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Degradation Modeling - A Key to Understanding Effects of Aging and Maintenance*

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ABSTRACT

Component degradation modeling is the analysis of component degradations for the purpose of developing models of the degradation process and its implications. Degradation modeling can encompass many different areas, from the microscopic modeling of material degradation processes to macroscopic modeling of times of occurrences of degradations. In this paper, we present basic concepts, approaches, and applications of degradation modeling using times of occurrences of component degradations and failures. Specific applications of the modeling approaches, performed for "active" components, are presented.

We discuss degradation modeling from the viewpoint of understanding the effects of aging and the role of maintenance in mitigating aging effects. We argue that degradation modeling is a key to understanding the effects of aging and maintenance and should be the principal focus of aging analysis. Since degradations generally occur before failures, detecting aging trends in degradations allows the aging effects to be corrected before they impact failures. Furthermore, degradations generally occur more frequently than failures, providing a larger data base for analyzing aging effects.

Degradation modeling approaches can have broader applications in aging-risk studies, in defining the effective maintenance practices, and in analyzing component reliability performance. Extensions of degradation modeling approaches to study the reliability effects of different maintenance intervals, different maintenance durations, and different maintenance efficiencies also are discussed. These extensions will help define maintenance activities that mitigate aging effects, and complement the evaluation of the effectiveness of existing maintenance practices. We present sensitivity analyses showing the effects of maintenance on component reliability.

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1. INTRODUCTION

Analyses of data on plant experience shows that components experience various forms of degradation that are detected and corrected through testing, maintenance, and repair. In fact, records on component reliability contain much more data on degradations as compared to failures. Importantly, aging is a degradation process and by analyzing component degradations we can obtain an understanding of the aging process and activities necessary to mitigate the age-related degradation.

In this paper, we discuss component degradation modeling, which is an analysis of component degradations for the purpose of developing models of the degradation process and its implications. Degradation modeling can encompass many different areas, from the microscopic modeling of material degradation processes to macroscopic modeling of times of occurrences of degradations. Here, our focus is on modeling the degradation process using the times of occurrences of component degradations and failures.

In this approach to degradation modeling, our objectives are to understand the effects of aging and the role of maintenance in mitigating the aging effects. We argue that degradation modeling is a key in obtaining this understanding and should be the principal focus of aging analysis. Since degradations generally occur before failures, detecting aging trends in degradations allows the aging effects to be corrected before they impact failures.

We discuss two types of applications of degradation modeling in understanding aging and maintenance effects. In the first, trends in occurrences of degradation are analyzed for aging effects and are compared to the failure occurrences to obtain an understanding of the effectiveness of maintenance (in preventing age-related degradations from transforming to failures). The second application shows how degradation modeling can be used to define effective maintenance practices.

2. DEFINITION OF DEGRADATIONS

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

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

For initial work, the gross definition of degradation can be used, which basically equates the occurrence of the degradation state to any occasion when corrective maintenance is required. Figure 1 illustrates the basic alternative for defining the degradation state.

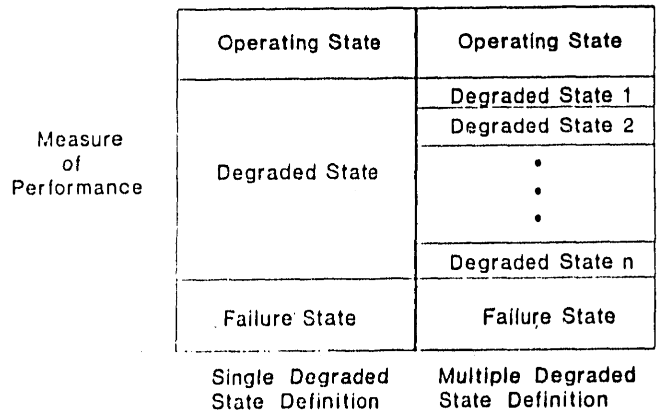

Figure 1. Alternatives for degraded state definitions

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

3. DEGRADATION MODELING APPROACHES

In this section, we discuss the general aspects of degradation modeling, as related to applications presented in this paper. Detailed mathematical formulations of degradation modeling are presented in References 1 and 3.

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

Table 1. Examples of Air Compressor Degradation and Failure Occurrences

Compressor Subcomponent	Classification	Failure Effect	Failure Mechanism
Jacket Heat Exchanger	D	Corrosion deposits built up by aftercooler	Mechanical debris; poor water chemistry
Bolts and Fasteners	D	Fractured stud on spacer	Mechanical vibration
Pistons	D	Brass fillings in high and low pressure regions found during P.M.	Mechanical wear
Piston	F	Oil leak at piston rod seal	Mechanical wear
Lube Oil System	F	Pump seized and became inoperable	High temperature, mechanical wear

We define the operating characteristics of a component in terms of four states; an operating state (o-state), a degraded state (d-state), a maintenance state (m-state), and a failure state (f-state). In one of the simplest models (used for the applications presented in Section 4), we make the following assumptions:

1. Degradation always precedes failure.

2. When a component is repaired after a failure, the operational state of the component reflects more restoration than when on-line maintenance is performed.

3. When maintenance is performed following detection of a degraded condition, the component is restored to a maintained state, which reflects less restoration than when repair is performed after a failure.

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

In this application, we focus on the frequency of occurrences of degradations and failures. Based on our assumptions, the component can be in a degraded state (d-state) through three processes:

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

- 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

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

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

The degradation rate is defined as the rate of degradation occurring after maintenance given that no previous degradation has occurred. Similarly, the failure rate is the rate of failure occurring after a degradation given that no previous failure has occurred. It is assumed that the effect of aging on a component can be manifested through either increased degradation occurrence or increased failure occurrence or both. Generally, earlier studies have focussed on increased failures due to aging. Here, the focus is on degradations, along with analysis of failures to seek relation between the two. The effectiveness of maintenance is measured in terms of its ability to prevent degradations from transforming to failures, i.e., it is the complement of the transition probability from degradation state to failure state.

In the second type of application (presented in Section 5), the basic (frequency-based) degradation model is extended to include test and maintenance related information whereby the effects of test and maintenance strategies, in terms of test and maintenance frequencies, duration, and efficiencies, can be determined (Reference 3). For this type of model, several characteristics of interest can be estimated: availability, probability of failure, and the expected time to failure. It is also possible to obtain an estimate of the effect of maintenance on the component.

The effect of maintenance on the component failure probability is estimated by comparing two cases of the model; one which includes a maintenance state, referred to simply as the "maintenance model" and the other without a maintenance state, called the "no maintenance" model. In this evaluation, the probability of failure is estimated as a function of different component operating characteristics: time to degradation, time from degradation to failure, and maintenance efficiency. By maintenance efficiency we mean the ability of maintenance to restore the component to an operational state. Maintenance efficiency is considered perfect, i.e., equal to 1, if every time maintenance is performed the component is restored to an operational state. Conversely, if every time maintenance is performed, the component is restored to a degraded state, the maintenance is considered totally inefficient, i.e., maintenance efficiency is zero.

4. DEGRADATION MODELING IN INTERPRETING AGE-RELATED DEGRADATION AND FAILURE DATA

In this section, we present an analysis of age-related degradation and failure data for selected components, namely Residual Heat Removal (RHR) pumps and air compressors (References 1 and 2). The primary focus of the analysis is to use the concept of degradation modeling, which provides us with an understanding of the aging of the active components. Based on the data analyses, we discuss the following:

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

Aging Effect on Degradation

The degradation data for the RHR pumps and air compressors were analyzed with the following objectives:

- to identify age groups where statistically significant time trends exist, and
- to determine the time trends and degradation rates, using regression analysis.

The details of the statistical analyses are presented in Reference 1. Here, we discuss the results and the characteristics of degradation rate.

Figure 2 shows the logarithm of the degradation rate that characterized the RHR pumps over 10 years (presented as 40 quarters). Statistical tests showed that the degradation behavior across these components are similar, and accordingly, a generic degradation characteristic was studied. 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 5 years of the 10 year period) shows a decreasing trend, and the last 5 years show an increasing trend, with the age of the component.

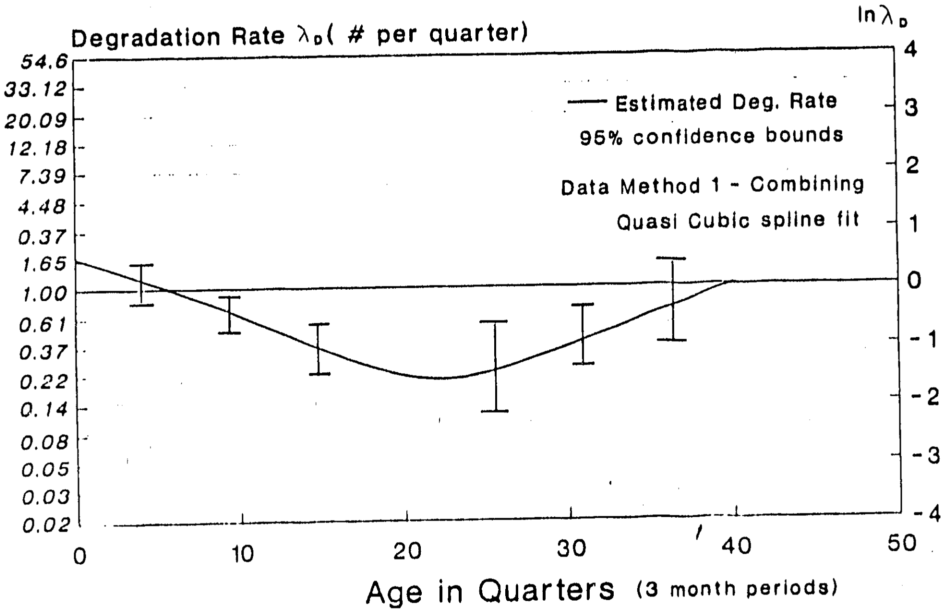

Figure 2. Age dependent degradation rate
(Component: RHR pumps; 3 plant data)

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 in the last 5 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 the range of uncertainty.

Figure 3 shows the logarithm of the degradation rate for the air compressors over 10 years (presented as 40 quarters). The method of data combining was used for this analysis. As stated, this generic degradation characteristic was obtained by combining data from 4 air compressors in a BWR unit.

The observations from the age-dependent degradation rate for air compressors are as follows:

1. The degradation rate shows significant age-dependence: the early life of the component (i.e., first 5 years) shows a decreasing trend and the last 5 years show an increasing trend. The age-dependent behavior is similar to that observed for RHR pumps.

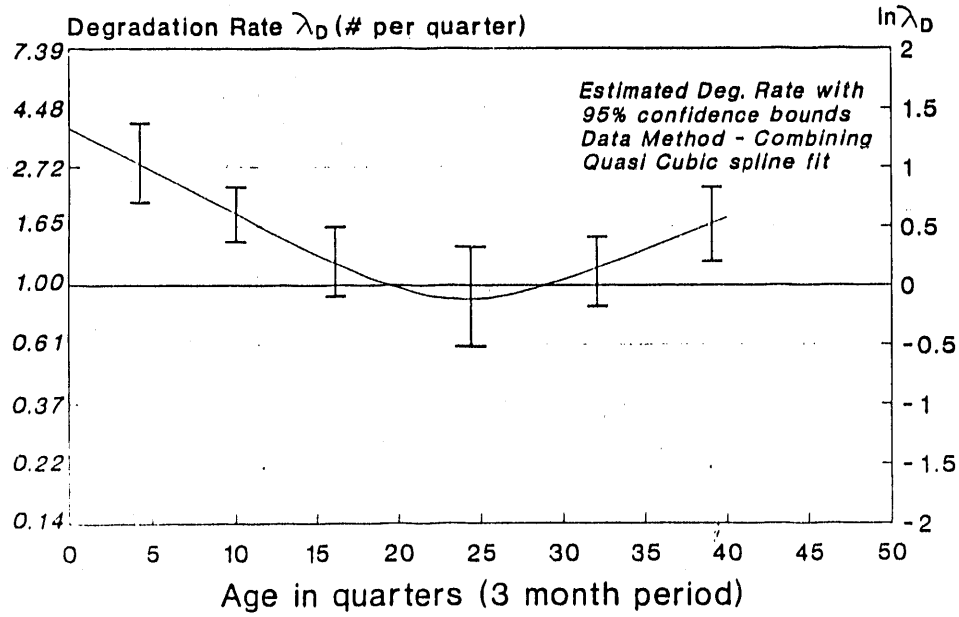

Figure 3. Age dependent degradation rate
(4 air compressors data)

2. The increase in degradation rate was smaller (about a factor 2) compared to the increase observed for the RHR pumps (about a factor of 10) in the last 5 years of life.

Aging Effect on Failures

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

- to identify age groups where statistically significant time trends exist, and

- to determine aging-failure rates where time trends exist, and to estimate a time-independent failure rate where time trends cannot be established.

Figure 4 gives the logarithm of the age-dependent failure rate 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 12 RHR pumps were the same, but the sparsity of data on aging failure required a slightly different analysis.

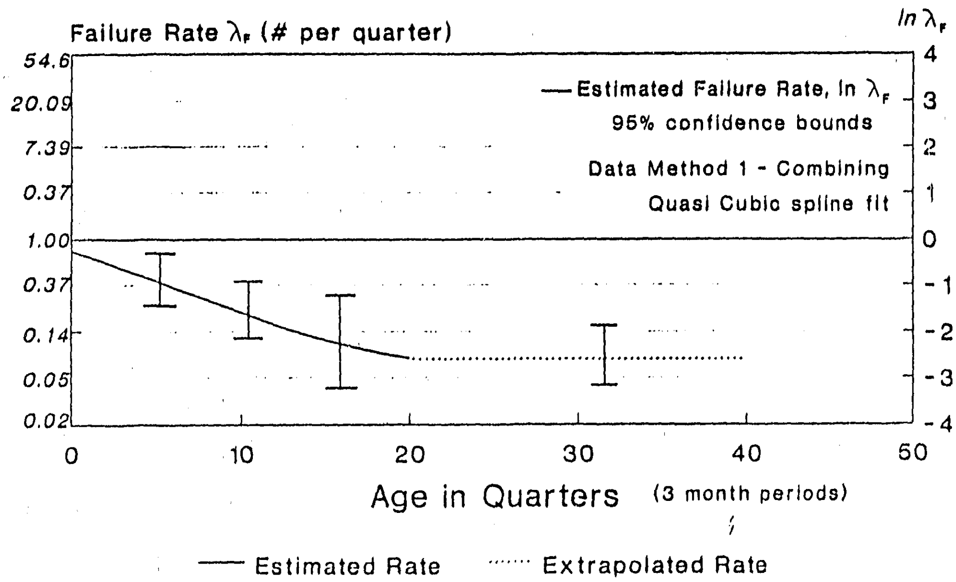

Figure 4. Age dependent failure rate
(Component: RHR pumps; 3 plant data)

The aging-failure data for the RHR pumps show only 3 failures during the last 5 years of the components' life (age 5-10) and, in general, the number of failures was small (18). The statistical trend testing, based on both data combining and pooling, showed a decreasing trend in the early life (first 5 years), but no trend in aging-failure could be established in the last 5 years. Because of the sparsity of the data, isotonic regression analysis was used to estimate failure rate for the first 5 years of RHR pumps where a decreasing trend was observed. For the last 5 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 a decreasing trend in the first 5 years, but only a constant failure rate can be estimated for the last 5 years of the overall 10 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 first 5 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 5 gives the logarithm of the failure rate for the air compressors. Statistical analyses were performed to determine trends in the failure rate using 25 age-related failures observed for the air compressors.

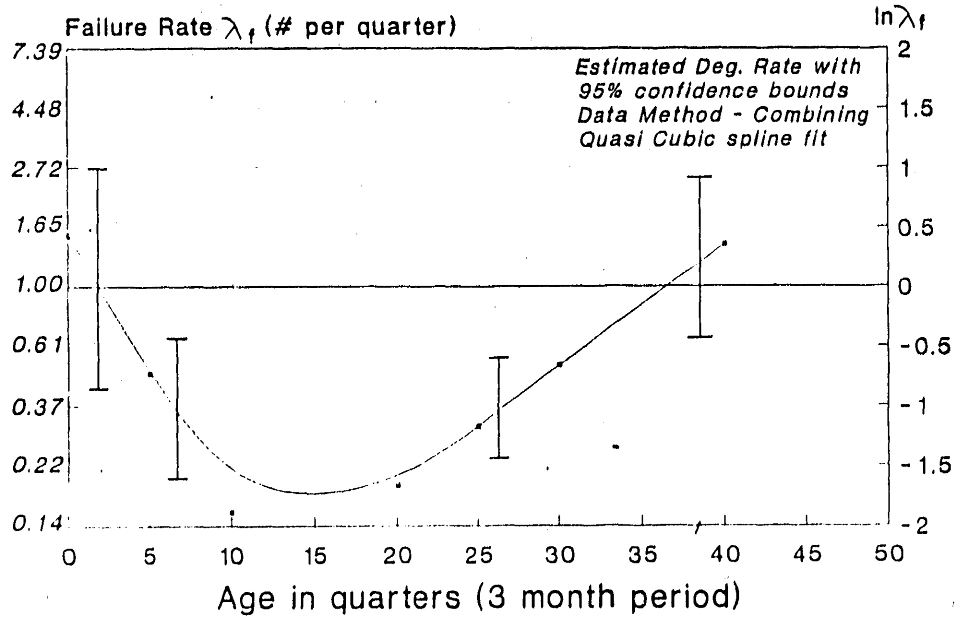

Figure 5. Age dependent failure rate
(Component: 4 air compressors)

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

1. The aging-failure rate of the air compressors shows a strong age-dependence with a decreasing trend in the first two and a half years and an increasing trend for the last 5 years of the overall 10 years.

2. The aging-failure rate shows a behavior similar to the degradation rate in the first 3 years, but differs after that. The aging-failure rate was significantly lower than the degradation rate in the first 5 years, but the difference decreased with increasing age. The aging-failure rate reached about the same level as the degradation rate at the end of ten years of operation.

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 RHR pumps and air compressors and provides interesting insights on aging of components.

1. The use of information on degradation and failure not only significantly increases 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 the RHR pumps and air compressors, analyses of degradation showed effects of aging.

2. The aging trend in the degradation during the last 5 years of the components' 10 years of operation 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. For the air compressors, the growth in degradation rate is accompanied by growth in the failure rate. In the degradation modeling approach, this finding signifies that maintenance does not prevent age-related degradation from resulting in faster growth in the failure rate.

3. The relation between degradation and aging-failure rate in the first 5 years of the RHR pumps remained the same, i.e., both curves were similar and the degradation rate was steadily higher than the aging-failure rate. For air compressors, the degradation rate was steadily higher than the failure rate, but the failure rate showed increasing trends slightly before the increasing trend is observed in the degradation rate.

4. 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.

Evaluation of Maintenance

As discussed in Section 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. The complement of maintenance ineffectiveness is maintenance effectiveness.

For the RHR pumps, the maintenance effectiveness is obtained (Figure 6) 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 10 quarters. The maintenance effectiveness for the air compressors (Figure 7) shows slightly different behavior. Effectiveness declines with the age of the component, a manifestation of the increased failure rate observed in the last 5 years. As discussed, the relationship among degradations, failures, and maintenance is complex, but extremely useful for studying aging in repairable components. A better understanding of maintenance effectiveness will allow us to estimate the aging-failure rate based on estimates of the degradation rate.

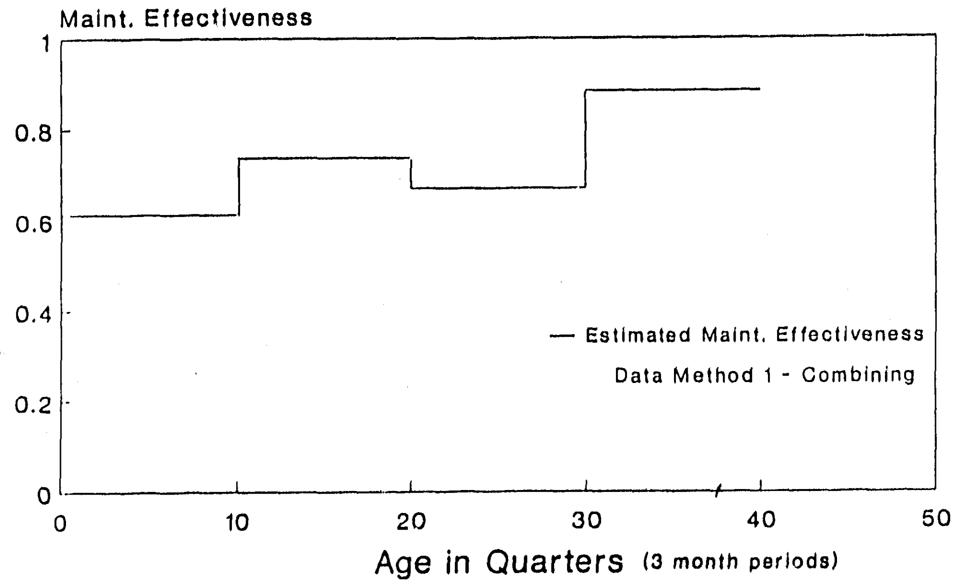

Figure 6. Maintenance effectiveness
(Component: RHR pumps; 3 plant data)

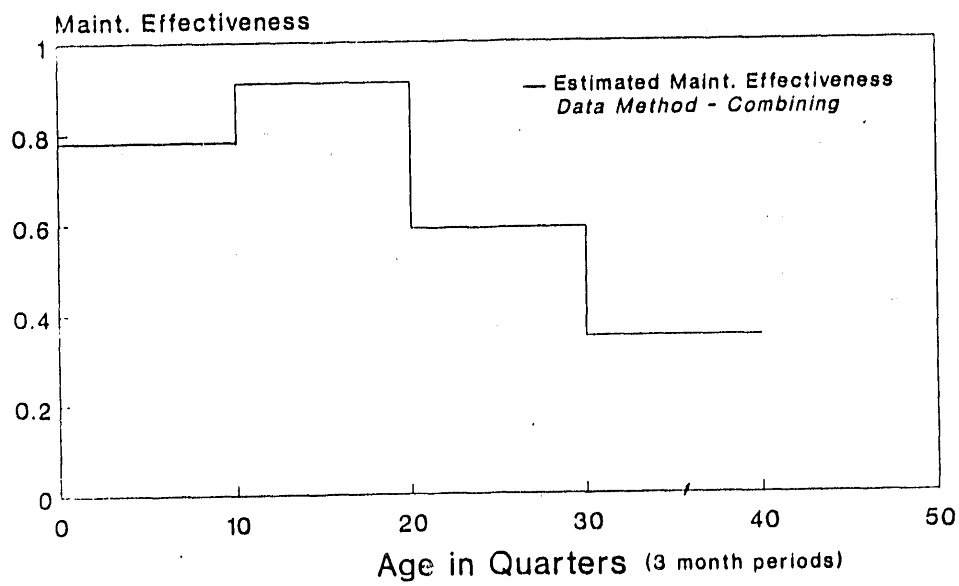

Figure 7. Maintenance effectiveness
(Component: air compressors)

5. SENSITIVITY ANALYSES TO STUDY EFFECTS OF MAINTENANCE CHARACTERISTICS

In this section, we present sensitivity analyses to study component reliability as a function of component operational and maintenance characteristics. The component reliability effect is studied in terms of the probability of failure. The component operational and maintenance characteristics are defined in terms of the parameters listed in Tables 2 and 3. Some results of these studies discussed below provide an understanding of the effect of maintenance and how maintenance activities can be defined to obtain the desired component reliability. We first discuss the "no maintenance" model, i.e., the effect on component failure probability when no maintenances are performed. Analysis of the same component (as defined by the parameter values) when maintenance is included are presented next. As stated before, a comparison of these two evaluations provides a quantitative measure of the effect of maintenance on the component.

Table 2: Parameter Values Fixed in the No Maintenance Model

Parameter	Average Time (Days)
Time from Operation to Failure (T_{of})	1095.0
Time from Failure to Operation (T_{of})	1.5
Time from Failure to Degradation (T_{fd})	15.0

Table 3: Parameter Values Fixed in the Maintenance Model

Parameter	Average Time (Days)
Time from Operation to Maintenance (T_{om})	365.0
Time from Operation to Failure (T_{of})	1095.0
Time from Degradation to Maintenance (T_{dm})	15.0
Time from Failure to Operation (T_{of})	1.5
Time from Failure to Degradation (T_{fd})	15.0

Figure 8 illustrates the no maintenance model. In this model the only corrective action that can be taken on the device is to perform repairs after total failure. The figure shows the probability of failure as a function of the average time from operation to degradation (T_{od}) and the average time from degradation to the failure state (T_{df}). All the other transition times used in the model were fixed at the values shown in Table 2.

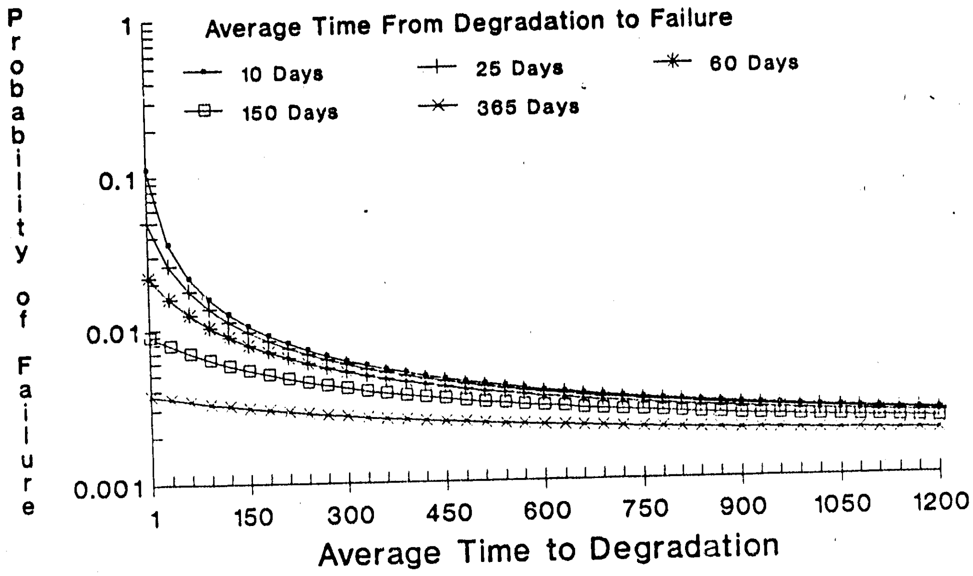

Figure 8. Sensitivity to the degradation rate with no maintenance

In Figure 8 it can be seen that the probability of failure decreases as either T_{od} or T_{df} is increased. Devices that take a longer time to pass from operation to a degraded state or take a longer time to pass from the degraded state to failure run a lower risk of failing. It can also be seen that T_{df} moderates the effect of T_{od}. If T_{df} is short then the probability of failure rapidly increases as T_{od} declines. If, on the other hand, T_{df} is long then a decline in T_{od} has little effect on the failure probability. A device that passes quickly to a degraded state, but then stays in the degraded state for an extended period of time has a low risk of failure.

In this case it can be seen that the greatest danger to the plant occurs when devices are aging in such a manner that both their transition time from operation to degradation, and their transition time from degradation to failure are increasing. As can be seen from the sudden upturn in Figure 8 there is a point where the failure probability starts to increase very rapidly. Preventative action must be take when a device reaches the steep part of this curve.

The no maintenance model only allows repair when a failure is detected. We now consider where maintenance is performed in the degraded state. Figure 9 illustrates the maintenance model. The probability of failure is shown as a function of the maintenance efficiency and T_{od}. In this figure T_{df} is fixed at 60 days, the average time in maintenance is fixed at three days, and the other parameters are fixed at the values which appear in Table 3.

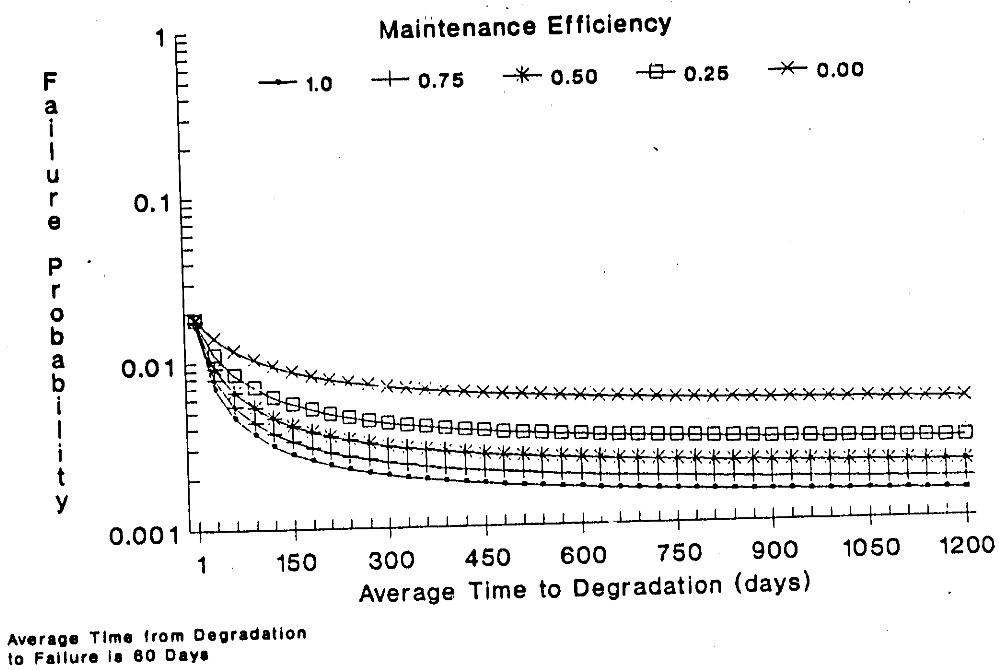

Figure 9. Sensitivity to maintenance

First, it can be seen by comparing Figure 1 to Figure 8 that the addition of a maintenance state reduces the probability of failure, thus confirming the obvious value of maintenance. The figure also shows that poor maintenance efficiency always produces a higher probability of failure than good values of maintenance efficiency. However, as T_{od} becomes smaller than say 200 days the probability of failure increases rapidly, and the difference between maintenance policies starts to diminish. As T_{od} approaches zero the difference between maintenance policies disappears.

As in the no maintenance model, there is also a point in the maintenance model where the probability of failure starts to increase rapidly. When a device has aged to the point where it starts to slip rapidly from the operational state to the degraded state action must be taken in order ameliorate the situation.

6. SUMMARY

In this paper, we have presented the concept of analyzing occurrences of component degradation, called degradation modeling, to obtain an understanding of the effects of aging and the role of maintenance in mitigating that effect. The applications presented show a number of benefits in modeling degradation occurrences as a part of component reliability studies. These can be summarized as follows:

1. Component degradation occurrences are identifiable in the available data bases and provide a larger data base, compared to failures, in the analysis of aging effects,

2. Aging trends are detectable in degradation occurrences and can provide early indications of aging,

3. The effectiveness of maintenance can be evaluated, which in turn can be used to alter maintenance practices, as necessary, to control age-related failures, and

4. The effect of maintenance on a component can be evaluated using degradation modeling approaches, which will help define maintenance activities necessary to mitigate aging effects.

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