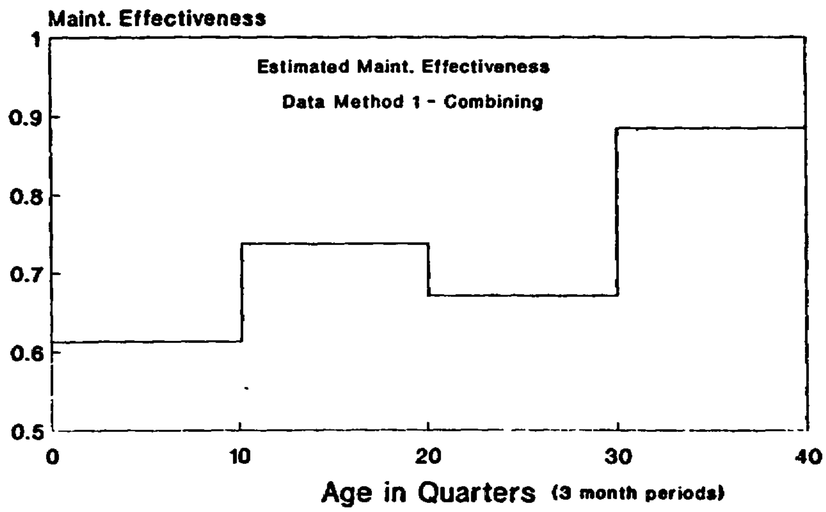

Figure 7. Maintenance effectiveness
(Component: RHR pumps; 3 plant data)

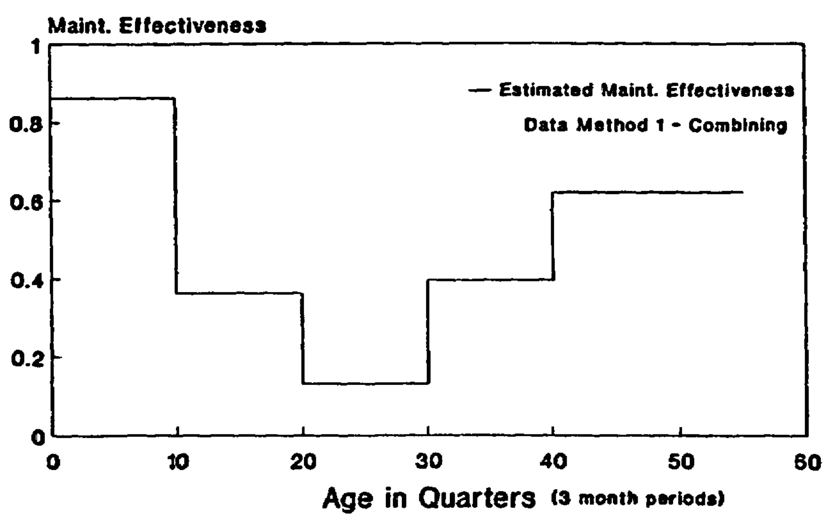

Figure 8. Maintenance effectiveness
(Component: SW pumps; 7 plant data)

6. SUMMARY AND INSIGHTS OF DEGRADATION MODELING ANALYSIS

The report presents the concept of the degradation modeling approach in an aging evaluation of the safety system components of nuclear power plants. The use of degradation modeling using information on component degradation was studied, along with the statistical approach to data analyses needed in such modeling. Applications to RHR pumps across three nuclear units and SW pumps across seven nuclear units were carried out to demonstrate the approach and the use of the modeling concept. In summary, we addressed the following aspects to derive insights on the component aging process:

1. use of degradation information to develop a degradation modeling approach for use in aging studies,
2. statistical approach to the analysis of information on degradation failure, and
3. aging and maintenance effectiveness evaluation using degradation information.

As discussed in the report, the degradation modeling approach can have broader applications in aging reliability studies. The simple models presented provide interesting insights that are summarized below; further developments and evaluations are necessary to develop this tool for understanding and modeling component aging.

1. <u>Benefit of using degradation information and degradation modeling</u>

Aging is manifested through degradation of components. As presented in this report, analysis of degradations provides an understanding of aging that cannot be obtained by studying age-related failures only. The other important aspect is that significantly more information is available on degradations compared to failures, that is, how current practices at plants are exhibited on component reliability and component reliability data bases. Degradation data enhance the data base for aging reliability and thus, the lack of data problem is reduced in this modeling approach.

2. <u>Statistical approach to analysis of aging data</u>

This report presents a statistical approach to analyzing aging data (degradation and failure data). Statistical tests are presented to demonstrate the similarity of component behavior so that data can be taken from a group of components. Statistical trend tests are presented to demonstrate the existence or lack of aging trends in the data before developing age-related rates using regression analyses. Using information on degradation and failure from twelve RHR pumps across three units, we demonstrated the statistical approach. A similar analysis is also presented for SW pumps. The uncertainty in the analysis also is controlled by using the statistical approach.

3. <u>Aging evaluation using degradation modeling approach</u>

In this report, RHR pump degradation and failure data were studied to understand the aging effect on the component. The result showed an aging effect on the rate of component degradation even though no aging effect on the aging failure rate could be established.

Similar results are also obtained for the SW pumps. The increase in the degradation rate may be indicative of future increases in the aging failure rate. We showed that component aging can be explained and demonstrated in a relatively short time studying degradations, whereas a much longer time is needed to demonstrate the aging effect through study of failure data.

4. Relations between degradations and failures

In degradation modeling, components are assumed to degrade in their path to age-related failures. This assumption is justified based on understanding of aging, but relations between degradations and failures are not yet known. Plant maintenances and operating practices clearly play a role. A large number of possibilities that define the relationship between degradations and failures exist, and deriving such relations will help define the required maintenance practices and help develop component reliability models for aging studies.

5. Evaluation of Maintenance Effectiveness

An important aspect of evaluating the aging process is to understand and characterize the role of maintenance performed on the component. A simple model was studied, based on degradation modeling approach, to obtain a parameter for maintenance effectiveness using age-dependent degradation and failure rates.

This parameter can define why component aging failure rates are being controlled. It can also define when maintenance is ineffective to control component aging. The relationship among degradations, failures, and maintenance effectiveness are thus elemental in explaining and modeling component aging reliability. The degradation modeling can further be developed to better model the role of maintenance in component aging.

6. Model for component aging reliability

The analysis presented demonstrates that information on component degradation can be used to express aging effects on components, and that statistical approaches can properly interpret this data. A component aging reliability model should be developed that incorporates this information and can take into account the effectiveness of maintenance in mitigating aging.

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APPENDIX A. MATHEMATICAL DEVELOPMENT OF DEGRADATION MODELING APPROACHES

A.1 Specific Degradation Models

Assume a component is being repaired and maintained. Assume, furthermore, that the component experiences both degradations and failures. We wish to derive relationships between the rate of degradation and the rate of failure for the component in a given environment and under a given test and maintenance program.

Degradation-Precedes-Failure Model

For one of the simplest models, we make the following assumptions:

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

We will call the state after a repair of a failure the "o-state." We will call the state after maintenance is performed the "m-state."

Equations for the Degradation and Failure Rates

Let

$$W_D(t) = \text{the degradation frequency at } t \tag{A-1}$$

$$W_F(t) = \text{the failure frequency at } t \tag{A-2}$$

Then under the above assumptions and assuming the component was operational at $t = 0$ we have the following balance equations for $W_D(t)$ and $W_F(t)$:

$$W_D(t) = f_{OD}(t, 0) + \int_0^t W_F(t')f_{OD}(t', t)\, dt' + \int_0^t W_D(t')f_{MD}(t', t)\, dt' \tag{A-3}$$

and,

$$W_F(t) = \int_0^t W_D(t')f_{DF}(t', t)\, dt' \tag{A-4}$$

where

$f_{OD}(t, 0)$ = probability density for a first degradation occurring at t given the component was restored to an operational state at t = 0

$f_{OD}(t', t)$ = probability density that a first degradation occurs at t given the component was restored to an operational state at t'

$f_{MD}(t', t)$ = probability density that a recurring degradation occurs at t with no intermediate failure given the component was maintained at t'

$f_{DF}(t', t)$ = probability density that a failure occurs at t with no intermediate observed degradation given the component was degraded and maintained at t'

We will call $f_{OD}(t', t)$, $f_{MD}(t', t)$, $f_{DF}(t', t)$ transition probability densities.

Function Forms for the Transition Probabilities

For general time-dependent and age-dependent modeling the transition probability densities are functions of both t' and t, or equivalently, are functions of t' and t − t'. For age-dependent evaluations, for example, t' is the age of the component and t − t' is the interval involved. For steady state modeling which we first address, the transition probability densities are functions only of the interval t − t'. We distinguish these cases below.

General Time Dependent and Age Dependent Functional Forms

$$f_{OD}(t', t) = f_{OD}(t', t - t') \quad \text{(A-9)}$$

$$f_{MD}(t', t) = f_{MD}(t', t - t') \quad \text{(A-10)}$$

$$f_{DF}(t', t) = f_{DF}(t', t - t') \quad \text{(A-11)}$$

Steady State Functional Forms

$$f_{OD}(t', t) = f_{OD}(t - t') \quad \text{(A-12)}$$

$$f_{MD}(t', t) = f_{MD}(t - t') \quad \text{(A-13)}$$

$$f_{DF}(t', t) = f_{DF}(t - t') \quad \text{(A-14)}$$

Steady State Failure and Degradation Equations

$$W_D(t) = f_{OD}(t) + \int_0^t W_F(x) f_{OD}(t - x)\, dx + \int_0^t W_D(x) f_{DF}(t - x)\, dx \quad \text{(A-15)}$$

$$W_F(t) = \int_0^t W_D(x) f_{DF}(t - x)\, dx \qquad \text{(A-16)}$$

Asymptotic Solutions

As $t \to \infty$ the asymptotic, steady state solutions for $W_D(t)$ and $W_F(t)$ are:

$$W_D = W_F P_{OD} + W_D P_{MD} \qquad \text{(A-17)}$$

$$W_F = W_D P_{DF} \qquad \text{(A-18)}$$

where,

$$P_{OD} = \lim_{t \to \infty} \int_0^t f_{OD}(t - x)\, dx = \int_0^\infty f_{OD}(x)\, dx \qquad \text{(A-19)}$$

$$P_{MD} = \lim_{t \to \infty} \int_0^t f_{MD}(t - x)\, dx = \int_0^\infty f_{MD}(x)\, dx \qquad \text{(A-20)}$$

$$P_{DF} = \lim_{t \to \infty} \int_0^t f_{DF}(t - x)\, dx = \int_0^\infty f_{DF}(x)\, dx \qquad \text{(A-21)}$$

The terms P_{OD} , P_{MD} , P_{DF} are corresponding transition probabilities:

P_{OD} = probability that a degradation occurs after the component is restored with no failure before a degradation (A-22)

= 1 under our assumption (A-23)

P_{MD} = probability that a degradation occurs after a maintenance before a failure occurs (A-24)

P_{DF} = probability that a failure occurs after a degradation and maintenance with no intermediate degradation (A-25)

Solving the Steady State Solutions .

The steady state balance equations are again

$$W_D = W_F P_{OD} + W_D P_{MD} \qquad \text{(A-26)}$$

$$W_F = W_D P_{DF} \qquad \text{(A-27)}$$

Under our model $P_{OD} = 1$ as indicated and hence,

$$W_D = W_F + W_D P_{MD} \tag{A-28}$$

$$W_F = W_D P_{DF} \tag{A-29}$$

From the above two equations we have,

$$\frac{W_D}{W_F} = 1 + \frac{W_D}{W_F} P_{MD} \tag{A-30}$$

$$\frac{W_D}{W_F} = 1 + \frac{P_{MD}}{P_{DF}} = \frac{P_{DF} + P_{MD}}{P_{DF}} = \frac{1}{P_{DF}} \tag{A-31}$$

$$\frac{P_{MD}}{P_{DF}} = \frac{W_D}{W_F} - 1 \tag{A-32}$$

$$\frac{P_{MD}}{P_{DF}} = \frac{W_D - W_F}{W_D} \tag{A-33}$$

<u>Interpreting the Steady State Relation</u>

The steady state solution is again:

$$\frac{W_D}{W_F} = \frac{1}{P_{DF}} \tag{A-34}$$

or

$$P_{DF} = \frac{W_F}{W_D} \tag{A-35}$$

Interpretations:

1. The larger the ratio 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 maintenance ineffectiveness 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 maintenance effectiveness is the failure frequency W_F itself which is equal to $W_D P_{DF}$.
5. The ratios W_F / W_D can be calculated for various components and failure modes. Statistical relationships involving W_F / W_D, component types, failure modes, and failure causes can be investigated.
6. The ratios W_F / W_D, or equivalently P_{DF}, can be used to predict W_F from knowledge of W_D under different scenarios, e.g. under aging scenarios.

Incorporation of Aging Effects

Assume aging occurs. At some threshold time (age t_0), the failure frequency W_F and degradation frequency begin to increase with age. Under what constraints will the same probabilities P_{DF} and P_{MD} which applied to the steady-state case also apply to the aging case? To answer this question consider again the general time dependent balance equations:

$$W_D(t) = f_{OD}(0, t) + \int_0^t W_F(x) f_{OD}(x, t - x)\, dx + \int_0^t W_D(x) f_{MD}(x, t - x)\, dx \tag{A-36}$$

$$W_F(t) = \int_0^t W_D(x) f_{DF}(x, t - x)\, dx \tag{A-37}$$

Translating the origin to t_0 gives:

$$W_D(t) = f_{OD}(t_0, t - t_0) + \int_{t_0}^t W_F(x) f_{OD}(x, t - x)\, dx + \int_{t_0}^t W_D(x) f_{MD}(x, t - x)\, dx \tag{A-38}$$

$$W_F(t) = \int_{t_0}^t W_D(x) f_{DF}(x, t - x)\, dx \tag{A-39}$$

Assume again the transition probabilities are only dependent upon the interval $t - x$, i.e.,

$$f_{OD}(t_0, t - t_0) = f_{OD}(t - t_0) \tag{A-40}$$

$$f_{MD}(x, t - x) = f_{MD}(t - x) \tag{A-41}$$

$$f_{OD}(x, t - x) = f_{OD}(t - x) \tag{A-42}$$

Then P_{DF} and P_{MD} will be the same as for the steady state case and the relations for $W_F(t)$ and $W_D(t)$ in the aging case are given by:

$$W_D(t) = f_{OD}(t - t_0) + \int_{t_0}^t W_F(x) f_{OD}(t - x)\, dx + \int_{t_0}^t W_D(x) f_{MD}(t - x)\, dx \tag{A-43}$$

$$W_F(t) = \int_{t_0}^{t} W_D(x) f_{DF}(t - x)\, dx \quad (A\text{-}44)$$

The last equation for $W_F(t)$ is the particularly relevant equation for predicting the failure frequency from the observed degradation frequency. If $W_D(x)$ was observed and $f_{DF}(t - x)$ were known, then $W_F(t)$ could be predicted from the above equation. Assuming the same $f_{DF}(t - x)$ as in steady-state behavior allows $f_{DF}(t - x)$ to be estimated from steady state data to apply to aging monitoring and prediction, we study models for the transition probability distributions.

Models for the Transition Probability Distributions

The simplest models for $f_{MD}(x)$, $f_{MF}(x)$, and $f_{OD}(x)$ involve assuming a constant rate of transferring from one state to another. Let:

λ_{MD} = the rate of a degradation occurring after a maintenance when (given) no previous degradation has occurred (A-45)

λ_{DF} = the rate of a failure occurring after a degradation when (given) no previous failure has occurred (A-46)

λ_{OD} = the rate of a degradation occurring after an operational restoration when (given) no previous degradation has occurred. (A-47)

Assume that λ_{MD}, λ_{DF}, and λ_{OD} are constant. Then $f_{MD}(x)$, $f_{MF}(x)$, and $f_{OD}(x)$ are given by:

$$f_{MD}(x) = \lambda_{MD} \exp(-\lambda_M x) = \frac{\lambda_{MD}}{\lambda_M} \lambda_M \exp(-\lambda_M x) \quad (A\text{-}48)$$

$$f_{DF}(x) = \lambda_{DF} \exp(-\lambda_M x) = \frac{\lambda_{DF}}{\lambda_M} \lambda_M \exp(-\lambda_M x) \quad (A\text{-}49)$$

and

$$f_{OD}(x) = \lambda_{OD} \exp(-\lambda_{OD} x) \quad (A\text{-}50)$$

where

$$\lambda_M = \lambda_{DF} + \lambda_{MD} \quad (A\text{-}51)$$

Estimation of the Transition Rates

The probability P_{DF} is given by:

$$P_{DF} = \int_0^{\infty} \lambda_{DF} \exp(-\lambda_M x)\, dx = \frac{\lambda_{DF}}{\lambda_M} \int_0^{\infty} \lambda_M \exp(-\lambda_M x)\, dx \tag{A-52}$$

or,

$$P_{DF} = \frac{\lambda_{DF}}{\lambda_M} \tag{A-53}$$

Therefore, the ratio λ_{DF} / λ_M can be estimated from the ratio W_F / W_D since $W_F = W_D P_{DF}$.

The degradation rate λ_{MD} also needs to be estimated. In general, λ_{MD} is age dependent even if we assume the ratio λ_{DF} / λ_M is constant. One scenario under which the ratio is the same but the transition rates can be age dependent is where the transition rates have the same time dependence:

$$\lambda_{DF} = k_{DF} g(t) \tag{A-54}$$

$$\lambda_{MD} = k_{MD} g(t) \tag{A-55}$$

where g(t) is a general time dependent or age-dependent function with possibly a threshold time t_0, i.e.

$$g(t) = \begin{cases} 1 & t < t_0 \\ h(t) & t > t_0 \end{cases}$$

In the above case the ratio of λ_{DF} / λ_M will not be time dependent or age dependent:

$$\frac{\lambda_{DF}}{\lambda_M} = \frac{k_{DF}}{k_{DF} + k_{MD}} \tag{A-56}$$

To estimate λ_{MD} in the age-dependent scenario, assume we observe times of degradations when the component is aging:

Times of degradations: $t_1, t_2, \ldots t_n$ (A-57)

Also, we may observe times of failures when the component is aging.

Times of failures: $u_1, \ldots, u_m$ (A-58)

We will not use the times of failure to estimate the transition rates since we may not have times of failures. When we have them, we can use them to check and refine the model.

Likelihood Estimation

Assume the times of degradation are measured with regard to the threshold time. Then the likelihood L for the times of degradation is:

$$L = \lambda_{MD}(t_1)\lambda_{MD}(t_2)...\lambda_{MD}(t_n)\ \exp\left(-\int_0^{t_{max}} \lambda_M(x)\ dx\right) \tag{A-59}$$

where,

$$\lambda_M(x) = \lambda_{MD}(x) + \lambda_{DF}(x) \tag{A-60}$$

and,

$t_{max} = t_n$, Time of last degrdation only measured. (A-61)

$t_{max} = t_{end}$, An observation time from t_n to t_{end} is also recorded where there are no further degradations. (A-62)

The above likelihood thus is a standard function which can be used to estimate parametric forms (e.g., Weibull or exponential) for $\lambda_{MD}(s)$ [and $\lambda_{DF}(s)$ using the determined ratio estimate k_{MF} / (k_{MF} + k_{MD})]. Thus we can predict the aging failure frequency using the balance equation for $W_F(t)$ and the steady state ratio k_{DF} / (k_{DF} + k_{MD}).

APPENDIX B. DATA BASE FOR AGING DEGRADATION AND FAILURE

B.1 Data Analysis

Data on degradation and aging failure were obtained for the analysis from the maintenance history of the components. The maintenance history includes activities (such as preventive and corrective maintenances, and testing) performed on the components from the day of its installation. Two sources of data were solicited: plant specific maintenance records and component reliability data base in Nuclear Plant Reliability Data System (NPRDS).

Data were collected for specific types of components where the maintenance history for each component was studied. We developed degradation and failure data bases for two types of components (residual heat removal (RHR) pumps, and service water (SW) pumps supplying cooling water to the RHR system). RHR pump data were obtained from plant maintenance records, whereas NPRDS (Ref. 5) was used for SW pump data. Both of these sources have individual component identification that is essential for obtaining the type of data desired for degradation modeling. The RHR pump data were taken from three BWR units, each consisting of four identical pumps. The SW pump data covered thirty-three BWR units in the NPRDS database, from twelve units experiencing 10 or more failures in each of six or more SW pumps.

B.2 Data Classification

Each record of maintenance or reported failure was classified into three categories, as defined in Table B.1. Plant-specific data, taken from the maintenance log, contain all three kinds of data, whereas the NPRDS covered mostly D and F type information. For this study, the N type of information is not used in the model, and hence, were not collected in this data analysis. However, this information will be useful later in judging the current preventive maintenance practices which can improve the maintenance effectiveness in a component.

Although these categories are not directly correlated with the severity levels (incipient, degraded, catastrophic) defined in NPRDS, comparing with NPRDS categorization it can be

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

Category	Description
N	Activities such as routine checks, inspections and testing that indicated no sign of degradation in the component. No particular maintenance was performed.
D	Activities indicating definite degradation in the component subassemblies. Maintenance was performed to ameliorate the degraded condition of the components.
F	Activities indicating degradation in the component such that it required immediate maintenance to be able to perform its design function.

noted that most incipient type failure data in NPRDS were categorized as type 'D' and some degraded data were judged type 'F' for this analysis. All of the catastrophic data were judged to be of 'F' category. Therefore, each record (identified in plant-specific maintenance history or NPRDS) was judged for relevance to age-related degradations and failures, and then was placed into one of the three categories.

Table B.2 lists the maintenance records for one RHR pump taken from a plant maintenance work request (MWR) or work authorization (WA) log list, and demonstrates the categorization of each of the items according to the scheme defined in Table B.1. The description of each of the records was used to classify the record in one of the three categories, as shown in, the last column (N, D, or F). The data for the SW pumps were taken from the NPRDS and are shown in Table B.3. Again, the last column of this figure indicates the classification of each record. We note that this categorization is at variance with the severity classification (catastrophic, degraded, and incipient) used in NPRDS. The reason is that NPRDS is not directed at aging evaluations, whereas this data analysis focussed on identifying age-related degradations and failures.

Table B.2. Maintenance Log for an RHR Pump at a BWR Unit

WA #	EQUIP. #	DESCRIPTION (ACTION TAKEN)	IDENT. DATE	FAILURE CLASS.
P21906	1P202B	ANNL PM-RHR PMP MOTOR INSPECTION OIL SAMPLES TAKEN/NO LEAKS FOUND	12/15/82	N
S24999	1P202B	INST VIB PICKUP MOUNT LOCATIONS FOR VIBRO PACK PICK UP ON RHR CANCELLED—NO WORK WILL BE PERFORMED UNDER THIS WA	7/08/82	N
U24318	1P202B	REBUILD MECH SEAL THAT WAS REMOVED FROM PUMP REBUILT SEAL, NEW "O" RINGS & SEAL FACES RETURNED TO STORES	3/16/82	D
P30491	1P202B	ANNL PM-RHR PMP SEAL HT XR CLEANED, INSPECTED, REPLACED GASKETS, REASSEMBLED, TORQUED TO 30 FT/LBS. CLEANED AND INSPECTED HELIFLOW COOLET AS PER IOM 155.	3/17/83	D
P31444	1P202B	EQ QL-RHR PUMP MOTORS REMOVED OIL SAMPLES FROM UPPER & LOWER BEARINGS. OK IS IN THE CHEM LAB. OIL LEVELS WERE AT THE PROPER LEVEL. SCREENS ON MOTOR WERE CLEAN. SPACE HEATERS OK.	9/08/83	N
P40859	1P202B	ANNL PM-RHR PMP SEAL HT XR A NEW SEAL WATER COOLER WAS INSTALLED UNDER WA #C44042 PMR 84-3014 DURING THE UNIT 1/UNIT 2 TIE IN OUTAGE. INSPECTION IS NOT NECESSARY AT THIS TIME.	4/18/84	F

N — No Degradation/Failure D — Degradation F — Failure

Table B.3. NPRDS Reported Data on SW Pumps

FAILURE START DATE	FAILURE END DATE	UNIT ID	UTILITY COMPONENT ID	FAILURE NARRATIVES	IN-SERV DATE (COMP)	FAILURE CLASS.
04/12/82	05/30/82	GPCEIH1	P41-C001A	PLANT SERVICE WATER PUMP FAILED TO MEET REQUIREMENTS OF ASME SECTION 11 IWP3000. THE CODE'S INTENT IS TO TRACK PUMP PERFORMANCE AND TO ASSURE THE PUMP PERFORMS PROPERLY. THE CAUSE OF THE FAILURE WAS DUE TO NORMAL WEAR AND NATURAL END OF LIFE. THE PUMP WAS REBUILT AND SATISFACTORILY TESTED AND RETURNED TO SERVICE.	12/31/75	F
04/02/84	04/25/84	GPCEIH1	P41-C001A	DURING PLANT OPERATION, OPERATIONS PERSONNEL DETERMINED THAT THE PLANT SERVICE WATER PUMP'S SHAFT SEAL WAS LEAKING EXCESSIVELY. REF MR 1-84-1885 FAILURE WAS CAUSED BY WEAR AND ABRASIVE WATER. THE PUMP'S SHAFT SEAL WAS REPLACED WITH A NEW ONE. THE PUMP SEAL WAS THEN SATISFACTORILY TESTED.	12/31/75	F
06/02/85	10/02/85	GPCEIH1	P41-C001A	WHILE OPERATING AT RATED POWER, OPERATIONS PERSONNEL DETERMINED THAT PLANT SERVICE WATER PUMP "A" WAS OPERATING AT A DECREASED FLOW AND PRESSURE. THERE WAS NO EFFECT ON THE PLANT. (REF MWO'S 18503078, A8504604, 18503227 AND DCR 84-59) THE CAUSE WAS ATTRIBUTED TO EROSION OF THE PUMP INTERNALS (NORMAL WEAR), CAUSING LEAKAGE PAST THE IMPELLER TO THE SUCTION SIDE OF THE PUMP. THIS WAS A CARBON STEEL PUMP. THE INTERNALS, DISCHARGE CASE AND SUCTION BELL OF THE PUMP WERE REPLACED WITH STAINLESS STEEL PARTS PER DESIGN CHANGE. THE PUMP WAS OPERATIONALLY CHECKED AND PERFORMED AS EXPECTED.	12/31/75	D
05/11/87	06/18/87	GPCEIH1	P41-C001A	DURING A PLANT REFUELING OUTAGE, OPERATIONS PERSONNEL LOCATED A SMALL LEAK ON THE A PLANT SERVICE WATER PUMP COUPLING. THIS DID NOT CAUSE ANY CHANGES IN PLANT PARAMETERS. REF: MWO 1-87-03880. THE CAUSE OF THE LEAK WAS FOUND TO BE A HOLE IN THE COUPLING COOLING WATER LINE. THIS WAS ATTRIBUTED TO NORMAL/CYCLIC WEAR. THE COOLING COIL WAS REMOVED AND REPAIRED. AFTER TESTING IT WAS REPLACED AND THE PUMP WAS RETURNED TO SERVICE.	12/31/75	D

D — Degradation F — Failure

For each component, a time-line plot was generated indicating the age of the component and times of degradations and failures based on maintenance data for the life of the component. Figure B.1 shows an example of such a plot. The in-service date for the component is considered the beginning of life for the component. Following replacement or overhaul, components were treated as new, i.e., as if the component was at the beginning of life.

The age of the component was calculated by the difference between the component in-service date (or overhaul date) and the problem identification date for maintenance. The age was expressed in quarter years. All maintenance records (types N, D, and F) for each component were plotted in a time-line fashion to recognize any patterns in the records (Figure B.1).

Data for Statistical Analysis

Two types of data, time to degradation (TTD) and time to failure (TTF), were developed for each component from the time-line plots. The TTD was used to obtain the degradation rate, while the TTF was used to obtain the failure rate of the component.

Both F- and D-type records were used to calculate TTD. In estimating the TTF, only F-type records were used. Both these parameters (TTD and TTF) are obtained as a function of component age from the maintenance records categorized as D or F. Continuity in the maintenance records was important to obtain this data.

Data Source Limitations

It was difficult to obtain complete maintenance records of aged components. Specifically, recently built plants have computerized lists of their maintenance activities and, thus, provide all three record categories (i.e., N, D, and F types). But they cover only the early years of a component's life. On the other hand, older plants did not have such a system at an

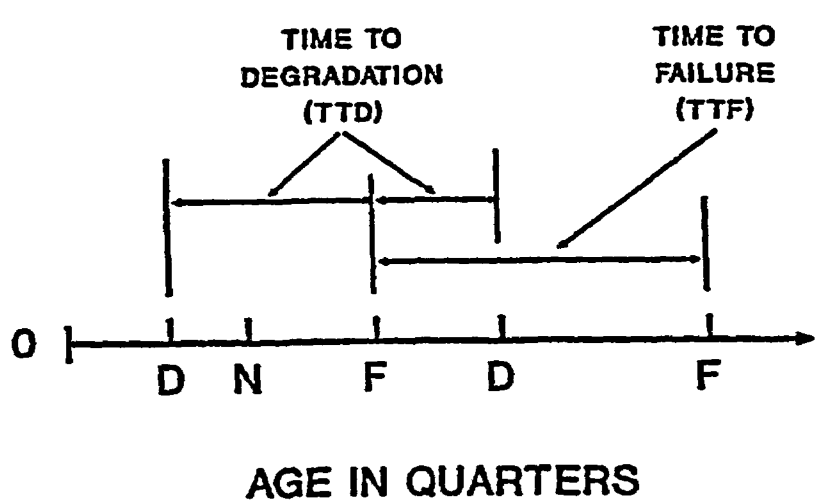

Figure B.1. Example of time-line of plot of degradation (D) and failure (F) times early age, so that information relating to their early life was not readily available in a form needed for this analysis. However, after the plant adopted a computerized system, the data were as complete as the new plants.

The data obtained from NPRDS are not as complete as those obtained from plant-specific maintenance records. Since utilities are not required to report all maintenance activities to NRPDS, only some maintenance of the component are obtained. Furthermore, data over the entire operating life are not always available in the data base.

RHR Pump Aging Data

Aging data on RHR pumps are obtained by analyzing plant maintenance records for three units. Since the units are of different age, data for RHR pumps in each covered different periods: 34 quarters for Unit 1, 25 quarters for Unit 2, and 50 quarters for Unit 3 (Table B.4). This table contains the observed dates both for degradations and failures. Table B.5 presents the failure data where only the observed failure times are recorded. As these tables show, significantly larger information on component aging is obtained by focussing on degradation data.

SW Pump Aging Data

Aging data on SW pumps supplying water to the RHR system were obtained from the NPRDS data base. The data gathered from twelve plant units were tested statistically for their compatability. Only seven units are found to have compatible data, and accordingly data from these plants were used in the analysis. Since each unit has three or more SW pumps, data from a total of forty three SW pumps form the data base for this evaluation. Table B.6 lists the pump data, except those relating to the pump seals.

A large number of data for the SW pump was related to degradation or failure of pump seals. Since these pumps use cooling water from an external source (e.g., sea, river, or pond), seal degradation/failures are in many cases attributed to intrusion of sands, sea weeds, and other external materials. These seal failures are not attributable to normal aging of the seals and hence, were excluded from this study.

In many cases, the data on a SW pump covered a brief period of the component operating life. This sparse data for a pump can create difficulty in calculating the time to degradation (TD) and the time to failure (TTF). Since the available data period did not necessarily cover the beginning of life of the component, the first failure/degradation occurrence was used to obtain TTD or TTF. Thus two data points are required to calculate one TTF data (see Figure B.1). This difficulty resulted in a small data set for SW pump failure analysis. Therefore, Table B.7 which lists the failure data contains only five data points while Table B.6 has identified a number of data points categorized as type 'F'.

Because of these difficulties, the NPRDS data source is found to be less useful compared to the maintenance records from a plant. Furthermore, the NPRDS data base for a component appears incomplete in comparison to plant maintenance records. In conducting degradation modeling analysis, a complete data of all detected degradations and failures are required which necessitate use of plant data bases that contain information collected during all test and maintenance of the component.

Table B.4. RHR Pump Aging Data: Degradation and Failure Times
(3 Nuclear Units; 4 Pumps Per Unit)

Time of Detection Mo	Dy	Yr	Plt	Comp	Svty	Time to Degradation (Tij)	Age (Ti)	1 / Tij (Yi)
5	1	80	1	a	D	1.33	1.33	0.750
1	15	81	1	a	D	2.88	4.21	0.347
3	16	82	1	a	D	4.73	8.94	0.211
10	28	82	1	a	D	2.47	11.41	0.405
9	8	83	1	a	D	3.50	14.91	0.286
2	17	84	1	a	D	1.82	16.73	0.549
7	1	84	1	a	D	1.49	18.22	0.672
7	26	85	1	a	D	4.33	22.56	0.231
5	12	80	1	b	D	1.46	1.46	0.687
1	15	81	1	b	D	2.76	4.21	0.363
3	16	82	1	b	D	4.73	8.94	0.211
10	28	82	1	b	D	2.47	11.41	0.405
3	17	83	1	b	D	1.60	13.01	0.625
4	18	84	1	b	F	4.40	17.41	0.227
7	26	85	1	b	D	5.14	22.56	0.194
3	10	86	1	b	D	2.54	25.10	0.393
1	9	87	1	b	F	3.38	28.48	0.296
5	10	88	1	b	D	5.40	33.88	0.185
6	7	80	1	c	D	1.73	1.73	0.577
1	15	82	1	c	F	6.53	8.27	0.153
3	16	82	1	c	D	0.68	8.94	1.475
10	28	82	1	c	D	2.47	11.41	0.405
9	8	83	1	c	D	3.50	14.91	0.286
6	8	84	1	c	D	3.06	17.97	0.327
8	7	84	1	c	D	0.66	18.62	1.525
7	26	85	1	c	D	3.93	22.56	0.254
2	2	87	1	c	D	6.18	28.73	0.162
4	25	80	1	d	D	1.27	1.27	0.789
5	12	80	1	d	D	0.19	1.46	5.294
3	16	82	1	d	D	7.49	8.94	0.134
10	28	82	1	d	D	2.47	11.41	0.405
12	15	82	1	d	D	0.52	11.93	1.915
3	17	83	1	d	D	1.08	13.01	0.928
4	18	84	1	d	F	4.40	17.41	0.227
5	5	84	1	d	D	0.19	17.60	5.294
6	29	84	1	d	D	0.60	18.20	1.667
7	26	85	1	d	D	4.36	22.56	0.230
7	28	86	1	d	D	4.08	26.63	0.245
1	4	83	2	a	D	0.03	0.03	30.000
8	25	83	2	a	F	2.57	2.60	0.390
11	8	83	2	a	D	0.81	3.41	1.233
2	2	84	2	a	D	0.99	4.40	1.011

Tij — Time intervals of observed events
Ti — Age at which an event is observed
Yi — Reciprocal of Tij

Table B.4. RHR Pump Aging Data: Degradation and Failure Times (3 Nuclear Units; 4 Pumps Per Unit)—Cont'd.

Time of Detection Mo	Dy	Yr	Plt	Comp	Svty	Time to Degradation (Tij)	Age (Ti)	1 / Tij (Yi)
8	7	84	2	a	F	2.06	6.46	0.486
5	8	85	2	a	F	3.07	9.52	0.326
1	16	86	2	a	D	2.81	12.33	0.356
4	19	88	2	a	F	9.14	21.48	0.109
1	4	83	2	b	D	0.03	0.03	30.000
7	28	83	2	b	D	2.27	2.30	0.441
11	8	83	2	b	D	1.11	3.41	0.900
6	19	84	2	b	F	2.51	5.92	0.398
8	2	84	2	b	F	0.48	6.40	2.093
1	30	86	2	b	D	6.09	12.49	0.164
2	11	86	2	b	D	0.12	12.61	8.182
3	24	87	2	b	D	4.53	17.14	0.221
12	17	87	2	b	D	2.92	20.07	0.342
2	4	88	2	b	D	0.58	20.64	1.731
1	4	83	2	c	D	0.03	0.03	30.000
2	1	83	2	c	D	0.30	0.33	3.333
3	4	83	2	c	D	0.37	0.70	2.727
5	25	83	2	c	D	0.90	1.60	1.111
9	27	83	2	c	D	1.36	2.96	0.738
2	16	84	2	c	D	1.60	4.56	0.625
5	16	84	2	c	D	1.00	5.56	1.000
8	15	84	2	c	F	0.99	6.54	1.011
3	7	85	2	c	D	2.30	8.84	0.435
2	3	89	2	c	F	15.84	24.69	0.063
1	4	83	2	d	D	0.03	0.03	30.000
1	11	83	2	d	D	0.08	0.11	12.857
4	12	83	2	d	D	1.01	1.12	0.989
3	5	84	2	d	F	3.64	4.77	0.274
8	2	84	2	d	D	1.63	6.40	0.612
8	15	84	2	d	F	0.14	6.54	6.923
9	20	84	2	d	F	0.39	6.93	2.571
3	7	85	2	d	D	1.91	8.84	0.523
12	17	87	2	d	D	11.22	20.07	0.089
8	1	74	3	a	D	1.00	1.00	1.000
12	5	74	3	a	F	1.38	2.38	0.726
12	15	75	3	a	D	4.17	6.54	0.240
9	20	76	3	a	D	3.11	9.66	0.321
11	21	76	3	a	D	0.68	10.33	1.475
12	26	76	3	a	D	0.39	10.72	2.571
1	16	79	3	a	D	8.39	19.11	0.119
3	16	82	3	a	D	12.83	31.94	0.078
6	3	82	3	a	D	0.86	32.80	1.169

Tij — Time intervals of observed events
Ti — Age at which an event is observed
Yi — Reciprocal of Tij

Table B.4. RHR Pump Aging Data: Degradation and Failure Times (3 Nuclear Units; 4 Pumps Per Unit)—Cont'd.

Time of Detection Mo	Dy	Yr	Plt	Comp	Svty	Time to Degradation (Tij)	Age (Ti)	1 / Tij (Yi)
10	23	82	3	a	D	1.56	34.36	0.643
2	25	83	3	a	D	1.41	35.77	0.709
3	3	85	3	a	D	8.20	43.97	0.122
7	1	86	3	a	D	5.37	49.33	0.186
4	23	75	3	b	F	3.97	3.97	0.252
12	18	78	3	b	D	14.78	18.74	0.068
3	10	82	3	b	D	13.13	31.88	0.076
4	4	82	3	b	D	0.27	32.14	3.750
5	1	82	3	b	D	0.30	32.44	3.333
6	8	82	3	b	D	0.41	32.86	2.432
8	1	82	3	b	D	0.59	33.44	1.698
10	23	82	3	b	D	0.91	34.36	1.098
2	9	83	3	b	D	1.23	35.59	0.811
3	1	85	3	b	D	8.36	43.94	0.120
4	23	82	3	c	D	32.36	32.36	0.031
10	23	83	3	c	D	6.06	38.41	0.165
3	1	85	3	c	D	5.53	43.94	0.181
9	14	74	3	d	F	1.48	1.48	0.677
3	18	76	3	d	D	6.16	7.63	0.162
11	4	76	3	d	D	2.51	10.14	0.398
5	1	82	3	d	D	22.30	32.44	0.045
10	23	82	3	d	D	1.91	34.36	0.523
12	1	82	3	d	D	0.42	34.78	2.368
1	1	83	3	d	D	0.39	35.17	2.571
1	1	84	3	d	D	4.06	39.22	0.247
3	1	85	3	d	D	4.72	43.94	0.212

Tij — Time intervals of observed events
Ti — Age at which an event is observed
Yi — Reciprocal of Tij

Table B.5. RHR Pump Aging Failure Data (3 Nuclear Units; 4 Pumps Per Unit)

Plt	Compt	FTij	FTi	FYi
1	2	17.41	17.41	0.057
1	2	11.07	28.48	0.090
1	3	8.27	8.27	0.121
1	4	17.41	17.41	0.057
2	1	2.6	2.6	0.385
2	1	3.86	6.46	0.259
2	1	3.07	9.52	0.326
2	1	11.96	21.48	0.084
2	2	5.92	5.92	0.169
2	2	0.48	6.4	2.083
2	3	6.54	6.54	0.153
2	3	18.15	24.69	0.055
2	4	4.77	4.77	0.210
2	4	1.77	6.54	0.565
2	4	0.39	6.93	2.564
3	1	2.38	2.38	0.420
3	2	3.97	3.97	0.252
3	4	1.48	1.48	0.676

FTij — Time intervals between observed failures
FTi — Age at which an event (failure) is observed
FYi — Reciprocal of FTij

Table B.6. SW Pump Aging Data: Degradation Times
(7 Nuclear Units)

Time of Detection Mo	Dy	Yr	Plt	Comp	Svty	Dscp	Time to Degradation (Tij)	Age (Ti)	1 / Tij (Yi)
3	7	74	4	d	d	pump	0.18	0.18	5.625
3	7	74	4	a	f	pump	0.18	0.18	5.625
8	14	86	5	g	f	drain	0.37	0.37	2.727
1	12	84	3	c	f	pump	0.51	0.51	1.957
7	10	74	4	c	d	impel	1.54	1.54	0.647
7	10	74	4	a	d	impel	1.37	1.54	0.732
7	10	74	4	d	d	impel	1.37	1.54	0.732
12	4	86	5	g	f	gasket	1.22	1.59	0.818
3	8	80	7	d	d	pump	2.09	2.09	0.479
3	15	86	7	b	f	impel	2.42	2.42	0.413
7	17	86	7	b	d	pump	1.36	3.78	0.738
5	15	86	5	a	d	impel	0.80	4.01	1.250
11	22	83	5	h	d	cooler	5.79	5.79	0.173
5	11	81	7	a	f	pump	6.84	6.84	0.146
10	22	85	2	b	f	supp	7.68	7.68	0.130
6	14	87	11	i	d	brgs	7.82	7.82	0.128
2	25	76	4	g	f	brgs	8.16	8.16	0.123
12	13	85	3	c	d	flange	1.08	8.24	0.928
3	3	86	3	c	d	brgs	0.94	9.19	1.059
5	15	86	3	d	f	brgs	9.99	9.99	0.100
5	23	86	3	e	d	lube	10.08	10.08	0.099
3	14	82	7	c	d	pump	10.27	10.27	0.097
8	8	86	2	d	d	sep	10.91	10.91	0.092
5	12	82	7	d	d	pump	8.82	10.91	0.113
3	3	85	5	c	d	pump	11.02	11.02	0.091
10	28	86	2	c	d	motor	2.17	11.80	0.462
6	3	85	5	d	f	valve	0.41	12.02	2.432
4	17	86	5	b	f	brgs	15.57	15.57	0.064
7	24	78	4	h	f	brgs	17.92	17.92	0.056
12	18	86	5	b	d	pipe	2.68	18.24	0.373
6	11	87	5	c	d	pump	8.30	20.22	0.120
8	6	85	7	d	d	brgs	13.10	24.01	0.076
10	16	80	4	c	f	pump	12.80	26.94	0.078
5	31	86	7	a	f	pump	4.18	27.34	0.239
6	22	86	7	c	f	diffu	17.31	27.58	0.058
1	1	87	7	g	d	brgs	5.56	29.73	0.180
5	12	87	7	c	f	pump	3.61	31.19	0.277

Tij — Time intervals of observed events
Ti — Age at which an event is observed
Yi — Reciprocal of Tij
impel — impeller
brgs — bearings
supp — support (hangers, snubbers)
sep — separator
diff — diffuser
lube — lube oil
p-m — pump-motor

Table B.6. SW Pump Aging Data: Degradation Times (7 Nuclear Units)—Cont'd.

Time of Detection Mo	Dy	Yr	Plt	Comp	Svty	Dscp	Time to Degradation (Tij)	Age (Ti)	1 / Tij (Yi)
3	25	88	7	d	d	brgs	10.71	34.72	0.093
6	2	85	6	a	f	pump	4.72	38.23	0.212
6	25	82	11	h	d	p-m	0.04	43.48	22.500
4	4	88	2	a	d	pump	10.17	44.79	0.098
5	11	87	6	a	d	cooler	7.88	46.11	0.127
8	27	85	4	e	d	drain	11.99	46.68	0.083
8	28	87	6	o	f	brgs	10.66	47.30	0.094
11	14	85	4	b	d	pump	4.66	47.53	0.215
7	30	86	4	b	d	pump	2.90	50.43	0.345
7	1	88	b	c	d	pipe	3.42	50.72	0.292
1	18	87	4	b	d	pump	1.92	52.36	0.520
6	10	87	4	b	d	drain	1.58	53.93	0.634
6	17	85	11	d	d	vent	12.69	55.56	0.079
10	5	85	11	f	d	pump	14.06	56.76	0.071

Tij — Time intervals of observed events
Ti — Age at which an event is observed
Yi — Reciprocal of Tij
impel — impeller
brgs — bearings
supp — support (hangers, snubbers)
sep — separator
diff — diffuser
lube — lube oil
p-m — pump-motor

Table B.7. SW Pump Aging Failure Data Times (7 Plants)

row	Mo	Dy	Yr	Plt	Comp	Svty	Dscp	FTij	FTi	FYi
1	12	4	86	5	g	f	gasket	1.222	1.59	0.819
2	6	3	85	5	d	f	valve	12.020	12.02	0.083
3	5	31	86	7	a	f	pump	20.500	27.34	0.048
4	5	12	87	7	c	f	pump	20.920	31.19	0.047
5	6	2	85	6	a	f	pump	38.230	38.23	0.026

FTij — Time intervals between observed failures
FTi — Age at which an event (failure) is observed
FYi — Reciprocal of FTij

APPENDIX C. STATISTICAL TESTS ANALYSES FOR DATA FROM DIFFERENT RHR PUMPS IN DEGRADATION AND FAILURE RATE

This appendix summarizes the statistical tests performed on degradation and failure data of the RHR pumps. The specific statistical tests and their purposes are as follows:

1. Tests to identify the similarity of degradation and failure of RHR pumps within a nuclear unit
   a. Mann–Whitney (M–W) U Test
   b. Kruskal–Wallis (K–W) Signed Rank Test
2. Test to identify the similarity of degradation and failure behavior across nuclear units
   a. Mann–Whitney (M–W) U Test
   b. Kruskal–Wallis (K–W) Signed Rank Test
3. Test to identify periods where there are significant time trends in degradations and failures
   a. Mann's Rank Test.

In the following, we briefly explain the tests performed and the results obtained. Only representative results are presented; similar results are obtained in other cases as indicated in the text.

C.1 Mann–Whitney U Tests for RHR Pumps Within Each Nuclear Unit

The Mann–Whitney U Test is conducted, based on the degradation data set, to see if the times between degradation T_{ij} (or equivalently $1 / T_{ij}$) in each of the 4 pumps are identically distributed within each of the 3 plants. The Mann–Whitney procedure is designed for tests of two independent samples; it is a variation of the Wilcox rank-sum procedure, and the computational form of its statistic U uses the rank sum. The test combines and ranks the data from two samples; these ranks are then summed over all observations in each sample and the statistic U_i is calculated as follows to compare the average ranks:

$$U_1 = n_1 n_2 + \frac{n_1(n_1 + 1)}{2} - T_1$$

$$U_2 = n_1 n_2 + \frac{n_2(n_2 + 1)}{2} - T_2$$

where T_i = sum of ranks associated with X_i values ($i = 1, 2$), and

n_i = sample size of X_i .

In our degradation data sets most samples have more than 10 observations, therefore, a normal approximation of test statistic Z is used in the test.

$$Z = \frac{U - \mu_u}{\sigma_u}$$

where,

$$\mu_u = \frac{\prod_i n_i}{2}, \quad \text{and} \quad \sigma_u^2 = \frac{(\sum n_i) + 1}{12} \prod_i n_i$$

The main assumptions of the Mann–Whitney Test are satisfied in our data, that is:

a. the samples are independent, and

b. the populations are identical except for possible differences in location.

However, in reality the Mann–Whitney Test enables us to identify any differences in the underlying distributions although it is particularly sensitive to differences in location (in terms of medians or means). Therefore, it is a strong statistical test to identify whether components belong to the same population.

The Mann–Whitney Test for each pair in each of the three plants did not reject the null hypothesis of identical samples (based on comparison of average ranks and significance level of 0.05). Table C.1 presents the results for the pumps in one of the plants; similar results are obtained for all three plants. Null hypothesis of identical samples was not rejected in any of the cases. Accordingly, the degradation behavior of the four RHR pumps belonged to the same population in each of the plants.

Table C.1. M–W Test Results for RHR Pumps in Plant 1

Comparison of Samples	Average Rank of 1st Sample	# of Values of 1st Sample	Average Rank of 2nd Sample	# of Values of 2nd Sample	Total Observ.	Test Statistic Z	p Value
Compt 1-Compt 2	10.75	8	8.5	10	18	−0.845	0.398
Compt 1-Compt 3	9.25	8	8.77	9	17	−0.145	0.885
Compt 1-Compt 4	8.44	8	11.14	11	19	0.992	0.321
Compt 2-Compt 3	9.65	10	10.39	9	19	0.245	0.806
Compt 2-Compt 4	8.6	10	13.18	11	21	1.656	0.098
Compt 3-Compt 4	9.16	9	11.59	11	20	0.874	0.382

C.2 Kruskal–Wallis (K–W) Signed Rank Test

K–W Signed Rank Test is similar to Mann–Whitney Test and is applied as a multiple comparison test to identify any abnormal component(s) in each of the plants. As with the M–W U Test, the K–W Test is a test of identical distribution and is particularly sensitive to location differences. The K–W Test is an extension of the M–W Test to cover situations involving multiple independent random samples. Thus, it provides an alternative distribution free test among all the components for each of the plants to identify any possible abnormal components.

Table C.2 shows test results for Plant 1. Similar results are obtained for the other two plants. The K–W Test results, showing a significance level greater than 0.05, justify results from Mann–Whitney Tests in Section C.1, i.e., the hypothesis that RHR pumps in each of the plants belong to the same population cannot be rejected.

C.3 Mann–Whitney U Test for RHR Pump Degradation Data Across Plants

The Mann–Whitney U Test is used to identify the similarity of RHR pump degradation across plants. Here, the purpose is to identify groups of plants where data can be combined to increase the sample size.

The test was performed, based on data pooled (referred to as Method 2 in Chapter 5.0) across 4 RHR pumps in each of the plants (Table C.3). Again, a null hypothesis of identical samples for each pair of plant's degradation data comparing medians based on average ranks of each plant is not rejected. This justified increasing the data base by using data across three plants.

Table C.2. K–W Test for Plant 1: Kruskal–Wallis Analysis of 4 RHR Pump Degradation Data

Pump	Sample Size	Average Rank
1	8	19.4375
2	10	15.7500
3	9	18.3333
4	11	23.9091

Test statistic = 2.97417   Significance level = 0.395625

Table C.3. M–W Test for Identifying Plant Groups

Comparison of Samples	Average Rank of 1st Sample	# of Values of 1st Sample	Average Rank of 2nd Sample	# of Values of 2nd Sample	Total Observ.	Test Statistic Z	ρ Value
Plant 1-Plant 2	23.304	23	27.911	28	51	1.164	0.244
Plant 1-Plant 3	25.304	23	27.31	29	52	0.498	0.619
Plant 2-Plant 3	30.125	28	27.241	29	57	−0.495	0.621

C.4 Kruskal–Wallis Test to RHR Pump Degradation Data Across Plants

Table C.4 presents the Kruskal–Wallis Test to RHR pump data across plants (obtained by data pooling across four pumps in a plant). Again, the result obtained supported the conclusion obtained with the Mann–Whitney Test.

C.5 Mann's Rank Test to Identify Age Groups with Significant Time Trends

Mann's Rank Correlation Test is used to identify time trends over age in failure and degradation data. Age intervals showing significant trends are also identified.

Tests are conducted to both degradation and failure data by two methods discussed before. Method 1, data combining, and Method 2, data pooling, show similar results (Table C.5).

A Type I error of 0.05 is used as a decision criterion for the significance level to define a trend with increasing age. For degradation data, a significant increasing time trend is found over the period of 19.5 to 38.6 (approximately 20 to 40) quarters, whereas a decreasing time trend is observed over the first 20 quarters. Similar results are obtained for both methods of using data from 12 RHR pumps. The significance levels and the Kendal's rank correlation coefficients are presented in Table C.5. For failure data, a decreasing trend is identified for the first twenty quarters, but there was no time trend in the remaining quarters.

Table C.4. K–W Test for Identifying Plant Groups

Pump	Sample Size	Average Rank
1	23	36.5870
2	28	43.6786
3	29	39.6034

Test statistic = –2.83185 Significance level = 1

Table C.5. Mann's Trending Test Results

Data Use Methods	Degradation Data Trending Test Results		Failure Data Trending Test Results	
Data Combining (Method 1)	Data Period (0, 19.5) quarters ρ = –0.338 Sig. Level = 0.001	Data Period (19.5, 38.6) quarters ρ = .2574 Sig. Level = 0.049	Data Period (0, 22) quarters ρ = –0.256 Sig. Level = 0.22	Data Period (22, 40) quarters Insufficient Data to Conduct Test
Data Pooling (Method 2)	Data Period (0, 21.6) quarters ρ = –0.106 Sig. Level = 0.281	Data Period (21, 39) quarters ρ = 0.285 Sig. Level = 0.055	Data Period (0, 20) quarters ρ = –0.396 Sig. Level = 0.035	Data Period (20, 40) quarters Insufficient Data to Conduct Test

APPENDIX D. ESTIMATION OF AGING EFFECT ON DEGRADATION AND FAILURES AND MAINTENANCE EFFECTIVENESS EVALUATION FOR RHR PUMPS

This appendix summarizes the estimation process using Cox's model (discussed in Chapter 4) to determine age-dependent degradation and failure rate for the RHR pumps. The estimation of a maintenance ineffectiveness factor, based on degradation rate, and failure rate is also discussed.

The steps for estimating rates are similar for degradation and failure:

1. For the defined age groups showing significant aging trends perform regression analysis to estimate the aging parameters defined by the Cox model.
2. For the data not showing any aging trend, obtain the time-independent rate.
3. Use spline fitting to obtain the aging effect for the entire period based on regression curves obtained for portions.

D.1 Regression Analysis to Obtain Aging Rates

For the age-groups showing significant trend with time, regression analyses 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.

Analyses are performed for both methods of using data from 12 RHR pumps. Degradation rate parameters a and b obtained are presented in Table D.1. Similar results for analyses of aging failure are presented in Table D.2. Since no trend could be established during 20 to 40 quarters of age, a constant failure rate is estimated.

D.2 Isotonic Regression Analysis

Isotonic regression analysis is performed to estimate failure rate in the interval 0–20 quarters. This approach of obtaining the time trend in failure data is especially powerful for few data, as is the case for the data on RHR pump failure. Results of isotonic regression for both the methods of using data across RHR pumps are presented in Tables D.3 and D.4.

D.3 Aging Rates Using Spline-Fitting

Degradation and aging-failure rates obtained as through regression analyses in different age intervals are used to obtain the aging effect over the entire age using spline-fitting.

Figures D.1 and D.2 show the aging effect in the degradation rate for ten years of RHR pump life data: Figure D.1 shows the results based on combining data (Method 1 of using data from 12 pumps) and Figure D.2 on pooling data (Method 2). The results are comparable, i.e., the aging effects on degradation are similar, the degradation rates obtained are not very different, and the uncertainties in the results are of similar magnitude.

Figures D.3 and D.4 present the aging effect on failures based on these two methods: both these curves show a decreasing trend for first 20 quarters of life. The constant failure

Table D.1. Estimation Results for Degradation Rate Analyses

Data Use Methods	Age Intervals	Aging Rate $\hat{b}$			Constant ln $\hat{a}$			Model	
		Estimated Parameter	Significance Level	Uncertainty Range (5% error)	Estimated Parameter	Significance Level	Uncertainty Range (5% error)	Significance Level	Standard Error of Est.
Method 1: Data Combining	0–20 (quarters)	−0.095	0.0006	CL: −0.1395 CU: −0.05086	0.541	0.025	CL: 0.06661 CU: 1.0149	0.0001	1.234
	20–40 (quarters)	0.105	0.046	CL: 0.00223 CU: 0.207	−4.161	0.012	CL: −7.325 CU: −0.9975	0.0455	1.2875
Method 2: Data Pooling	0–20 (quarters)	−0.0285	0.1314	CL: −0.0659 CU: 0.00887	0.365	0.06	CL: −0.0247 CU: 0.7549	0.131	0.7453
	20–40 (quarters)	0.095	0.0278	CL: 0.0113 CU: 0.1777	−3.111	0.018	CL: −5.633 CU: −0.5882	0.028	0.9638

CU = Upper (95%) range
CL = Lower (5%) range

Table D.2. Estimation Results for Failure Rate Analyses

Data Use Methods	Age Intervals	Aging Rate b̂			Constant ln â			Model	
		Estimated Parameter	Significance Level	Uncertainty Range (5% error)	Estimated Parameter	Significance Level	Uncertainty Range (5% error)	Significance Level	Standard Error of Est.
Method 1: Data Combining	0–20 (quarters)	–0.1338	0.025	CL: –0.2477 CU; –0.01995	–0.249	0.584	CL: –1.211 CU: 0.7122	0.0247	0.9309
	20–40 (quarters)	0.0146	0.876 Not Significant	Not Significant	–2.958† –2.595*	0.3582† 0.95*	CL: –3.255* CU: –1.934*	0.877 Not Significant	0.3691† 0.2659*
Method 2: Data Pooling	0–20 (quarters)	–0.1513	0.027	CL: –0.282 CU: –0.021	–0.665	0.26	CL: –1.9123 CU: 0.5821	0.03	1.146
	20–40 (quarters)	8.509E-3	0.8418 Not Significant	Not Significant	–3.709† –3.497*	0.142† 0.05*	CL: –3.798* CU: –3.197*	0.842 Not Significant	0.166† 0.1212*

*Based on direct estimation
†Based on regression analyses

Table D.3. Isotonic Regression for Failure Rate Estimation (Data Combining—Method 1)

Time Interval T_i (quarter)	1.48	2.38	2.6	3.97	4.77	5.92	0.48	3.86	6.54	1.77	0.39	8.27	3.07	17.41	11.96	18.15	11.07
$\hat{T}_i$ (1st Grouping)						3.2				2.9		5.67		14.68		14.61	
T_i' (2nd Grouping)	1.48	2.38	2.6	3.97	4.77			3.05				5.67			14.65		
T_i'' (3rd Grouping)	1.48	2.38	2.6	3.97			3.91					5.67			14.65		
T_i''' (4th Grouping)	1.48	2.38	2.6		3.94							5.67			14.65		
Failure Rate $\lambda_i = 1 / T_i'''$	0.676	0.42	0.385		0.254							0.176			0.068		
($\ln \lambda_i$)	(−0.39)	(−0.868)	(−0.955)		(−1.377)							(−1.737)			(−2.69)		
No. of Failures (m)	17																
Test Statistic (V_m)	$V_m = \frac{1}{m}\sum_{i=1}^{m-1} T_i \Big/ \left(\frac{1}{m}\right) T_m \doteq 0.497$																
Significance Level (α)	$\alpha \ll 0.001 \Rightarrow$ Reject H_0 (Constant Failure Rate)																
Trend	Decreasing Failure																

Table D.4. Isotonic Regression for Failure Rate Estimation (Data Pooling—Method 2)

Time Interval FT_i (quarter)	8.1	1.99	12.3	7.2	10.4	4.3	0.5	0.8	3.49	11.99	11.3	71	36.6	28.89	34.1
FT_i (1st Grouping)	5.05		9.75			5.07		0.8	3.49	11.65			45.49		34.1
FT_i' (2nd Grouping)	5.05					5.207			3.49	11.65				39.79	
FT_i'' (3rd Grouping)	5.05						4.348			11.65				39.79	
FT_i''' (4th Grouping)				4.69						11.65				39.79	
Failure Rate $\lambda_i^F = 1 / T_i'''$				0.213						0.086				0.025	
($\ln \lambda_i^F$)				(−1.546)						(−2.453)				(−3.688)	
No. of Failures (m)	15														
Test Statistic (V_m)	$\frac{1}{m} \sum_{i=1}^{m-1} T_i \Big/ \left(\frac{1}{m}\right) T_m = 0.817$														
Significance Level (α)	$\alpha << 0.001 \Rightarrow$ Reject H_0 (Constant Failure Rate)														
Trend	Decreasing Failure														

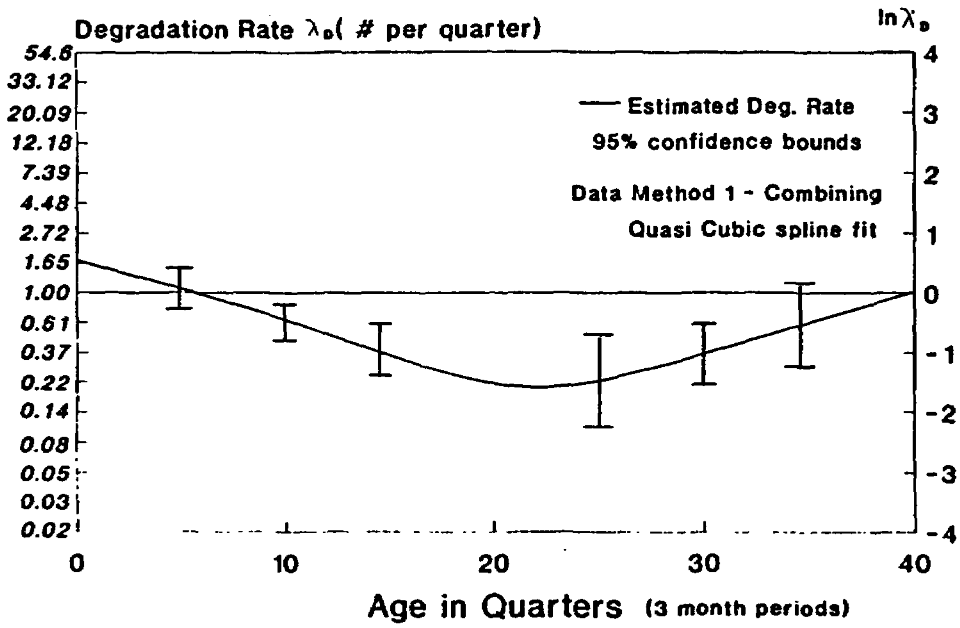

Figure D.1 Age dependent degradation rate
(Component: RHR pumps; 3 plant data)

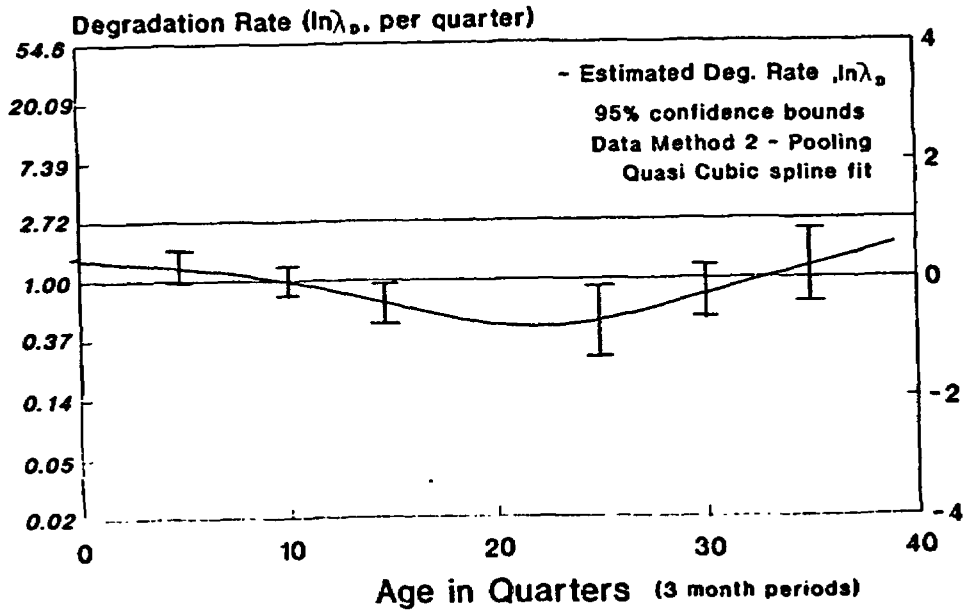

Figure D.2 Age dependent degradation rate
(Component: RHR pumps; 3 plant data)

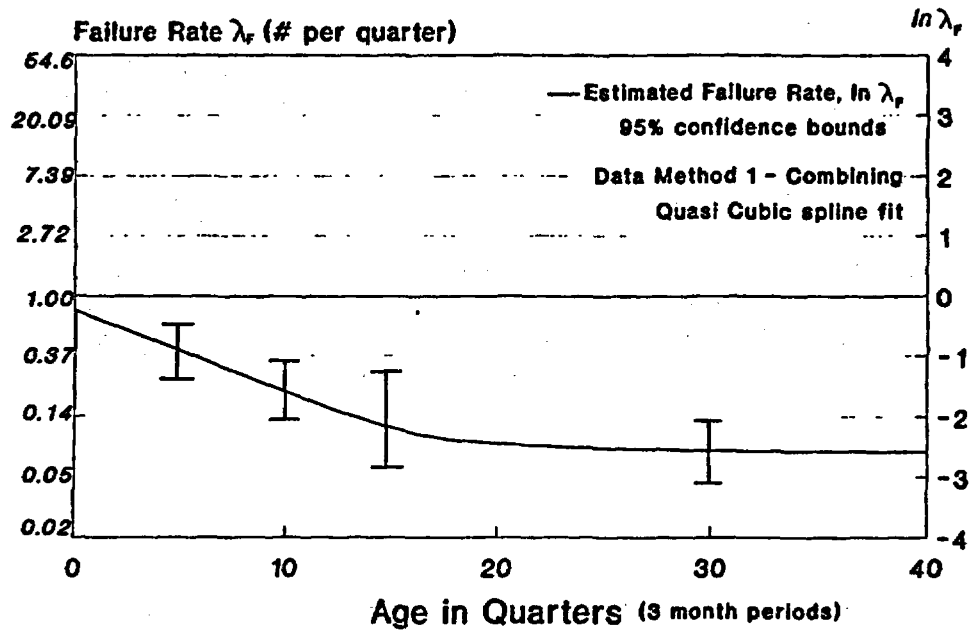

Figure D.3 Age dependent failure rate
(Component: RHR pumps; 3 plant data)

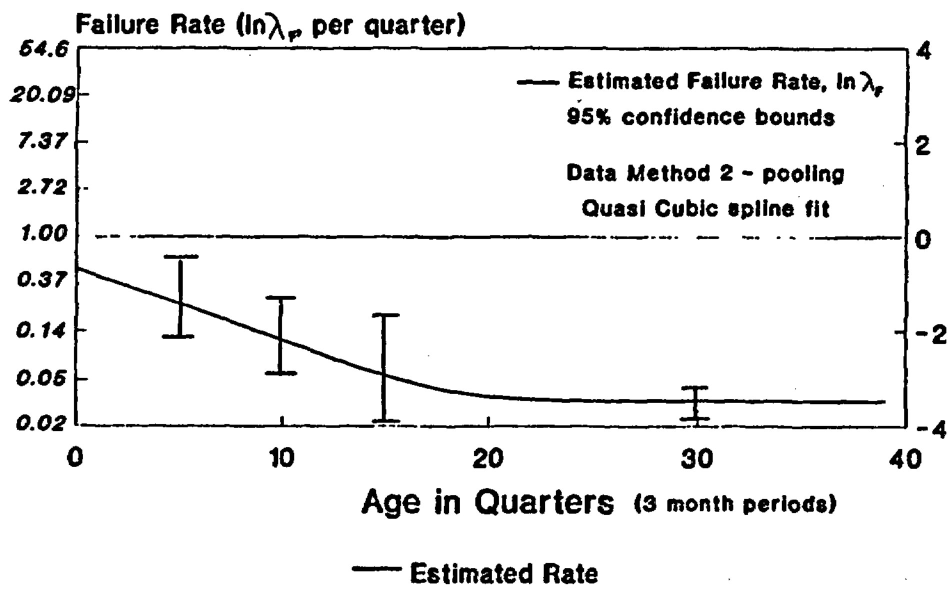

Figure D.4 Age dependent failure rate
(Component: RHR pumps; 3 plant data)

rate obtained for the remaining 20 quarters is slightly different; Method 1 (data combing) is slightly higher than Method 2 (data pooling). The uncertainty ranges are similar, but they are larger than those for degradation rates.

Figures D.5 and D.6 compare the aging rates obtained from linear regression analyses with those estimated by isotonic regression analyses. The failure rate obtained from linear regression analysis appears to be a good approximation of that obtained from isotonic regression.

D.4 Evaluation of Maintenance Ineffectiveness (or Effectiveness)

Maintenance ineffectiveness is defined in Chapter 3 as the transition probability from a degraded state to a failure state, where maintenance is performed every time the component is detected to be in the degraded state. Mathematically, using steady state solution, maintenance ineffectiveness, P_{DF}, is expressed as:

$$P_{DF} = \frac{\bar{W}_F}{\bar{W}_D} \tag{D-1}$$

where $\bar{W}_F$ is the average failure frequency and $\bar{W}_D$ is the average degradation frequency.

The above expression is truly applicable to steady state solution, but is an approximate model in age-dependent situation. In our analyses, aging effect on degradations and failures show different effects (as discussed effects) and the age-dependent degradation and failure rates are used to obtain the average parameters.

We obtain maintenance ineffectiveness in every 10 quarters by using a piecewise approximation to $\bar{W}_F$ and $\bar{W}_D$ for equally separated age intervals of 10 quarters.

Let,

$$\bar{W}_F(t_a, t_b) = \frac{1}{t_b - t_a} \int_{t_a}^{t_b} \lambda_F(t)\, dt$$

$$\bar{W}_D(t_a, t_b) = \frac{1}{t_b - t_a} \int_{t_a}^{t_b} \lambda_D(t)\, dt$$

and,

$$\begin{aligned} t_a &= 10(i-1) \text{ quarters}, \\ t_b &= 10i \text{ quarters}, \end{aligned} \qquad i = 1, 2, 3, 4$$

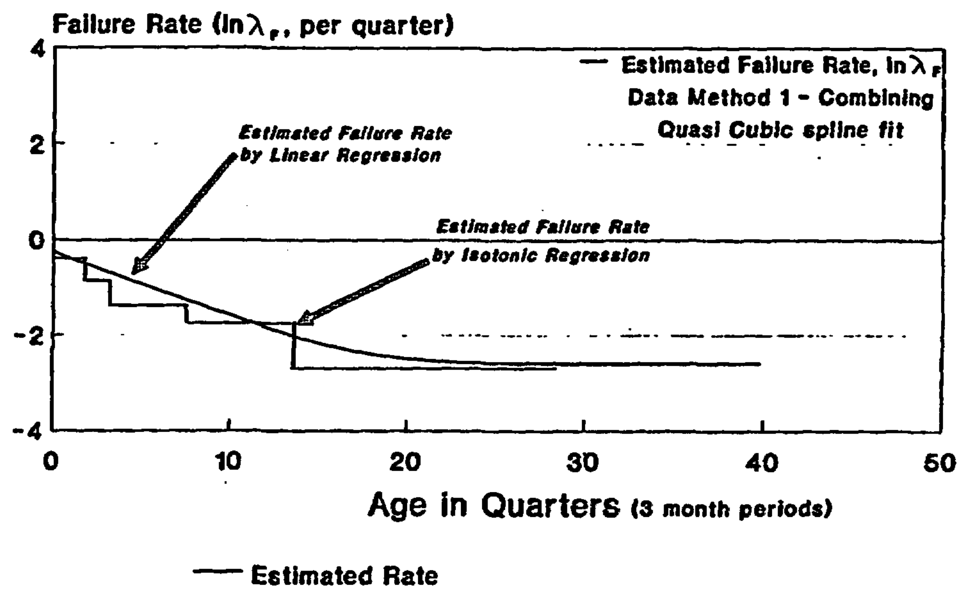

Figure D.5 Age dependent failure rate (Component: RHR pumps; 3 plant data)

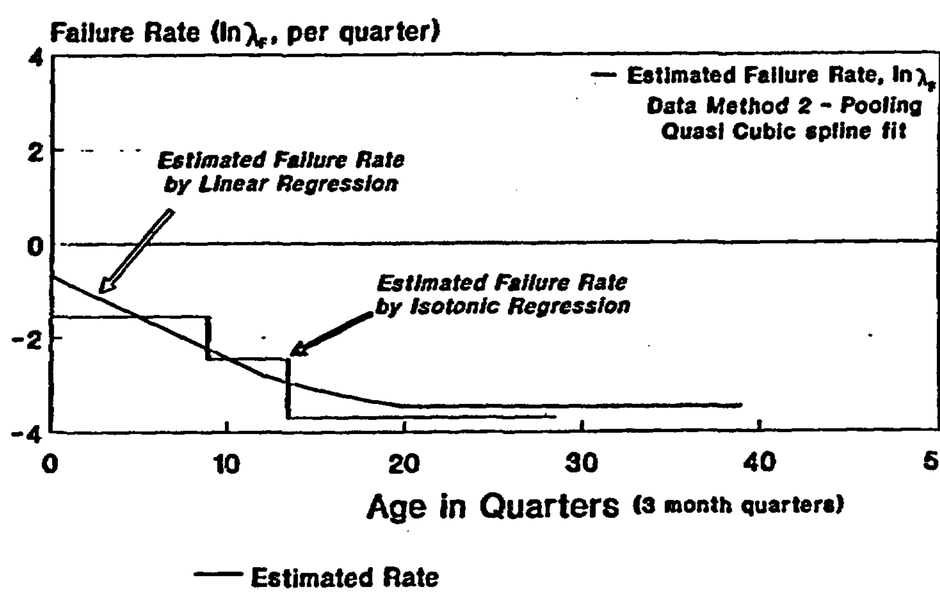

Figure D.6 Age dependent failure rate (Component: RHR pumps; 3 plant data)

Therefore,

$$P_{DF}(t_a,\ t_b) = \frac{\overline{W}_F(t_a,\ t_b)}{\overline{W}_D(t_a,\ t_b)}\ .$$

The maintenance ineffectiveness factor obtained for each 10 quarters are calculated from $\lambda_F(t)$ and $\lambda_D(t)$ obtained previously. Table D.5 shows the results on two methods of using data for 12 RHR pumps.

Table D.5. Maintenance Ineffectiveness Calculation for RHR Pump

Method	Age (quarters)	(# of Failures / Quarter) $\hat{W}_F$	Expected Degradation Frequency (# of Degradations / Quarter) $\hat{W}_D$	Maintenance Ineffectiveness (Transition Probability) $p_{DF} = \hat{W}_F / \hat{W}_D$
Data Pooling	0–10	2.651	12.538	0.2114
	10–20	0.58	9.428	0.585
	20–30	0.32	1.371	0.2334
	30–40	0.32	12.87	0.0249
Data Combining	0–10	4.298	11.09	0.387
	10–20	1.127	4.289	0.2629
	20–30	0.76	2.312	0.3288
	30–40	0.76	6.606	0.115

APPENDIX E. ANALYSIS OF AGE-RELATED DEGRADATION AND FAILURE DATA FROM SERVICE WATER (SW) PUMPS

This appendix presents results of age-related degradation and failure data analyses for Service Water (SW) pumps using the degradation modeling approach. The methodology used for the SW pumps is similar to that used for the RHR pumps (presented in appendices C and D).

Here, we summarize the results of the statistical tests, the estimation of aging rates and the evaluation of maintenance effectiveness for the SW pumps.

E.1 K-W Signed Rank Test for SW Pumps Within Each Nuclear Unit

K-W signed rank test was conducted for the Service Water pump data to identify those pumps with similar distribution of degradation times within each nuclear unit. The test was applied as a multiple comparison test to identify any abnormal component(s) in each of the plants. K-W test is more efficient, compared to Mann-Whitney (M-W) test, when applied to a larger sample. For each of the plant, four to eight SW pump data were analyzed and accordingly, K-W test was chosen.

Table E.1 shows test results for plant 1, similar results are obtained for the other 6 plants (Table E.2 through Table E.7). The results justify the hypothesis that the SW pumps in each of the plants can be assumed to belong to the same population. Accordingly, the degradation data for the pumps in each of the plants were combined for further analysis.

E.2 K-W Test to SW Pump Degradation Data Across Plants

Table E.8 presents the K-W test of Service Water pump data (obtained by combining across all the SW pumps data in each plant) across plants. The results supported the conclusion that the component degradation (and failure) data from the underlying 7 different nuclear units have similarities in their data distributions, thus can be combined together to investigate the common aging behavior of SW pumps. Method 1, called data combining, of using data from multiple components across different nuclear units was used. Data pooling (Method 2) was not tried in this case.

E.3 Mann's Rank Test to Identify Age Groups with Significant Time Trends

Mann's rank correlation test was used to identify time trends in degradation data. Age intervals showing significant trends are identified as well.

Table E.9 summarizes the results to type I error of 0.05 is used on a decision criteria for the significance level to define a trend with increasing age.

For degradation data, a significant increasing time trend is found over the age period of approximately 23 to 55 quarters; whereas a decreasing time trend is obtained over the first 23 quarters. For the available failure data, no trend could be established.

Accordingly, a constant failure rate is estimated for the study period (60 quarters).

Table E.1. K–W Test for Plant 1: Kruskal–Wallis Analysis of 4 SW Pump Degradation Data

Pump	Sample Size	Average Rank
a	1	3-0
b	1	2-0
c	1	1-0
d	1	4-0

Test statistic = 3   Significance level = 0.3916

Table E.2. K–W Test for Plant 2: Kruskal–Wallis Analysis of 3 SW Pump Degradation Data

Pump	Sample Size	Average Rank
c	3	2-0
d	1	4-0
e	1	5-0

Test statistic = 3.2   Significance level = 0.2018

Table E.3. K–W Test for Plant 3: Kruskal–Wallis Analysis of 7 SW Pump Degradation Data

Pump	Sample Size	Average Rank
a	2	2.5
b	4	7.5
c	2	8.5
d	2	2.5
e	1	11.00
g	1	10.0
h	1	13.00

Test statistic = 9.779   Significance level = 0.13427

Table E.4. K–W Test for Plant 4: Kruskal–Wallis Analysis of 6 SW Pump Degradation Data

Pump	Sample Size	Average Rank
a	1	3.0
b	2	7.0
c	2	7.5
d	1	2.0
g	2	2.5
h	1	6.0

Test statistic = 6.26   Significance level = 0.281

Table E.5 K–W Test for Plant 5: Kruskal–Wallis Analysis of 2 SW Pump Degradation Data

Pump	Sample Size	Average Rank
a	2	2.5
c	2	2.5

Test statistic = 0   Significance level = 1

Table E.6. K–W Test for Plant 6: Kruskal–Wallis Analysis of 5 SW Pump Degradation Data

Pump	Sample Size	Average Rank
a	2	6.0
b	2	2.0
c	3	8.33
d	4	7.75
g	1	6.0

Test statistic = 4.42949   Significance level = 0.3509

Table E.7. K–W Test for Plant 7: Kruskal–Wallis Analysis of 8 SW Pump Degradation Data

Pump	Sample Size	Average Rank
a	1	9.0
b	3	4.6
c	2	6.0
d	1	11.0
f	1	12.0
g	1	4.0
h	2	4.0
i	1	8.0

Test statistic = 6.7948   Significance level = 0.4505

Table E.8. K–W Test for Identifying Plant Group

Pump	Sample Size	Average Rank
1	4	37.5
2	5	22.4
3	13	25.53
4	9	25.44
5	4	35.00
6	12	34.75
7	12	32.50

Test statistic = 4.763   Significance level = 0.5745

Table E.9. Mann's Trending Test Results

Data Use Methods	Degradation Data Trending Test Results		Failure Data Trending Test Resnlts
Data Combining	Data Period (0, 23) quarters $\rho = -0.567$ Sig. Level=0.0001	Data Period (23,55) quarters $\rho = 0.5147$ Sig. Level = 0.0039	Insufficient Data to Perform Significant Test
Trending	Significant decreasing	Significant increasing	no significant trend (assume constant)

E.4 Estimation of Aging Effect on Degradation and Failures

As in the case with the RHR pumps, the same estimation process is used in this case in determining age-dependent degradation and failure rates.

For the age-groups showing significant trend with time, regression analysis was performed to obtain the aging rates. For degradation data, decreasing trend was defined for the age period 0-23 quarters and increasing trend was defined for the remaining life 23-55 quarters.

Degradation rate parameters $\hat{a}$ and $\hat{b}$ are presented in Table E.10. For aging failure rate, since no trend could be established during the observed time period of ages, a constant failure rate is estimated in the age interval 0-40 quarters to be 0.089/quarters (or –2.4783 in nature logrithm scale). It's 95% confidant internal is estimated as [–0.817, –4.1397] in the log scale.

E.5 Aging Rates Using Spline-Fitting

Figure E.1 presents the spline-fitting curve of the aging effect on degradations for SW pumps. The degradation rate curve shows a rapid decrease during the first 15 quarters followed by a significant increase for the remaining 40 quarters. The behavior of the degradation rate follows a "bathtub" curve as was observed also in the case of RHR pumps. The failure rate curve, showing a constant rate, is presented in Figure E.2.

E.6 Maintenance Effectiveness Evaluation for SW pumps

The maintenance ineffectiveness factor $P_{DF}(t_a, t_b) = \dfrac{\bar{W}_F(t_a, t_b)}{\bar{W}_D(t_a, t_b)}$ was calculated for each 10 quarters based on λ_F's and λ_D's obtained previously. The maintenance effectiveness is the complement of maintenance ineffectiveness. The results are presented in Table E.11 and shown in Figure E.3.

Table E.10 Estimation Results for Degradation Rate Analyses

Data Use Methods	Age Period	Aging Rate $\hat{b}$			Constant ln $\hat{a}$			Model	
		Estimated Parameter	Significance Level	Uncertainty Range (5% error)	Estimated Parameter	Significance Level	Uncertainty Range (5% error)	Significance Level	Standard Error of Est.
Data Combining	0–23 (quarters)	−0.1527	−0.0001	CL: −0.2207 CU: −0.0848	0.1698	0.589	CL:−0.4669 CU: −0.8065	0.0001	1.0406
	23–55 (quarters)	0.0365	0.0285	CL: 0.00438 CU: 0.0686	−3.2534	0.0001	CL: −4.578 CU: −1.9287	0.029	0.6285

Table E.11. Maintenance Ineffectiveness Calculation Results

Data Use	Age Period (quarters)	(# of Failures / Quarter) W_F	Expected Degradation Frequency (# of Degradations / Quarter)	Maintenance Ineffectiveness (Transition Probability) $1-P_{MF} = 1-(W_f/W_D)$
Data Combining	0–10	0.839	6-0727	0.8618
	10–20	0.839	1.3176	0.3633
	20–30	0.839	0.966	0.1315
	30–40	0.839	1.392	0.3973
	40–45	1.26	3.318	0.6208

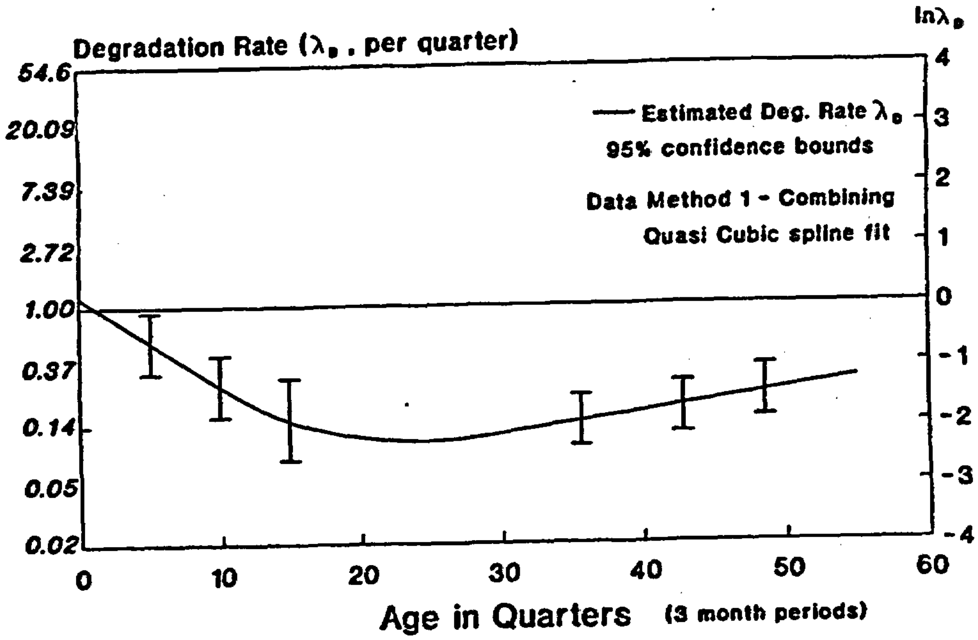

Figure E.1 Age dependent degradation rate
(Component: SW pumps; 7 plant data)

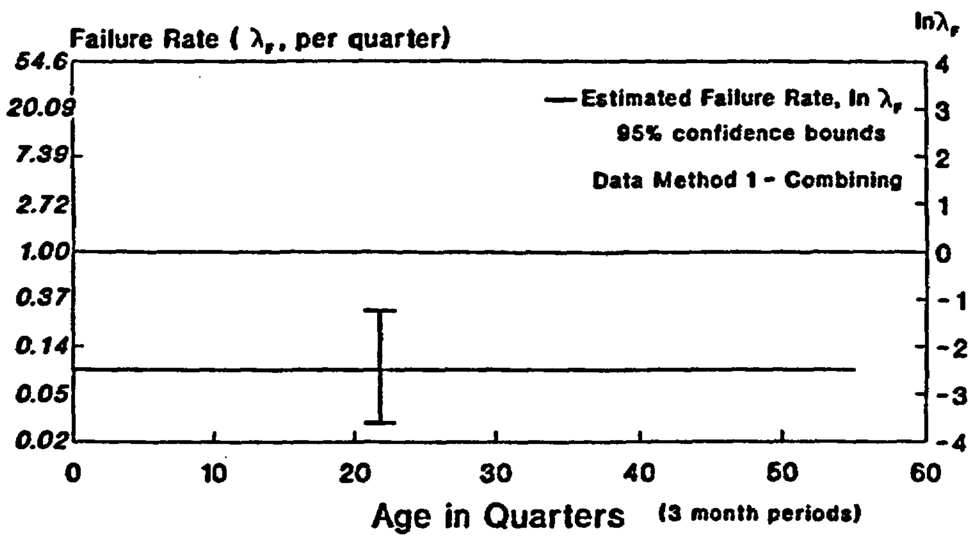

Figure E.2 Age dependent failure rate
(Component: SW pumps; 7 plant data)

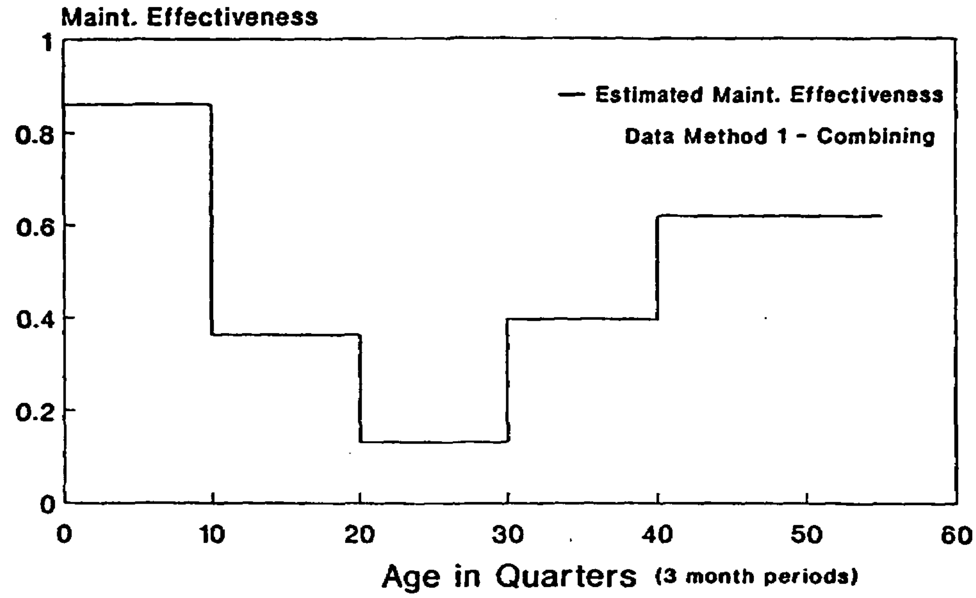

Figure E.3 Maintenance effectiveness
(Component: SW pumps; 7 plant data)

APPENDIX F. DEFINITIONS OF TERMS

In this appendix, we provide a definition of the terms frequently used in this report. Here, we present concise definitions, and more detailed defintions for some of the terms using mathematical expressions are presented in the report. The defintions being developed by a Workshop on NRC/Industry Consensus Terminology in Aging are used in arriving at these descriptions.

Aging:	Aging signifies changes in physical characteristics of a component that occurs with time or use due to aging mechanisms. In this study, changes (increase) in component degradation and failure characteristics are considered evidence of aging.
Component States:	Component state defines the component status in regard to the function it is intended to provide. In this report, the status of a component is defined in terms of three different states – operating state, failure state, and degraded state – which are defined below.
Operating State:	A component is capable of performing its function according to the specified success criterion. This implies that the comoponent performance parameters are within the defined limits and no noticeable abnormalities are present.
Failure State:	The component is not capable of performing its specified operation according to a success criterion. In order to restore the component to a state in which it is capable of operation, some kind of repair or replacement action is necessary.
Degraded State:	The component is in such a state that it exhibits reduced performance but insufficient degradation to declare the component unavailable according to the specific success criterion. The definition of degraded state for this study is that the component is in a state in which degradation has exceeded a threshold requiring maintenance.
Degradation Rate:	Degradation rate is the rate per unit time at which the degradation occurs. The degradation rate is, in general, a function of the age of the comoponent. If time is not the relevant age variable, then the rate can be defined per unit age variable such as the rate per cycle, or per demand.
Failure Rate:	The failure rate is defined as the probability of a failure occuring per unit time. Equivalently, the failure rate is the expected number of failures per unit time.

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11. ABSTRACT (200 words or less)

This report describes a degradation modeling approach to analyze data on component degradation and failure to understand the processes in aging of components. As used here, degradation modeling is the analysis of information on component degradation in order to develop models of the process and its implications. This particular modeling focuses on the analysis of the times of component degradations to model how the rate of degradation changes with the age of the component. The methodology presented also discusses the effectiveness of maintenance as applicable to aging evaluations.

The specific applications which are performed show quantitative models of component degradation rates and component failure rates from plant-specific data. The statistical techniques which were developed and applied allow aging trends to be effectively identified in the degradation data, and in the failure data. Initial estimates of the effectiveness of maintenance in limiting degradations from becoming failures also were developed. These results are important first steps in degradation modeling and show that degradation can be modeled to identify aging trends.

12. KEY WORDS/DESCRIPTORS (List words or phrases that will assist researchers in locating the report.)

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