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Risk Evaluations of Aging Phenomena: the Linear Aging Reliability Model and Its Extensions

William E. Vesely

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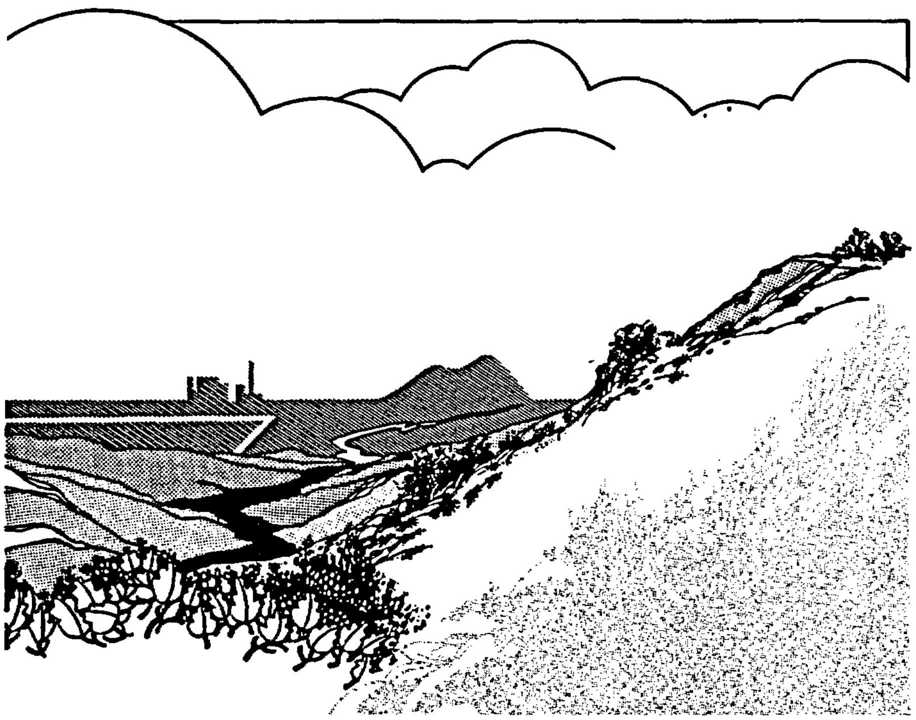

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RISK EVALUATIONS OF AGING PHENOMENA: THE LINEAR AGING RELIABILITY MODEL AND ITS EXTENSIONS

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ABSTRACT

A model for light water reactor safety system component failure rates due to aging mechanisms has been developed from basic phenomenological considerations. In the treatment, the occurrences of deterioration are modeled as following a Poisson process. The severity of damage is allowed to have any distribution, however, the damage is assumed to accumulate independently. Finally, the failure rate is modeled as being proportional to the accumulated damage. Using this treatment, the linear aging failure rate model is obtained. The applicability of the linear aging model to various mechanisms is discussed. The model is also extended to cover nonlinear and dependent aging phenomena. The implementation of the linear aging model is demonstrated by applying it to the aging data collected in the U.S. Nuclear Regulatory Commission's Nuclear Plant Aging Research Program.

FIN No. A6831—Root Causes of Component Failures

EXECUTIVE SUMMARY

One of the highest priorities in evaluating aging implications at nuclear plants is to determine the risk and reliability implications of aging. In determining the risk and reliability implications of aging, the goal is to relate aging descriptions and measures to risk and reliability characteristics. The work described in this report is a step in this direction. In this work, failure rates of aging components are related to the aging mechanisms that cause the deterioration and damage in the component. The component failure rates can then be used in probabilistic risk analysis (PRA) models to determine the risk impacts of aging.

The component failure rate due to an aging mechanism is obtained by modeling the aging process and its effects on the component failure probability. The stochastic nature of the aging phenomena is incorporated in the model. A simple expression is obtained for the failure rate, which is shown to be linearly proportional to the exposure time to the mechanism. This exposure time is the effective age of the component with regard to the mechanism; hence, the failure rate is simply a linear aging failure rate. The report shows how the linear aging model can be extended to cover nonlinear and dependent aging phenomena.

The aging models developed in this report are particularly useful for applications. Because of the simplicity of the expressions obtained, present data, even gross data, can be used to investigate the risk effects of aging. The component failure rates that are determined can be utilized in present PRAs to determine how system unavailabilities, core melt frequency, and public risks change with plant age.

The developed models can be used to evaluate the effectiveness of present testing and maintenance in controlling aging, the dominant contributors to aging risks, and the regulatory and research issues that are associated with aging. The models are applied in the report to demonstrate how aging effects can be incorporated in component reliability evaluations and system unavailability calculations. The applications show that aging as observed in collected data has significant effect on the component failure probability and component reliability if the aging is not effectively detected and controlled by testing and maintenance. The linear aging model is also applied to demonstrate the handling of aging contributions in calculating system unavailability. A model of the auxiliary feedwater system for Arkansas Nuclear Unit 1 is specifically analyzed. System unavailabilities are calculated using available aging data and assuming different testing effectiveness in detecting and correcting aging failure modes. Depending on the types of tests performed, it is shown that aging can either have a small effect on system unavailability or can cause system unavailability to significantly increase with plant age to the point of being essentially unavailable for any accident. Figure ES-1 illustrates the results that are obtained. The figure shows the system unavailability versus plant age for a model of the auxiliary feedwater system for Arkansas Nuclear Unit 1 under various data assumptions and testing assumptions described in the report. The "with aging" curve incorporates the aging contributions, and the "averaged" curve ignores aging and treats all failures as being random as is done in the usual PRA calculation.

The work done here is a good first step in directly measuring the risk and reliability effects of aging. Future work should involve:

- Performing more detailed data and statistical analyses to obtain mechanism-specific failure rates
- Modeling more accurately test and maintenance effects
- Developing systematic procedures for utilizing the models
- Quantifying uncertainties
- Developing experimental designs for identifying regulatory and research issues
- Relating the aging failure rates to load conditions, environmental effects, and material properties for condition monitoring purposes.

By doing this work, the risk and reliability impacts of aging will be better understood, and be more effectively controlled where necessary to ensure acceptable risks from aging.

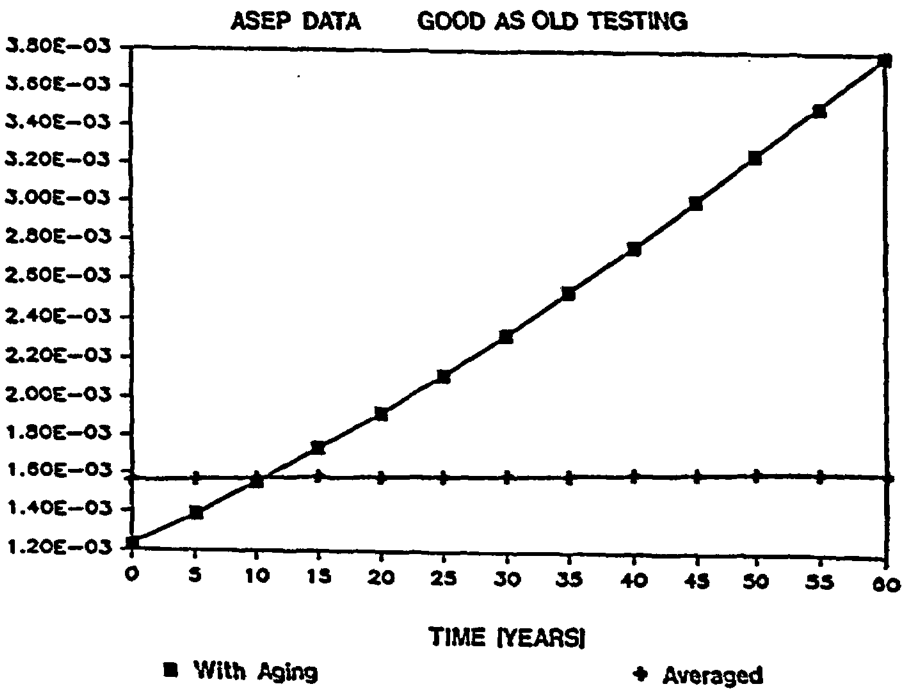

Figure ES-1. System unavailability versus age.

ACKNOWLEDGMENTS

Vesna B. Dimitrijevic developed the software approaches for performing the system unavailability and data analyses and carried out the evaluations. Holly Gibson carried out the actual software executions and assisted in the evaluations.

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FIGURES

RISK EVALUATIONS OF AGING PHENOMENA: THE LINEAR AGING RELIABILITY MODEL AND ITS EXTENSIONS

1. INTRODUCTION

Aging occurs when the physical and operating properties of nuclear power plant structures and components degrade. Various mechanisms and stressors cause the physical and operating characteristics to degrade and, hence, cause aging. Some of the mechanisms and stressors present in light water reactors (LWRs) include neutron and gamma fluxes, which cause irradiation damage; pressures and temperatures, which cause fatigue and material toughness changes; and stress corrosion, which causes cracking and fractures.

When the properties of nuclear power plant structures and components degrade, then their reliabilities can degrade. The reliability is determined by such quantities as the frequency of failure, frequency of an initiating event (such as a pipe break), failure rate, and unavailability. When the reliabilities of structures and components degrade, then the safety and risk of the plant can be adversely affected.

The relationship whereby aging mechanisms cause property changes that cause reliability changes, which in turn affect plant safety, is the tie, or overall relationship, between aging and plant safety. To understand and control the effects of aging on nuclear power plant safety, it is, therefore, important to identify and model the individual relationships involved in the overall relationship between aging and safety.

The identification and modeling of the individual relationships involves determining and measuring the property changes caused by various mechanisms occurring in plant environments and under plant operating conditions. It involves determining the relationships between property changes and reliability by relating failure rates and reliability parameters to property characteristics. Finally, it involves relating component and structure reliability to plant safety and risk by constructing and evaluating plant safety analyses and plant risk analyses.

In this work, we will focus on the relationships involving aging mechanisms, property changes, and component failure rates. Specifically, we will develop models that express the component failure rate and component reliability in terms of parameters that characterize the rate and severity of specific aging mechanisms. We relate the component failure rate to aging mechanism characteristics, bypassing the property and physical change relationships.

We proceed in this manner, relating the failure rate directly to aging mechanism parameters, because available component failure data will allow us to directly estimate the aging mechanism parameters and, hence, the aging failure rates for the components. With estimates of the component aging failure rates, we can then determine the impacts of aging on public health risk, core melt probability, and other risk measures using risk models such as probabilistic risk analyses (PRAs).

The models that we will develop will allow physical property considerations and condition monitoring considerations to be incorporated in the future. This can be done by relating the aging mechanism characteristics to material and physical property changes. Using the models that relate failure rates to the aging mechanism characteristics, the component failure rates can then be expressed in terms of the material and physical property characteristics. This will allow condition monitoring measurements to be related to reliability implications, which is necessary for effective application of condition monitoring.

The models we develop that relate component failure rates to aging parameters are termed component aging reliability models. The component aging reliability models can be used to give the component failure probabilities in terms of aging mechanism parameters that are obtainable from data and engineering knowledge. The component failure probabilities produced by the component reliability models can then be used in PRA models to calculate public health risk, core melt probability, system unavailability, and other risk measures. Because the component failure probabilities will in general be time or age dependent, time-or age-dependent PRA models will need to be utilized in order to determine the system and plant level risk implications. Various time (age)-dependent PRA approaches exist and can be utilized, once the component failure probabilities are determined using the component aging reliability models in this report.[1-3]

It is important that the component aging reliability models that are developed be compatible with the data and knowledge that exist. If the component model has more parameters than can meaningfully be determined from present data or engineering knowledge, then the model will be overspecified. Examples of models that can be overspecified when only sparse data are available include the more or less standard statistical approaches that utilize the Weibull distribution, gamma distribution, or another statistical distribution to statistically fit sequences of failure times. In these approaches, the time to failure distribution of an aging component is described by a statistical distribution with unknown parameters. The parameters are then empirically determined by fitting (according to some criterion) the statistical distribution to the data. The potential problem with these more or less standard approaches is that significant amounts of detailed failure time data are needed to estimate, with any precision, values for the parameters. Furthermore, the parameters are rather abstract and it is difficult to interpret their engineering implications.

Our objective in this work is to develop component aging reliability models that are compatible with sparse data and have an engineering justification and an engineering interpretation. Because failure data exhibiting aging behavior is rather gross and summarized in its present form,[4-7] the models need to be as parsimonious as possible, having as few parameters as possible but still having a valid foundation.

2. DERIVATION OF THE LINEAR AGING MODEL

We will show how a straightforward component aging reliability model can be developed from basic aging mechanism considerations. The model will be applicable for a variety of aging mechanisms acting on various components. First, we will derive the model in a simplified manner and then more formally derive the model giving in more detail the conditions when the model is applicable. We will also show how the model can be extended to cover more general aging mechanisms.

We will spend some time in developing the model because we feel it is important to have an understanding of the model. Also, we feel it is important to understand the assumptions and relations that make up the model. The model we develop is sometimes termed the linear failure rate model, which for our applications can be more appropriately called the linear aging model. The development of the model as applied to aging mechanisms and aging processes is, to our knowledge, new and has not been presented before.

To begin, consider a specific aging mechanism such as corrosion, wear, or vibration, and let $\lambda(t)$ be the failure rate for the component failing at age t due to this mechanism:

$\lambda(t)$ = the component aging failure rate for failure at age t due to a specific aging mechanism . (1)

Note that we have used the symbol "t" to denote the component age. Instead of time as a measure of age, the symbol t can stand for any other age measure, such as number of startup cycles. The appropriate age measure will depend upon the specific aging mechanism being considered. Time will be appropriate, for example, for corrosion occurring in a component, while number of cycles will be appropriate for fatigue due to cycling of the component.

The component aging failure rate, $\lambda(t)$, for component failure at age t due to an aging mechanism is the key component reliability characteristic needed. From the aging failure rate, the component failure probability and other related characteristics, such as the component unavailability, can be determined.[8,9]

The basic definition of the component aging failure rate, $\lambda(t)$, is

$\lambda(t)$ = the probability per unit time that the component fails at age t due to the aging mechanism . (2)

This is a standard definition of a time-dependent failure rate with the age measure replacing time. Note that in the above definition, the probability of failure is not conditioned on the fact that no failure occurred before t. The failure rate, $\lambda(t)$, is not a first failure rate. The failure occurring at age t can be the first, second, or any subsequent failure. In general, based on the sparse data available, it is often not known whether a failure is the first or not.

In the above definition, the "probability of failure per unit time" can be replaced by the "frequency of failure." Thus, an alternative definition of the aging failure rate, $\lambda(t)$, is

$\lambda(t)$ = the frequency of component failure at age t due to the aging mechanism . (3)

This frequency of failure definition is often used instead of the previous failure rate definition when it is not known whether the failure is a first failure or not, as applies here.

To obtain the aging failure rate, $\lambda(t)$, in terms of basic aging mechanism characteristics, we first model the aging failure rate as being proportional to the amount of degradation that has occurred from the aging mechanism:

$\lambda(t) \propto$ to the amount of degradation that has occurred to age t from the aging mechanism . (4)

In Equation (4), the symbol "$\propto$" means "is proportional to." The above characterization of the effect of the aging mechanisms can be interpreted as saying that the probability of failure is proportional to the amount of degradation that has occurred. Equation (4) is a general characterization of the aging mechanism or process as continually deteriorating the component by continually increasing the failure rate. In references on general stochastic modeling of physical processes, the above characterization is sometimes termed a characterization of cumulative damage processes with no threshold.[10-12]

Now the amount of degradation that occurs by age t can be characterized as being equal to the rate the degradation occurs x the age x the severity of damage produced each time a degradation occurs. If we let

$$D = \text{the total amount of deterioration experience by the component to age } t \quad , \tag{5}$$

$$r = \text{the rate the component experiences deterioration due to the aging mechanism} \quad , \tag{6}$$

and

$$x = \text{the severity of deterioration incurred by the component each time it is affected by the aging mechanism} \quad , \tag{7}$$

then

$$D = rtx \quad . \tag{8}$$

Equation (8) is a general definition of the deterioration, or damage, in terms of the deterioration rate and deterioration severity. If the rate of deterioration or the severity of deterioration randomly varies, the rate, r, and severity, x, in Equation (8) are taken as average values.

Now by the cumulative damage characterization in Equation (4), the aging failure rate, $\lambda(t)$, is proportional to the amount of deterioration, D:

$$\lambda(t) = kD \quad , \tag{9}$$

where k is the probability conversion constant and is equal to the probability of failure per unit degradation. Substituting Equation (8) into Equation (9), we have

$$\lambda(t) = krtx \quad , \tag{10}$$

or rearranging the right-hand side

$$\lambda(t) = krxt \quad . \tag{11}$$

Equation (11) shows that for the cumulative damage characterizations of aging, the aging failure rate is linearly proportional to the age t with the proportionality constant being equal to krx:

$$\lambda(t) = at \quad , \tag{12}$$

where

$$a = krx \quad . \tag{13}$$

We can term the constant "a" the aging acceleration rate, or simply the aging rate, because it gives the rate at which the failure rate increases (the units of a are per unit time squared, as for an acceleration). The above model as given by Equations (12) and (13) can be appropriately termed the linear aging model, or linear aging failure rate, because the aging failure rate is linearly proportional to the age. The linear aging failure rate is discussed sometimes in the literature as a special case of the Weibull distribution, which is an empirical type of statistical distribution.[13,14] However, the above derivation shows the basis and interpretation of the model in terms of aging mechanism properties.

For implementation, the constants k, r, and x, or equivalently the constant a, can be determined for specific components and specific aging mechanisms. The constant a is most directly determined from data, while the more basic constituent factors (k, r, and x) are determined from condition monitoring and component property considerations. Before we discuss the utilizations of Equations (12) and (13), we will more formally derive Equations (12) and (13) and show how the linear aging model can be extended.

3. MORE FORMAL DERIVATION OF THE LINEAR AGING MODEL

Consider again a specific aging mechanism that causes the component to deteriorate with age. The amount of deterioration can range from negligible to significant, depending upon the specific stresses the component experiences while on standby or while operating.

To be general, we will model the deterioration as being random in both the times at which the deteriorations occur and the severity of damage incurred by the component each time a deterioration occurs. If there is little variability associated with the deterioration, then the component will undergo a very regular, continual deterioration, aging process. If there is high variability to the deterioration, then the component will undergo a highly irregular aging process. We will develop our model to cover both extremes as well as intermediate cases.

Assume the occurrence of the deteriorations can be described by a Poisson process with a constant occurrence rate, r. This implies that the probability of occurrence of a deterioration in some small age interval is proportional to the size of the interval and is independent of the past number of deteriorations that have occurred. The probability, $P_n(t)$, of n deteriorations occurring in age t is then given by the Poisson distribution:

$$P_n(t) = \frac{(rt)^n e^{-rt}}{n!} \qquad n=0,1,... \tag{14}$$

Figure 1 shows some of the different shapes the Poisson distribution can assume for different values of the parameter $m = rt$. For $m < 1$, the most probable event is that no deterioration will occur ($n = 0$). The next most probable event is that one deterioration occurs if any deteriorations do occur. For $m < 1$, $P_n(t)$ is thus j-shaped, like a geometric distribution.

For $m >> 1$, $P_n(t)$ becomes bell-shaped like a normal distribution. The most probable number of occurrences is m, the mean of the Poisson. The standard deviation of the Poisson is m, and the relative variation in the number of deteriorations as measured by the ratio of the standard deviation to the mean is $1/\sqrt{m}$. Hence, if $m >> 1$, the relative variation in the number of occurrences from the average (or most probable value) is small. On the other hand, for $m << 1$, the relative variation is quite large.

Thus, the Poisson covers the range from highly irregular deterioration ($m << 1$) to highly regular deterioration ($m >> 1$) and cases between. Because the damage from a particular deterioration occurrence has not been restricted and can be of any size, the spectrum of possible cumulative damage from the deteriorations that is covered is quite general.

The restrictions the Poisson has in terms of age modeling are that the probability of a deterioration is proportional to the age interval (if the interval is small) and the occurrence of a deterioration is independent of past deteriorations that have occurred. The probability of a deterioration being proportional to the age interval implies that the age scaling is linear, to use the terminology of cumulative damage process modeling (Reference 13).

The occurrence of a deterioration being independent of past deteriorations implies that the deteriorations occur in the form of independent, incremental stresses that are incurred by the component as it ages. We will show how we can drop the independence assumption and only assume the deterioration process is stationary (in statistical expectation) and still obtain the same linear failure rate model. Because the assumption of being stationary is rather general, the independence assumption is not necessarily constraining, particularly when we can extend the model to include nonlinear aging behavior and nonlinear age scaling.

Now that we have characterized the occurrences of deteriorations by a Poisson distribution, we need to characterize the severity of deterioration incurred at each occurrence. The severity of deterioration can be the amount of damage incurred by an individual applied stress or the size of physical or material property change that occurs in a time interval in an aging environment. We will allow the size of the deteriorations to have any distribution, f(x). The only constraint is that the distribution has a finite mean value, say x. We assume, however, that the severity of deteriorations in different occurrences (i.e., the severity increments) are independent and have the same general distribution, f(x).

The assumption of independent severity increments needs discussion. For an applied stress, this independence assumption implies that the damage incurred as a result of the stress is independent of the past damage incurred. Thus, the damage accumulates in independent increments. The independence assumption is also applicable when a change in material properties incurred as a result of an

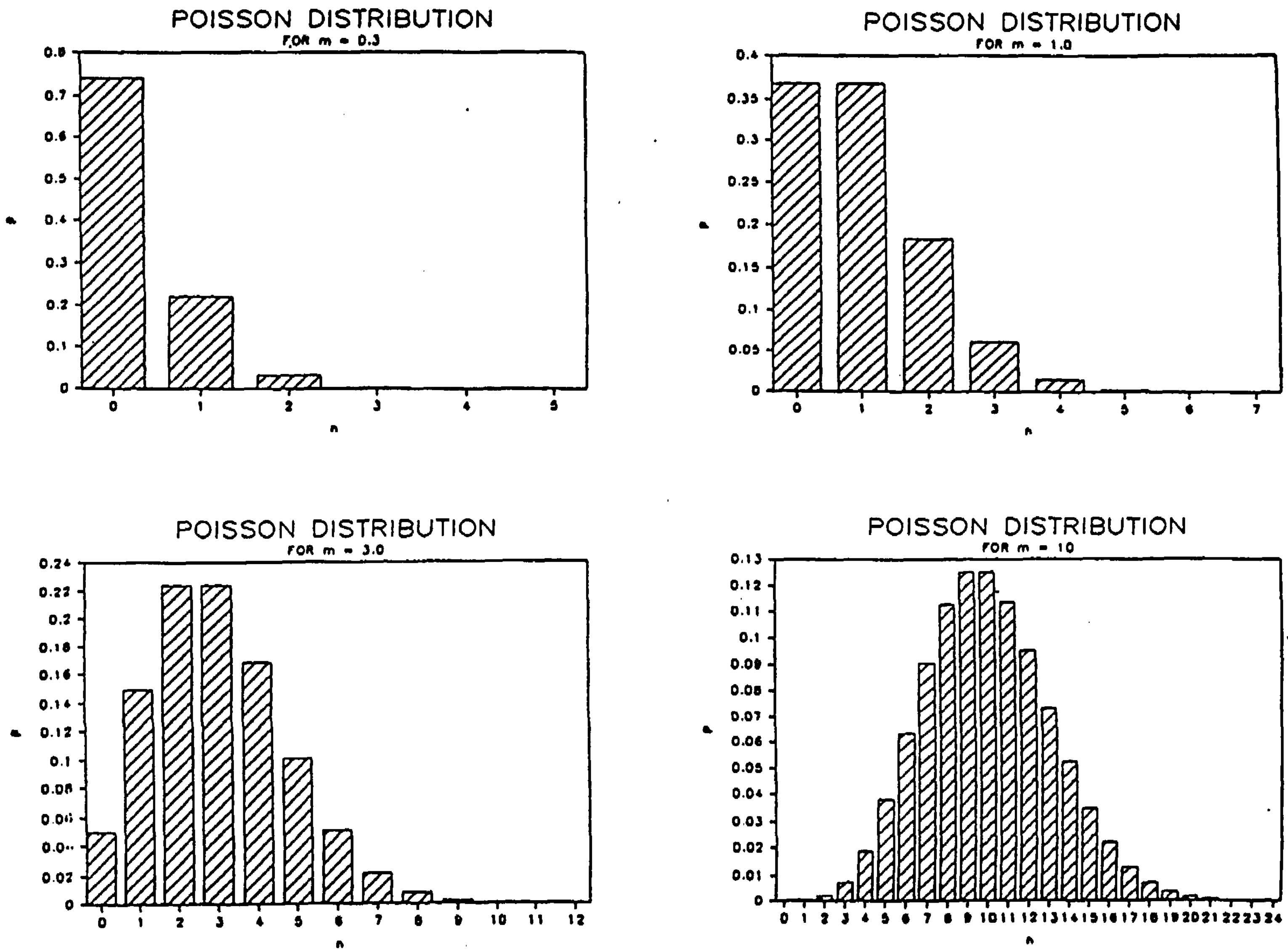


Figure 1. Poisson distribution shapes.

exposure to an aging environment does not affect the further change in material properties due to the environment. The independence assumption is applicable to such aging processes as linear wear, linear material buildup, and linear elastic-related phenomena.

For certain aging mechanisms, the damage or change incurred is not independent, but instead is dependent upon the past accumulated damage or change. Vibration and some forms of corrosion are examples of such mechanisms, where the damage incurred can be dependent upon the past vibration or corrosion experienced. When the damage or change incurred is positively dependent upon the past accumulation (i.e., grows larger as the accumulations increase), then the independence assumption will underestimate the aging effects. The discrepancy will increase as the aging effects increase. For these dependent aging mechanisms, the linear aging model can still be used but will provide a lower bound on the aging effects. A later section shows how the linear aging model can be extended to cover dependent aging mechanisms.

As a last step in our more formal development of the linear aging model, we need to relate the deterioration of the component at a given age to its failure rate. We will model the failure rate as being directly proportional to the deterioration that has occurred. This is the most straightforward characterization. The extensions to a general nonlinear age scaling and to dependent aging mechanisms can serve to cover cases where there is a more complicated relationship.

To express the proportionality relationship between the failure rate and the deterioration, let the failure rate be denoted by $\lambda(t)$ for the component failing at age t due to the specific aging mechanism. The basic definition of the failure rate is given by Equation (2) or (3). By the proportionality characterization, the failure rate is directly proportional to the specific amount of deterioration, D, the component has experienced from the aging mechanism to age t:

$$\lambda(t) = kD \quad , \tag{15}$$

where k is the probability conversion constant.

What is different from the previous failure rate versus deterioration relationship [Equation (9)] is now the deterioration, D, is a random variable. For any given age t, D can randomly vary depending upon the previous history of the stresses incurred. Consequently, $\lambda(t)$ at a given age t can randomly vary depending upon the random values D can assume. The deterioration, D, and the failure rate, $\lambda(t)$, are thus stochastic functions versus age. Figure 2 shows an example of a possible realization of the number of deteriorations and the accumulated deterioration for a constant value for the severity of each deterioration.

As previously stated, the treatment of the deterioration and the failure rate as random functions provides a general framework for describing a wide variety of aging behaviors. To obtain the final expression for the aging failure rate, $\lambda(t)$, we need to use Equation (15) and probabilistically combine, or convolute, the probability of various numbers of deteriorations occurring with the various sizes each deterioration may have. This will account for all the possible histories (realizations) and their likelihood in determining the expected value of $\lambda(t)$.

Using the Poisson distribution for the number of deteriorations, the general distribution, f(x), for the size of each deterioration, and the deterioration relationship given by Equation (15), the expected value for $\lambda(t)$ can be expressed in terms of the equation

$$\lambda(t) = \sum_{n=0}^{\infty} P_n(t) \int_0^{\infty} f_n(D) kD dD \quad , \tag{16}$$

where $P_n(t)$ is the probability that n deteriorations occur in age t, and $f_n(D)$ is the probability distribution for the total deterioration, D, given n deteriorations have occurred. For a given deterioration, D, the failure rate, $\lambda(t)$, is equal to kD, which is the additional factor in the above equation. The failure rate for a specific deterioration, kD, is thus averaged over all possible values of n and D to obtain the expected failure rate, $\lambda(t)$.

Now, for n deteriorations occurring, the total deterioration, D, is the sum of n independent deteriorations, x. Hence, $f_n(D)$ is the n-fold convolution of the individual distributions, f(x). Consequently,

$$\int_0^{\infty} f_n(D) D dD = n\bar{x} \quad , \tag{17}$$

where $\bar{x}$ is the average value of the distribution, f(x). The quantity x is the average severity, or damage, associated with each deterioration occurrence.

Substituting Equation (17) into Equation (16), we have

$$\lambda(t) = \sum_{n=0}^{\infty} P_n(t) k n \bar{x} \quad . \tag{18}$$

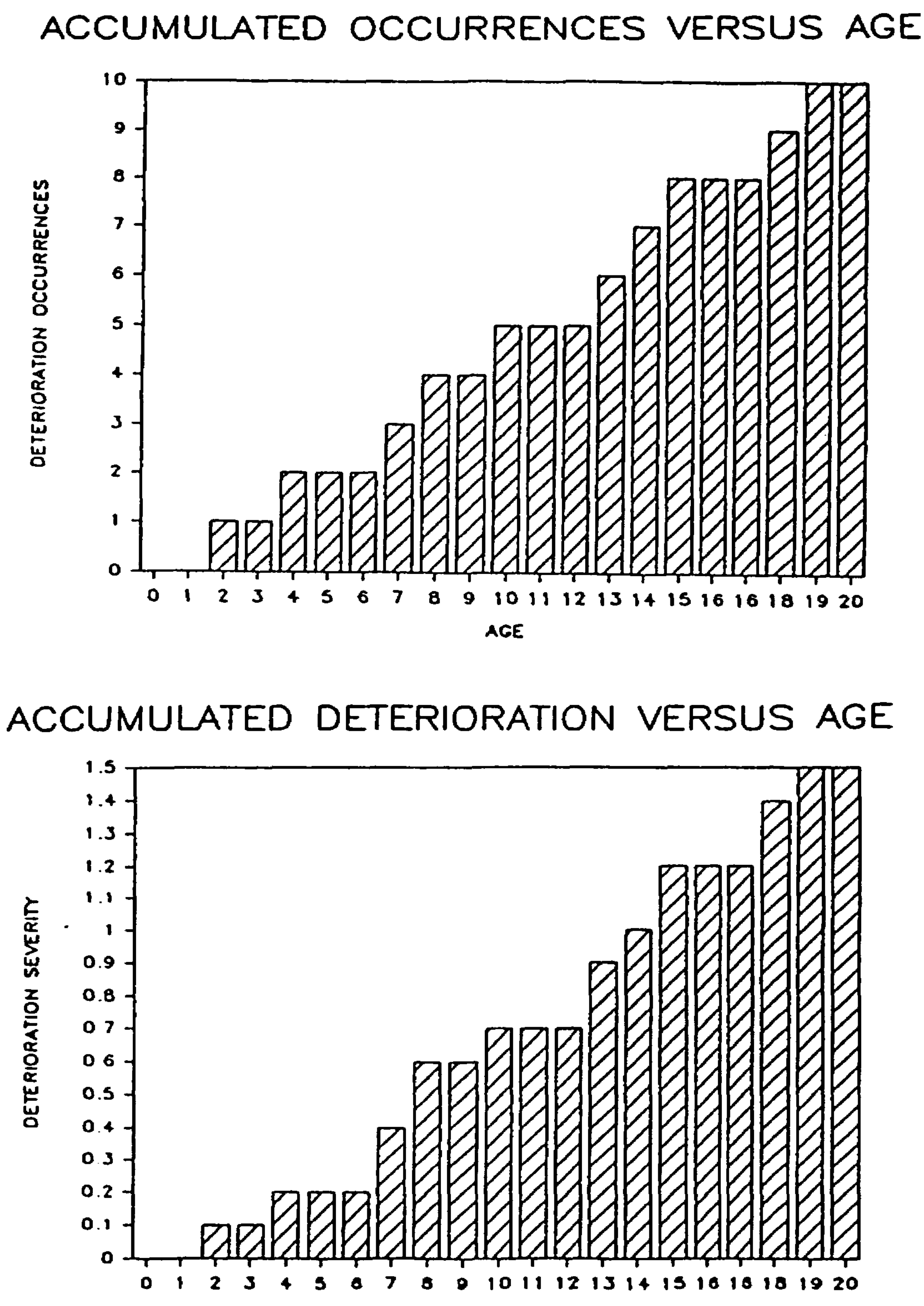


Figure 2. Stochastic deterioration behavior.

This can also be written as

$$\lambda(t) = k\bar{x}\sum_{n=0}^{\infty} P_n(t)n \quad . \tag{19}$$

Now for the Poisson distribution with rate parameter, r, the mean number of occurrences is rt. Hence,

$$\sum_{n=0}^{\infty} P_n(t)\, n = rt \quad . \tag{20}$$

Thus, Equation (19) becomes

$$\lambda(t) = k\bar{x}rt \quad . \tag{21}$$

We thus arrive at essentially the same straightforward result that the aging failure rate, $\lambda(t)$, is linearly proportional to the age t with the proportionality constant equal to kxr; thus,

$$\lambda(t) = at \quad . \tag{22}$$

with

$$a = k\bar{x}r \quad . \tag{23}$$

This result is the same as that derived earlier in a less formal fashion [Equation (12)] with $\bar{x}$ replacing x and r now being interpreted as the rate of occurrence parameter for the Poisson distribution.

4. APPLICABILITY TO STATIONARY PROCESSES

The above results [Equations (22) and (23)] were obtained by modeling the deterioration occurrence as a Poisson process. The same results are obtained for stationary processes, which are more general than the Poisson process. This can be seen by going back to Equation (19), which did not yet incorporate the Poisson distribution model. Equation (19) is again

$$\lambda(t) = k\bar{x}\sum_{n=0}^{\infty} P_n(t)n \quad . \tag{24}$$

where again $P_n(t)$ is the probability that n deteriorations occur in age t.

If, instead of using the Poisson model for $P_n(t)$, we assume the deterioration occurrences are regular with an expected value proportional to the age, then

$$\sum_{n=0}^{\infty} P_n(t)n = rt \quad , \tag{25}$$

where r is the expected occurrence rate. Equation (24) is the key equation, which is necessary to obtain the linear aging model and not the more restrictive Poisson model. Processes characterized by Equation (25) are termed stationary processes in stochastic modeling.[15]

If Equation (25) is substituted into Equation (24), then we have

$$\lambda(t) = k\bar{x}rt \quad , \tag{26}$$

which is the same result as derived with the Poisson model utilization. The rate, r, instead of being the Poisson occurrence rate, is now the more general expected occurrence rate. Thus, the linear aging model is applicable to not only Poisson deterioration processes but to any deterioration process that is stationary and is characterized by Equation (25).

5. EXTENSION TO NONLINEAR AGE SCALINGS

The previous model can be extended to incorporate any general, nonlinear aging process. This will change the linear age scaling to a nonlinear age scaling and, consequently, will change the linear aging failure rate to a nonlinear aging failure rate.

To extend the results, we model the deterioration occurrence not as a homogeneous Poisson process but as a nonhomogeneous Poisson process. The nonhomogeneous Poisson process allows the rate of deterioration to be any function of the age.

For a general nonhomogeneous Poisson process, the probability, $P_n(t)$, that n deteriorations occur in age t is given by

$$P_n(t) = \frac{[Q(t)]^n e^{-Q(t)}}{n!} \tag{27}$$

The function Q(t) can be any function of the age. Because of the nonhomogeneous Poisson property, Q(t) is the expected number of deteriorations that will occur to age t:

$$\sum_{n=0}^{\infty} nP_n(t) = Q(t) \quad . \tag{28}$$

Q(t) is also directly proportional to the expected deterioration that will occur to age t (with proportionality constant equal to $\bar{x}$). Because Q(t) is directly proportional to the expected deterioration to age t, Q(t) gives the scaling on which the deterioration occurs as compared to the direct age measure scale t. In effect, Q(t) gives the conversion from the direct age scale to the deterioration scale. On the deterioration scale, the aging is linear. In cumulative damage modeling, for example, a power scaling is sometimes used for those cases where the linear age scale is found not to be applicable (Reference 10), that is,

$$Q(t) = at^b \quad . \tag{29}$$

To extend the linear aging failure rate model to cover nonlinear processes, we utilize the nonhomogeneous Poisson distribution in the equation for the failure rate, $\lambda(t)$. Starting again with Equation (19), we have

$$\lambda(t) = k\bar{x} \sum_{n=0}^{\infty} P_n(t)n \quad . \tag{30}$$

Treating $P_n(t)$ as a nonhomogeneous Poisson distribution and using Equation (28), we have

$$\lambda(t) = k\bar{x}Q(t) \quad . \tag{31}$$

Equation (31) is, consequently, the generalization of the linear failure rate model given previously by Equation (22). Instead of being proportional to the age t, the failure rate is generalized to be proportional to the deterioration scaling, Q(t).

Because Equation (28) is the key equation in deriving Equation (31), we see that Equation (31) will be obtained for any stationary aging process, not only Poisson, that satisfies Equation (28). This is similar to the generalization that was made earlier for applicability of the linear failure rate model to a general stationary deterioration process.

6. APPLICATIONS OF THE MODELS WHEN SEVERAL AGING MECHANISMS ACT ON THE COMPONENT

Both the linear and nonlinear aging models derived in the previous sections can be applied to situations where different aging mechanisms act on the component. Because of the additive property of the Poisson (sums of Poissons are another Poisson), the overall aging failure rate of the component is then the sum of the individual aging mechanism failure rates. The individual aging mechanism failure rates can be either linear or nonlinear.

Consequently, if K different aging mechanisms act on the component, each with failure rate $\lambda_K(t_K)$, then the total aging failure rate, λ_A, is the sum of the individual failure rates

$$\lambda_A = \lambda_1(t_1) + \lambda_2(t_2) + \ldots + \lambda_K(t_K) \quad . \tag{32}$$

In the most general case indicated above, each aging mechanism can have its own associated age t_K, which represents the time of exposure of the component to the particular aging mechanism. If all the aging mechanisms have the same associated age, say t, then the total aging failure rate, λ_A, is

$$\lambda_A = \lambda_1(t) + \lambda_2(t) + \ldots + \lambda_K(t) \quad . \tag{33}$$

In the above formulas, each individual aging failure rate, $\lambda_K(t_K)$, [or $\lambda_K(t)$] can be either linear or nonlinear. If they are all linear, then the overall aging failure rate is linear.

7. INCORPORATION OF CONSTANT FAILURE RATE CONTRIBUTIONS

A constant failure rate contribution representing non-aging, random failure causes can be added to the aging failure rate to obtain the total component failure rate. If λ_T is the total component failure rate, then

$$\lambda_T = \lambda_0 + \lambda_A \quad , \tag{34}$$

where λ_0 is the constant failure rate contribution and λ_A is the aging failure rate contribution given by Equation (32) or (33).

A constant failure rate contribution can also be added to a particular aging mechanism failure rate. The constant failure rate contribution can represent the residual failure rate when there is no deterioration experienced in the particular age interval. For example, the residual failure rate may represent damage already existing in an installed component. For a residual constant failure rate contribution, Equation (9) generalizes to

$$\lambda(t) = c + kD \quad , \tag{35}$$

where c is the constant residual failure rate contribution. Using Equation (35) to obtain the expected value of $\lambda(t)$, we have

$$\lambda(t) = \sum_{n=0}^{\infty} P_n(t) \int_0^{\infty} f_n(D)\,(c+kD)dD \quad , \tag{36}$$

which using the previous results can be shown to give

$$\lambda(t) = c + at \quad , \tag{37}$$

where again

$$a = k\bar{x}r \quad . \tag{38}$$

The linear aging failure rate is simply generalized to include a constant term c representing the residual, constant failure rate contribution. From an engineering standpoint, the generalized linear failure rate given by Equation (37) can be viewed simply as a straightline approximation to the wear-out portion of the bathtub curve.

8. EXTENSION OF THE LINEAR AGING MODEL TO COVER DEPENDENT AGING MECHANISMS

As stated, the linear aging model treats the severity of deterioration that occurs at any time to be independent of the past accumulated deterioration. To generalize this treatment, we will allow the severity to be linearly dependent on the size of the past deterioration. To still allow the deteriorations to be random, we will treat the mean of each severity occurrence as being linearly dependent upon the past accumulated deterioration. Because we allow the variation (variance) of each severity to be of any size, this dependency model is rather general, covering loose to very strong dependencies.

In terms of equations, the linear dependency model can be expressed as

$$\bar{x} = \alpha + \beta D \quad . \tag{39}$$

where $\bar{x}$ is the mean, or average size, of a deterioration occurrence given a past accumulated deterioration, D, and α and β are constants. The constant β represents the strength of the dependency. If β is zero, then the deteriorations are independent of one another and we obtain the previous linear aging model.

Equation (16) can be rewritten as

$$\lambda(t) = \sum_{n=1}^{\infty} P_n(t) k E[x_1 + \ldots + x_n] \quad , \tag{40}$$

where $E[x_1 + \ldots + x_n]$ is the expected value of $x_1 + \ldots + x_n$. We determine $E[x_1 + \ldots + x_n]$ in steps. Let $E[x_1 + \ldots + x_n; x_1 + \ldots + x_{n-1}]$ be the expected value of $x_1 + \ldots + x_n$ given $x_1 + \ldots + x_{n-1}$ (i.e., keeping $x_1 + \ldots + x_{n-1}$ fixed). Then, using the linear dependency model given by Equation (39), we obtain

$$E[x_1 + \ldots + x_n; x_1 + \ldots + x_{n-1}] = \alpha + (\beta + 1)(x_1 + \ldots + x_{n-1}) \quad . \tag{41}$$

Similarly,

$$E[x_1 + \ldots + x_n; x_1 + \ldots + x_{n-2}] = \alpha + \alpha(\beta + 1) + (\beta + 1)^2(x_1 + \ldots + x_{n-2}) \quad . \tag{42}$$

Proceeding in this manner, we obtain

$$E[x_1 + \ldots + x_n; x_1] = \alpha + \alpha(\beta + 1) + \alpha(\beta + 1)^2 + \ldots + \alpha(\beta + 1)^{n-2} + (\beta + 1)^{n-1} x_1 \quad . \tag{43}$$

Finally, averaging over x_1, we obtain

$$E[x_1 + \ldots + x_n] = \alpha + \alpha(\beta + 1) + \alpha(\beta + 1)^2 + \ldots + \alpha(\beta + 1)^{n-1} \quad . \tag{44}$$

The above power series can be re-expressed as

$$E[x_1 + \ldots + x_n] = \frac{\alpha}{\beta}((\beta + 1)^n - 1) \quad . \tag{45}$$

Therefore, Equation (40) becomes

$$\lambda(t) = \sum_{n=1}^{\infty} P_n(t) k \frac{\alpha}{\beta}((\beta + 1)^n - 1) \quad . \tag{46}$$

By using the identity

$$\sum_{n=1}^{\infty} P_n(t) z^n = e^{rt(z-1)} - e^{-rt} \quad , \tag{47}$$

Equation (46) becomes

$$(t) = k \frac{\alpha}{\beta}(e^{rt\beta} - e^{-rt} - 1 + e^{-rt}) \tag{48}$$

or

$$\lambda(t) = k \frac{\alpha}{\beta}(e^{rt\beta} - 1) \quad . \tag{49}$$

For small β, expanding the exponential to first order, we have

$$\lambda(t) \cong k \frac{\alpha}{\beta}(1 + rt\beta - 1) = k \alpha rt \quad , \tag{50}$$

which is again the linear aging model with $\alpha = \bar{x}$. Thus, the above model generalizes the linear aging model to cover nonlinear aging dependencies.

9. DETERMINATION OF THE RELIABILITY IMPLICATIONS OF AGING

Once the failure rate is determined, the component reliability characteristics can be determined using reliability technology approaches. For example, a basic component reliability characteristic is the component-failure probability, or unreliability, $F(t)$, which is defined as

$$F(t) = \text{the probability that the component fails by age } t \text{ if the aging mechanism is not detected by testing or maintenance} \quad . \tag{51}$$

Then, in terms of the aging failure rate, $\lambda(t)$, the failure probability, $F(t)$, is given by

$$F(t) = 1\text{-}\exp(-\int_0^t \lambda(t')dt') \quad , \tag{52}$$

where "exp" denotes the exponential function. For a linear aging failure rate,

$$\lambda(t) = at \tag{53}$$

and the failure probability, $F(t)$, is given by

$$F(t) = 1\text{-}\exp(-\frac{1}{2}at^2) \quad . \tag{54}$$

If the failure rate represents a specific aging mechanism, then $F(t)$ gives the probability that the component fails by age t due to the specific mechanism, assuming no other mechanisms act on the component. If the failure rate represents several mechanisms, then $F(t)$ gives the probability that the component will fail by age t due to any of the mechanisms.

When no testing or maintenance is performed, then $F(t)$ also is the probability that the component is down at age t, which is termed the component unavailability. The component unavailability is the quantity generally required for probabilistic risk analyses (PRAs). When testing or maintenance is performed on the component, then the component unavailability will depend on the effect of the test or maintenance in detecting and correcting the specific causes and mechanisms of failure.

Two extremes of testing (or maintenance) effects are "good as new" testing and "good as old" testing, as termed in the reliability literature. For good as new testing, the component is restored to as good as new after the test. With regard to an aging mechanism, for good as new testing or maintenance on the mechanism, the age of the component with regard to the specific mechanism is set back to zero after the test or maintenance. The component is thus effectively replaced with a new component with regard to the aging effects of the particular mechanism.

For good as old testing or maintenance, the component is restored to an as good as old condition after the test or maintenance. With regard to an aging mechanism, for as good as old testing or maintenance, the age of the component is not set back to zero but remains at the value before the test or maintenance. Thus, the test or maintenance only ensures that the component is up, but does not remove the accumulated effects of the aging mechanism.

If $q(t)$ is the component unavailability at age t, then for the two extremes, $q(t)$ is given by:

$$q(t) = 1\text{-}\exp(\frac{1}{2}a(t-t_N)^2) : \text{good as new} \tag{55}$$

and

$$q(t) = 1\text{-}\exp(\frac{1}{2}a(t^2-t_N^2)) : \text{good as old} \quad , \tag{56}$$

where t_N is the time of the last good as new or good as old test or maintenance, respectively.

The good as new and good as old effects, as stated, are extreme effects and there are a wide spectrum of intermediate effects that can also be modeled. The particular effects of a test or maintenance on an aging mechanism will depend on the characteristics of the test or maintenance and the translation of these characteristics into appropriate component rejuvenation or age resettings. Also, if the aging mechanism is arrested or controlled, then either the occurrence or severity of the deterioration is decreased, which in turn decreases the acceleration rate parameter, a, in the linear aging failure rate. These effects can also be modeled.

In summary, the reliability characteristics of each component are capable of being obtained with knowledge of the failure rate and with appropriate modeling of testing, maintenance, and aging-arresting activities. With the reliability characteristics of the component determined, system unavailabilities as a function of plant age, core melt frequencies as a function of plant age, and public risks as a function of age can, thereby, be determined. The risk and safety impacts of aging can, consequently, be determined, and the dominant contributors to any significant increases in the risk as the plant ages will be identified. By appropriately modeling different testing or maintenance strategies, or by modeling possible aging-arresting activities, effective strategies for reducing risk and extending life can, thereby, be identified.

10. DEMONSTRATION OF THE COMPONENT RELIABILITY EFFECTS OF AGING

A strong feature of the linear aging model is its ease of implementation. Because the linear aging model involves only one macroscopic parameter (the aging rate, a), detailed time history data are not necessarily required to estimate the aging rates for various aging mechanisms. The need for less data is supplemented with knowledge of the aging mechanisms involved and the adequacy of the phenomenological descriptions used in the linear model.

When more detailed data exist, the extensions of the linear model can be tested to determine if they more adequately describe the aging behavior beyond the uncertainties in the data. As indicated in Section 8, the linear model is also obtained as a first order expansion to the more complex, dependent aging model and can serve as a first order approximation to these more complex models. (It is interesting to note that the linear aging model can also be derived from the Arrhenius equation[16] for thermal, molecular deterioration by assuming a constant operating temperature and assuming the failure rate is proportional to the accumulated reaction rate.) In the applications that have been performed, the linear aging model has proven to be a flexible and useful model. When data existed to test the applicability of the linear model versus its extensions, the linear model generally was found to be consistent with the data when uncertainties were considered. (Appendix A contains illustrations of the consistency of the linear model with observations of the time-dependent failure behavior of piping.)

To demonstrate initially the application of the linear aging model, we will utilize aging rates that are consistent with the generic aging data described in References 4 through 7 and collected through the Nuclear Plant Aging Research (NPAR) Program[17] being conducted by the Office of Nuclear Regulatory Research for the U.S. Nuclear Regulatory Commission (NRC). The data described in these references basically consist of the fractions of component failures that are due to categories of aging mechanisms. The data are averaged over different plants and different component ages, and the data have uncertainties associated with their classification and counting.

The aging data that we use are thus rather gross and have nonnegligible uncertainties. However, even with the grossness and uncertainties, we will show how the data can be utilized in the linear aging model to investigate the effects of aging on component reliability. The example calculations will demonstrate that the linear aging model does not necessarily require detailed or precise data for exploratory evaluations. For more detailed or precise applications, the aging root cause data collected in the NPAR Root Cause Data Program being conducted by the Idaho National Engineering Laboratory (Reference 7) can be used. We will use these data for the system evaluations discussed in the next section.

To estimate the aging rate for the generic data collected in the NPAR Program, we will use a moments method type of estimation approach. The moments method approach is a common statistical estimation technique particularly useful for grosser data.[18] Later, we will outline more detailed statistical procedures that can be used when the data are more detailed and precise. These more detailed procedures can include tests to determine whether nonlinear scalings or the dependency extension of the model is required. The moments method approach that we now describe matches the observed number of aging failures with the predicted (expected) number to obtain the aging rate.

For an aging mechanism or category of aging mechanisms, the expected number, $n_A(T_1,T_2)$, of aging failures of a component occurring from age interval T_1 to T_2 is

$$n_A(T_1,T_2) = \int_{T_1}^{T_2} at\,dt \tag{57}$$

$$= \frac{1}{2} a(T_2^{\,2} - T_1^{\,2}) \quad . \tag{58}$$

Note that for a category of aging mechanisms, the above result assumes the exposure time or age of the component with regard to these different mechanisms is the same.

The expected number, $n_R(T_1,T_2)$, of random failures of the component occurring in the same interval is

$$n_R(T_1,T_2) = \lambda_0(T_2-T_1) \quad , \tag{59}$$

where λ_0 is the constant failure rate due to random, non-aging mechanisms.

We have as observed data, the fraction of failures due to aging. The expected fraction, $f_A(T_1,T_2)$, of aging failures in the interval T_1 to T_2 is the ratio of $n_A(T_1,T_2)$ to $n_A(T_1,T_2) + n_R(T_1,T_2)$.

$$f_A(T_1,T_2) = \frac{n_A(T_1,T_2)}{n_A(T_1,T_2) + n_R(T_1,T_2)} \tag{60}$$

$$= \frac{\frac{1}{2} a (T_2^2 - T_1^2)}{\frac{1}{2} a(T_2^2 - T_1^2) + \lambda_0 (T_2 - T_1)} \tag{61}$$

This can be expressed as

$$f_A(T_1,T_2) = \frac{aT_A}{aT_A + \lambda_0} \quad , \tag{62}$$

where

$$T_A = \frac{1}{2}(T_1 + T_2) \tag{63}$$

and, hence, T_A is the midpoint, or average, of the interval during which the observations are taken. Equivalently, T_A is the average age or time of exposure to the aging mechanism.

Thus, the expected fraction $f_A(T_1,T_2)$, of aging failures depends only upon the aging rate, a, the average age or exposure time, T_A; and the constant failure rate, λ_0. Note that the fact that $f_A(T_1,T_2)$ depends only upon the average age or average exposure time, T_A, makes $f_A(T_1,T_2)$ robust to uncertainties in T_1 and T_2. Note also that where more than one aging mechanism is identified, the term aT_A in the denominator of Equation (62) would be replaced by the sum of aT_A over the different aging mechanisms. Each aging fraction, $f_A(T_1,T_2)$, would then be the expected fraction of failures due to a particular aging mechanism out of the set classified.

In the moments method type of approach we will use, we substitute the observed fraction of aging failures for $f_A(T_1,T_2)$ and solve for the aging rate, a. We first express a in terms of $f_A(T_1,T_2)$ using Equation (62):

$$a = \frac{f_A}{1-f_A} \frac{\lambda_0}{T_A} \quad , \tag{64}$$

where we have simply used f_A for $f_A(T_1,T_2)$. To determine the aging rate, a, we not only need the aging fraction, f_A, which we base on data, but also the constant failure rate, λ_0, for the component and the average component age, T_A. We will use the data base compiled in the NRC Accident Sequence Evaluation Program (ASEP)[19] for the constant failure rate (after correcting by $1-f_A$ to remove the aging contribution). We will use several values for T_A, which represent different characteristic ages represented in the aging data. In the next section where we examine aging effects on system unavailability, we will utilize an aging failure data base that more precisely determines T_A.

In addition to the above moments method approach, maximum likelihood approaches, including Cox's partial likelihood approach,[20] can be used to estimate aging rates. The maximum likelihood approach is applicable when the age of the component and the aging mechanism causing failure are recorded as data. Cox's approach is applicable when competing aging mechanisms act on a component and the mechanisms have the same exposure times. Standard tests on the Poisson occurrence rate can also be used to check the applicability of the linear aging rate and the nonlinear or dependent extensions best fitting the data, when they are indicated as being needed. Thus, the model allows a wide variety of statistical analyses to be performed, depending upon the form of data and objectives of the analyses.

Applying the moments method approach, Figure 3 shows the failure probability (or unreliability), F(t), versus age for a single component with an aging rate, a, of $2 \times 10^{-4}/y^2$ (or $2 \times 10^{-12}/h^2$) and an average exposure time of 5 years. In the figure, a is the aging rate and T is the average age or exposure time, T_A. The aging rate in Figure 3 is characteristic of foreign material buildup in a valve (References 4 and 7). No surveillance tests and maintenances are assumed to be performed to detect or correct the buildup problem. The failure probability curve due to random failures is the failure probability from the constant failure rate, λ_0. It is also basically the same as the curve that would be obtained if *all* failures were treated as random, as done in PRAs. As observed, the aging effects become increasingly significant after 25 years. Figure 4 shows the same results as Figure 3 but on a log scale (to the base 10); the unavailabilities are in parentheses beside their corresponding log values.

When multiple components age, then there is a multiplicative effect on the failure probability. Figures 5 and 6 show the failure probability for two components both failing and three components failing, respectively, from aging and from random mechanisms. The figures plot the log of the failure probability. The individual components each have the failure probability shown in Figure 3. As observed, aging has a compounding effect on the probability of multiple components failing; in this case, multiple valves failing due to material buildup.

To explicitly illustrate the impacts of aging, Figures 7 through 9 show the ratio of the aging failure probability to the random failure probability. The figures are plots of the ratios of the curves of the

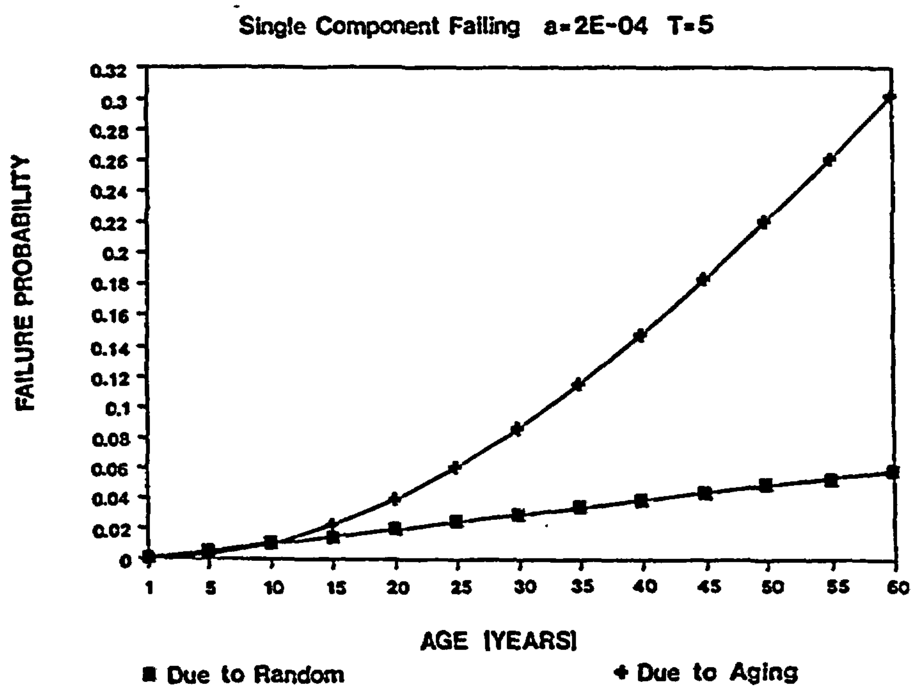


Figure 3. Failure probability versus age (single component failing).

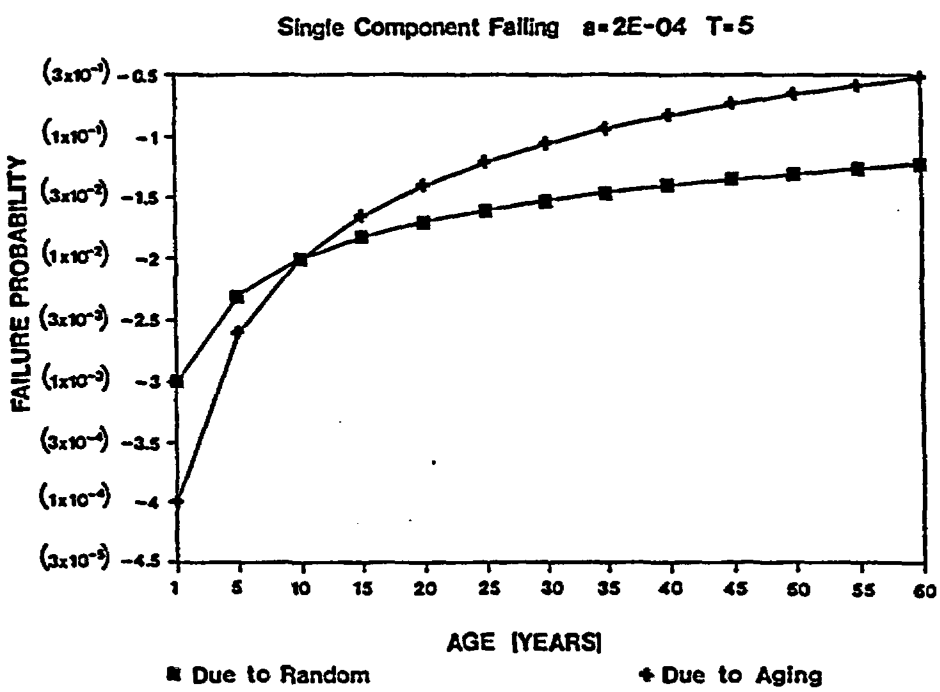


Figure 4. Failure probability versus age (single component failing).

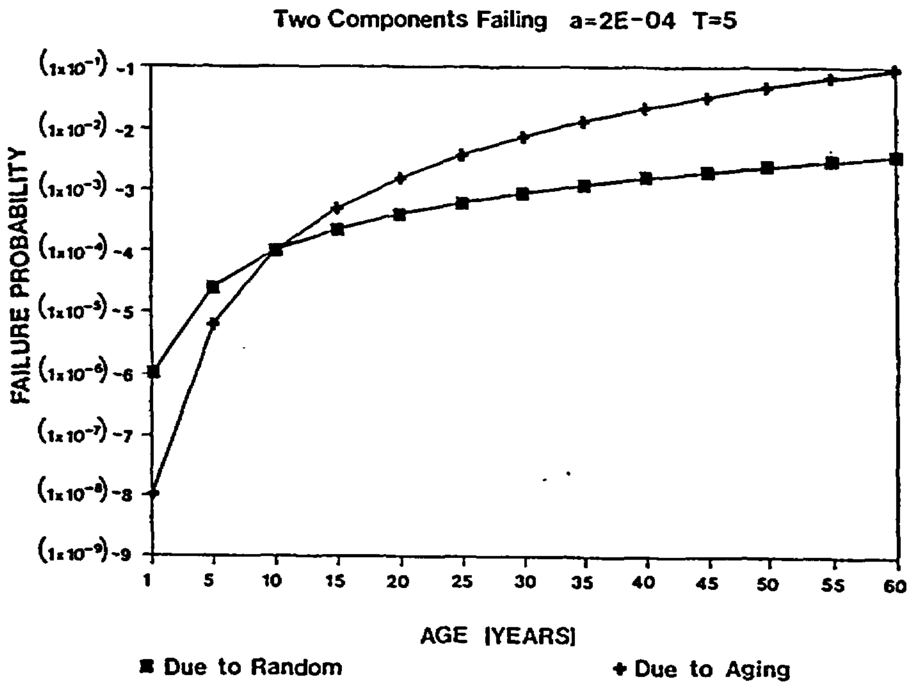


Figure 5. Failure probability versus age (two components failing).

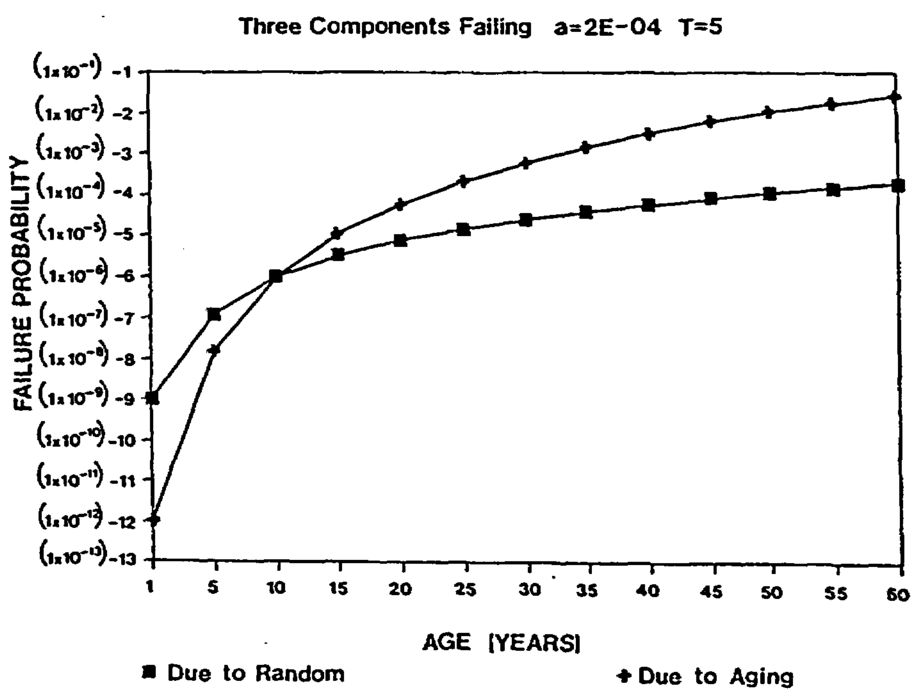


Figure 6. Failure probability versus age (three components failing).

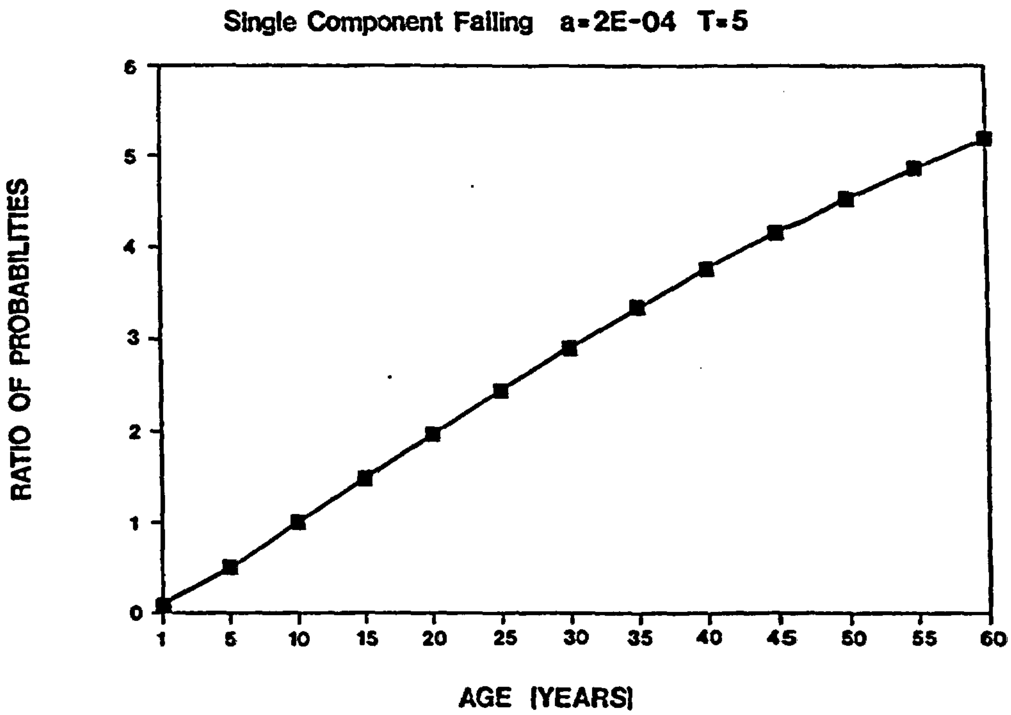


Figure 7. Ratio of aging to random failure (single component failing).

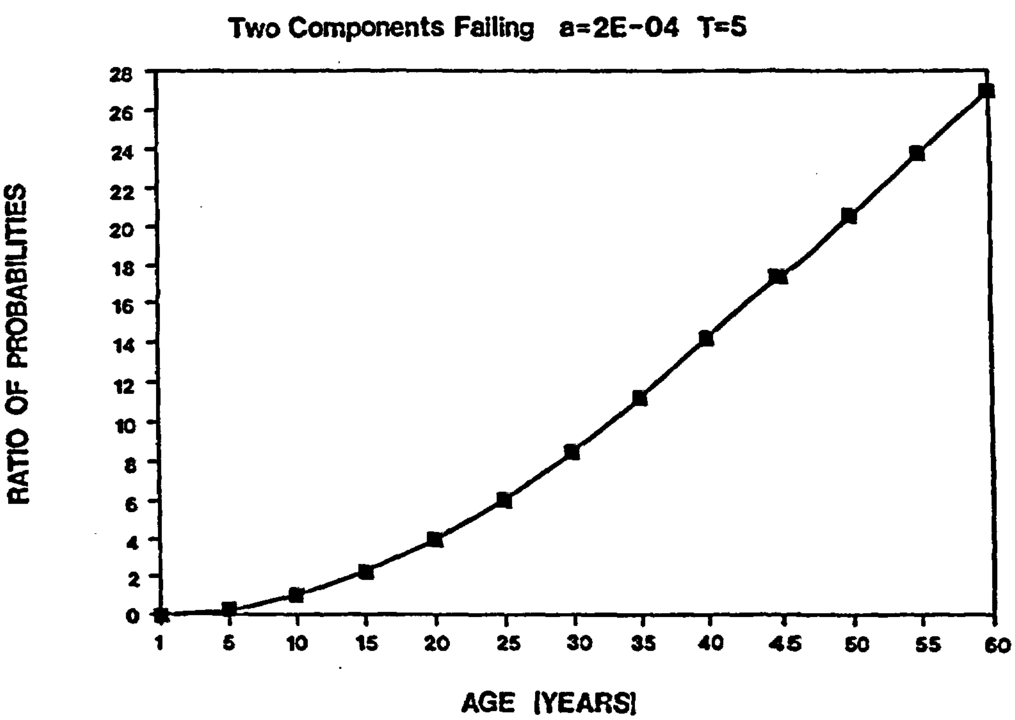


Figure 8. Ratio of aging to random failure (two components failing).

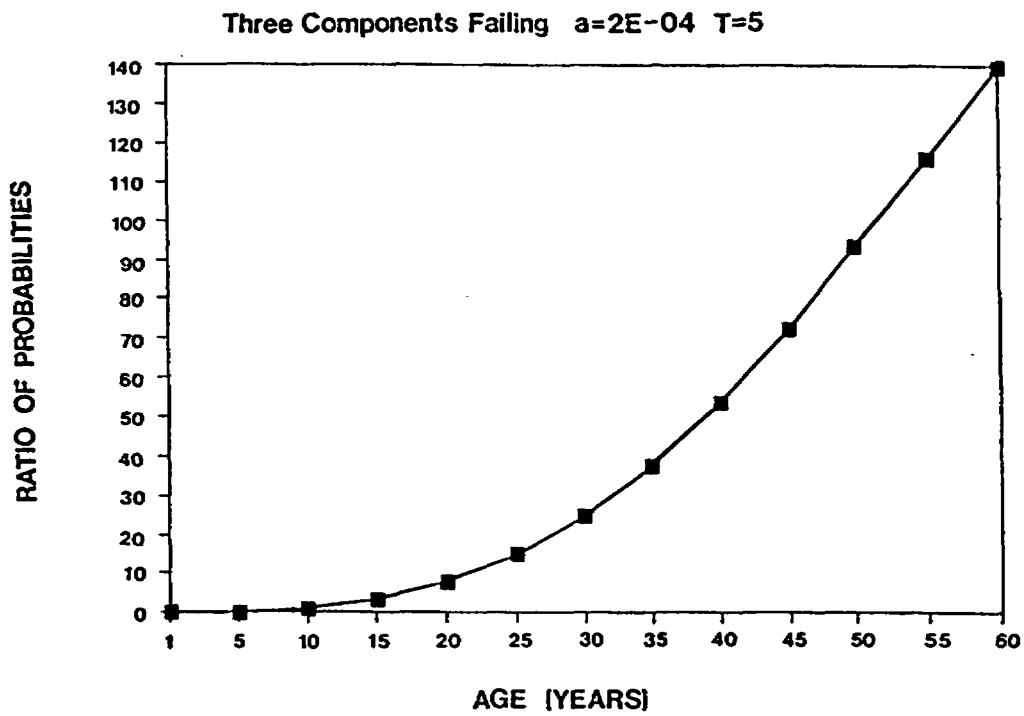


Figure 9. Ratio of aging to random failure (three components failing).

previous figures and more vividly show the significant impacts of aging for the data used when no testing or maintenance is performed to detect or correct the aging mechanism.

Figures 10 through 12 show similar failure probability curves as the proceeding figures but for an aging rate, a, of $2 \times 10^{-6}/y^2$ ($2 \times 10^{-14}/h^2$). Based on the data sources (References 4 and 7), this aging rate is characteristic of corrosion-related aging in a pump. Again, it is assumed that no testing and maintenance is performed to detect or correct the corrosion. As before, these figures show significant impacts of aging. Appendix B contains additional figures of the failure probability versus aging for an average exposure time of T = 2 years. The curves show similar behaviors as the curves shown here, with the aging impacts being proportionately greater because of the proportionately smaller exposure times.

In addition to the above calculations and those shown in the appendix, various other calculations of the component failure probability (or unreliability) were performed. These calculations used the aging fractions in References 4 through 7, which generally varied from 0.2 to 0.8 (i.e., 20 to 80% of the failures were aging related) depending upon the aging mechanism and component involved.

All these calculations showed the same general behavior as shown above and in the appendix. In general, the aging observed in nuclear data such as recorded in References 4 through 7 resulted in the component failure probability significantly increasing above the random failure (or PRA calculated) value at some age before 40 years. Aging caused the failure probability of a single component whose age was more than 20 years but less than 40 years to increase anywhere from a factor of 3 to more than a factor of 30 over the random or PRA failure probability value. The specific size of increase and the time trend depended upon the specific component, mechanism, and data. The fact that aging caused these effects in less than 40 years is significant because U.S. nuclear power plant lifetimes are now all 40 years and extensions of this lifetime are being considered.

These aging effects on single component failure probabilities were multiplied when the probabilities of two components failing or three components failing were calculated. The increases for two components failing ranged anywhere from a factor of 10 to more than a factor of 1000 over the random or PRA value. These increases are due to common cause effects and illustrate that aging can simultaneously increase component failure rates, due to the same or even different mechanisms. The aging components can also be similar or different, which shows the broad pervasive effects of aging.

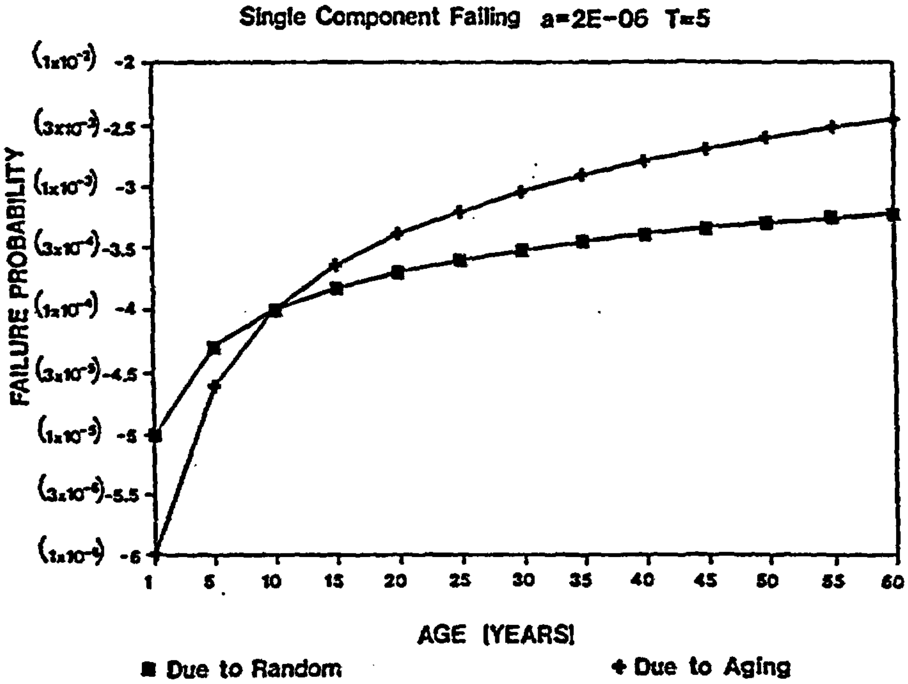


Figure 10. Failure probability versus age (single component failing).

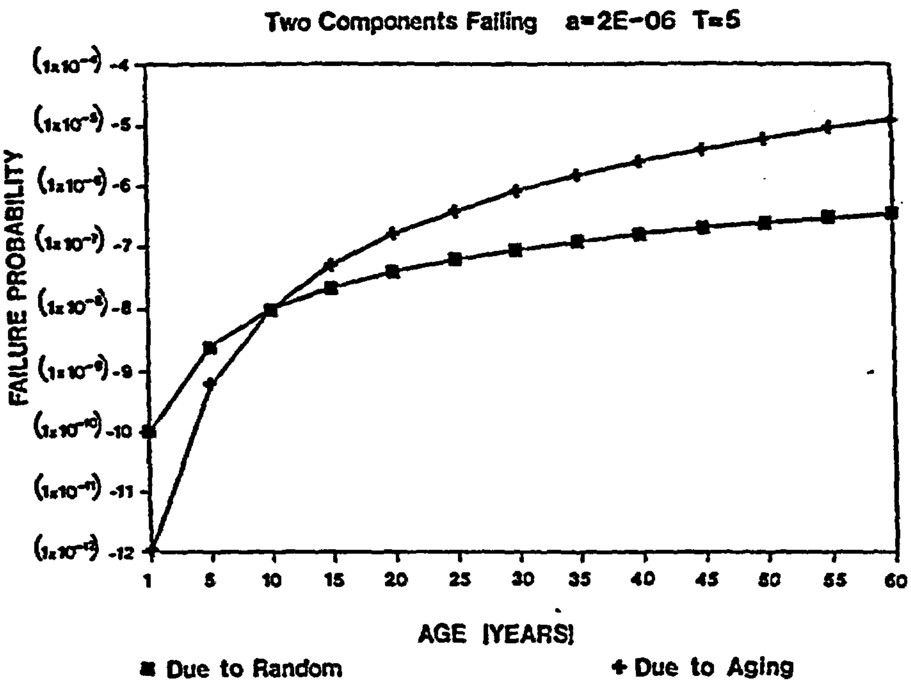


Figure 11. Failure probability versus age (two components failing).

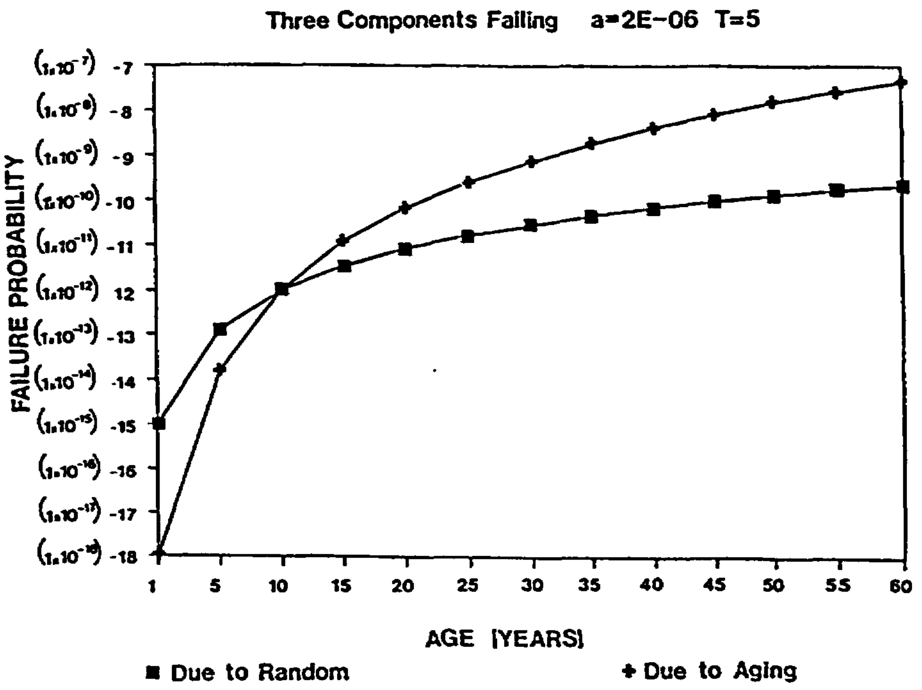


Figure 12. Failure probability versus age (three components failing).

The above impacts of aging represent maximum impacts, obtained under the assumption that no testing or maintenance is performed to detect or control the aging mechanisms. In actual practice, testing and maintenance are performed and most equipment is rejuvenated and the aging impacts generally will be smaller than those that were displayed above. However, in specific cases, the aging impacts can be as large as obtained even if testing and maintenance are performed, if the testing and maintenance are ineffective in detecting and controlling aging mechanisms. For example, air tests or low pressure tests of piping are generally ineffective in detecting stress corrosion degradation in piping. Valve controller tests are also ineffective in testing for fatigue or corrosion in valve bodies. Thus, we must be careful in assessing the effectiveness of a test or maintenance on a specific aging mechanism when that test or maintenance is performed. In the next section, we initially investigate effects of testing in evaluating aging impacts on system unavailability.

Even though the results we obtained are limited in assuming no testing or maintenance is performed on the aging mechanisms, they are very useful for several reasons. The results indicate that the models developed are practical for evaluating and studying the reliability impacts of aging, even if only gross data are used. They further indicate what data need to be obtained if more precise results are desired. Finally, the results indicate that the data collected at nuclear plants imply that aging can have significant effects on component reliability if the aging is not effectively detected and controlled.

The linear aging model we have used could perhaps be questioned for its validity in quantifying the aging impacts, in that other models could perhaps have been used on the gross data that is available. However, the aging mechanism treatments in the linear aging model are consistent with the descriptions of the aging mechanisms in the data. The mechanisms described in the data cause deterioration or damage to be accumulated in the component, which in turn increases the probability of failure of the component; however, this is the same phenomena flexibly modeled in the linear aging model. Appendix C contains some trend implications from the linear aging model that are further checked with data; the checks further indicate the consistency of the linear aging model with the data.

11. DEMONSTRATION OF THE SYSTEM RELIABILITY EFFECTS OF AGING

When aging causes nuclear power plant component failure probabilities and unavailabilities to increase, then safety system unavailabilities, the core melt frequency, and public risks will also be impacted. To demonstrate the system unavailability effects of aging, we consider the system logic diagram shown in Figure 13. The logic diagram is a simplified diagram of the auxiliary feedwater (aux-feed) system of Arkansas Nuclear Unit 1 (ANU-1), as modeled in the Interim Reliability Evaluation Program (IREP) conducted by NRC.[21]

The major components, other than the water storage tank, are shown in the diagram. The system consists of two trains, each containing a turbine-driven pump (TDP), a motor-operated valve (MOV), and piping (PIP). There is also PIP to the storage tank. The storage tank was not included because of the unavailability of storage tank aging data. The controls to the system were also not included because aging effects of the primary components were of prime concern.

Figure 13 also shows the data that are used for the aging evaluations. The ASEP component failure rates are those given in the ASEP data base (Reference 19). The piping failure rate is for all the piping in the pertinent leg of the system. The WASH-1400 failure rates are those used in the WASH-1400 study.[22] The ASEP failure rates, which are derived from a more recent and more extensive data base, are higher than those of WASH-1400, particularly for the turbine pump. The WASH-1400 failure rates will be used in sensitivity studies to show the effects of aging if the turbine pumps and motor-operated valves were more reliable.

From Figure 13, test periods of 30 days are assumed for the pumps and valves, which is generally consistent with technical specifications. The piping is assumed not to be effectively tested, particularly for aging mechanisms such as stress corrosion cracking, which deteriorate the piping but still allow water passage. The assumption of no effective testing is a conservative assumption, but because the piping failure rate is so small, its failure probability will have little overall effect. The piping failure rate will be increased by a factor of 10 in a sensitivity study to show the impacts when the failure rate is higher and no effective testing is performed.

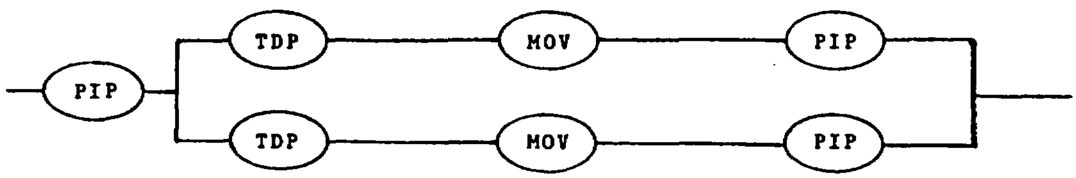
The remaining data in Figure 13 involve aging parameters for the components. The aging fractions and average component exposure times, or average ages, when failing from aging mechanisms are taken from Reference 7. The data in Reference 7 apply to pumps and valves in service water systems and are assumed to be applicable here for the auxiliary feedwater system. The aging data could be somewhat conservative for the auxiliary feedwater system because of the sometimes harsher environments of the service water system, however, the aging fractions are generally representative of those seen in other systems (References 4, 6, and 7). The average ages are also on the order of 10 years, which are not conservative compared to data for other systems.

The aging acceleration rates, or simply the aging rates, a, in Figure 13 are computed using Equation (64). The ASEP failure rates adjusted for the aging contribution (i.e., multiplied by one minus the aging fraction) are used as the constant failure rates, λ_0, in determining the aging rates, a. The major aging mechanisms identified in Reference 7 for this data were erosion, wear (particularly on the pumps), and binding (on the valves). Different aging mechanisms could be experienced for the aux-feed system, but as long as the aging rates are similar, the component failure probabilities will be similar. Details of the aging mechanisms are important in assessing the effectiveness of testing and maintenance performed. We will perform sensitivity studies assuming different testing effectiveness.

Figure 14 shows the aux-feed system unavailability[a] versus the age of the plant assuming good as old testing on the pumps and valves. As discussed in Section 9, for good as old testing, the pumps and valves are restored to an operating (or up) condition if found failed but the components are not replaced with new ones and undetected aging mechanisms continue. The curve indicated "with aging" uses the linear aging model and treats the remaining failure rate contribution as being random with a constant failure rate. The horizontal line identified as "averaged" is the system unavailability that would be calculated assuming all failures are random (i.e., using the constant total failure rates for all the components). This averaged calculation is the usual PRA evaluation.

a. The unavailability is the probability that the system is down and will not be able to start if required. Plotting times are at the end of a test interval.

SYSTEM DIAGRAM



TDP = TURBINE DRIVEN PUMP

MOV = MOTOR OPERATED VALVE

PIP = CONNECTING PIPING

DATA UTILIZED

COMPONENT	ASEP FAILURE RATE (1/hr)	WASH-1400 FAILURE RATE (1/hr)	TEST PERIOD (days)	AGING FRACTION	AVERAGE AGE AT FAILURE (days)	AGING ACCELERATION RATE ($1/hr^2$)
TURBINE DRIVEN PUMP TDP	$5x10^{-5}$	$2.5x10^{-6}$	30	0.11	4000	$5.73x10^{-11}$
MOTOR OPERATED VALVE MOV	$8x10^{-6}$	$3x10^{-6}$	30	0.1470	3576	$1.37x10^{-11}$
PIPING PIP	$1x10^{-10}$	--	--	0.75	4347	$7.19x10^{-16}$

Figure 13. Simplified system diagram and data utilized.

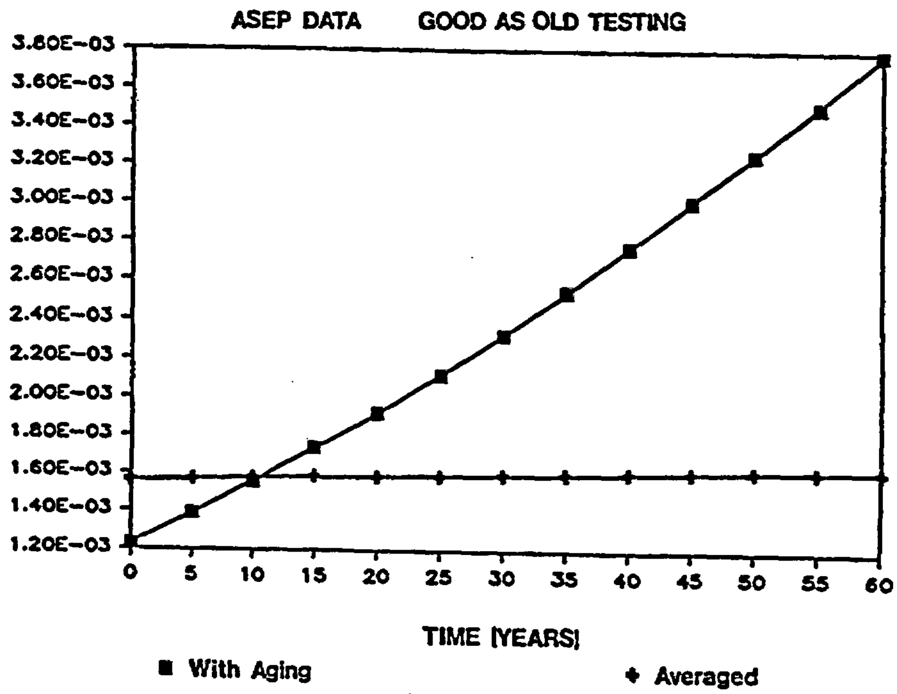


Figure 14. System unavailability versus age (ASEP data, good as old testing).

As observed from Figure 14, with good as old testing, the system unavailability increases with plant age, increasing by approximately a factor of 2.5 over 40 years and a factor of 3 over 60 years. At 40 years, the unavailability incorporating aging is nearly a factor of 2 higher than the averaged, or PRA value. The factor of 2 to 3 increase in system unavailability may seem small, but if similar increases occurred in other systems, then the resulting core melt frequency could be increased significantly more because of the compounding of the system effects. Predicting the impacts on the core melt frequency is, of course, purely conjecture and a full PRA analysis would be needed to determine the actual effects.

Figure 15 shows the unavailability contribution from the minimal cut sets of the system; a specific contribution is simply the probability that the system is failed due to specific components being failed. As observed, the dominant contribution is from the two turbine pumps being failed (TDP*TDP) followed by one motor-operated valve and a turbine pump being failed (MOV*TDP). The piping, even though not tested, has a low contribution because of its low failure rate. As observed, the contributions change with age because of the different relative changes in the component unavailabilities with age.

If the tests and maintenance on the pumps and valves are not able to restore the components to an operating condition if found failed, then the system unavailability rapidly rises with plant age. Figure 16 illustrates this worst case effect. This case is quite unrealistic because it assumes complete ineffectiveness of the tests in being able to detect the components being in a failed state due to aging mechanisms. However, it does illustrate the sensitivity of the system unavailability with regard to the adequacy of testing and corrective maintenance in being able to detect component failures due to aging and to restore the components to an operating condition.

Figure 17 shows another extreme case where the tests on the pumps are assumed to have maximum effectiveness with regard to detecting and correcting failure contributions (good as new). The other components have testing (or no testing) as in Figure 14. For this good as new case, pump failures due to aging are always detected and the aging damage is completely removed so the pump is as good as new with regard to the aging mechanism. As observed, effective tests on the pumps significantly control system aging effects and limit the increase in system unavailability to be less than a factor of 1.3 in 40 years (a 30% increase) and to be less than a factor of 1.5 in 60 years (a 50% increase). This compares to a factor of 2 to 3 increase in the unavailability with moderately effective testing (good as old) shown in Figure 14

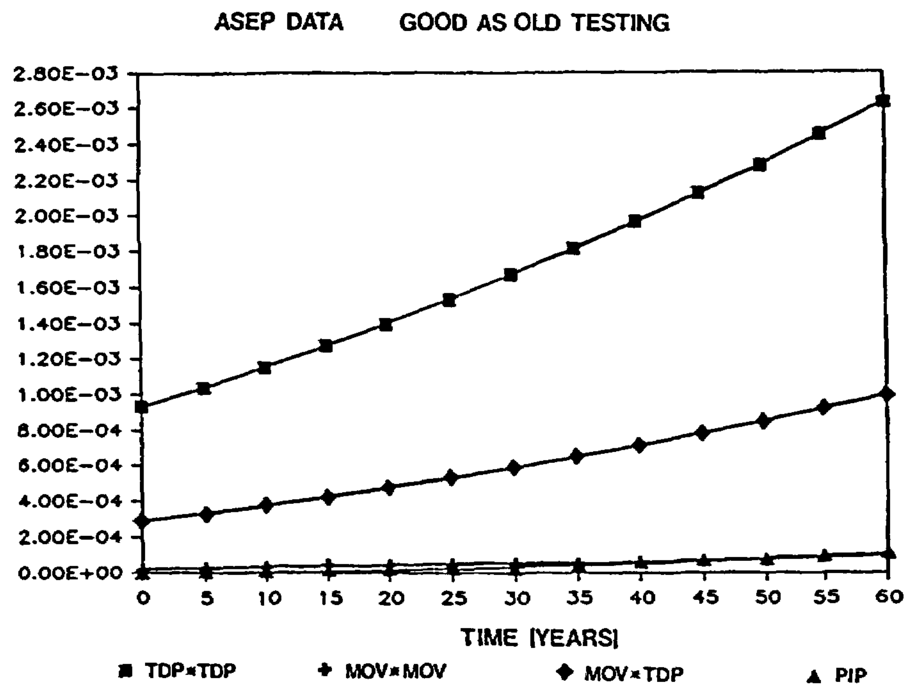


Figure 15. Minimal cut set unavailabilities (ASEP data, good as old testing).

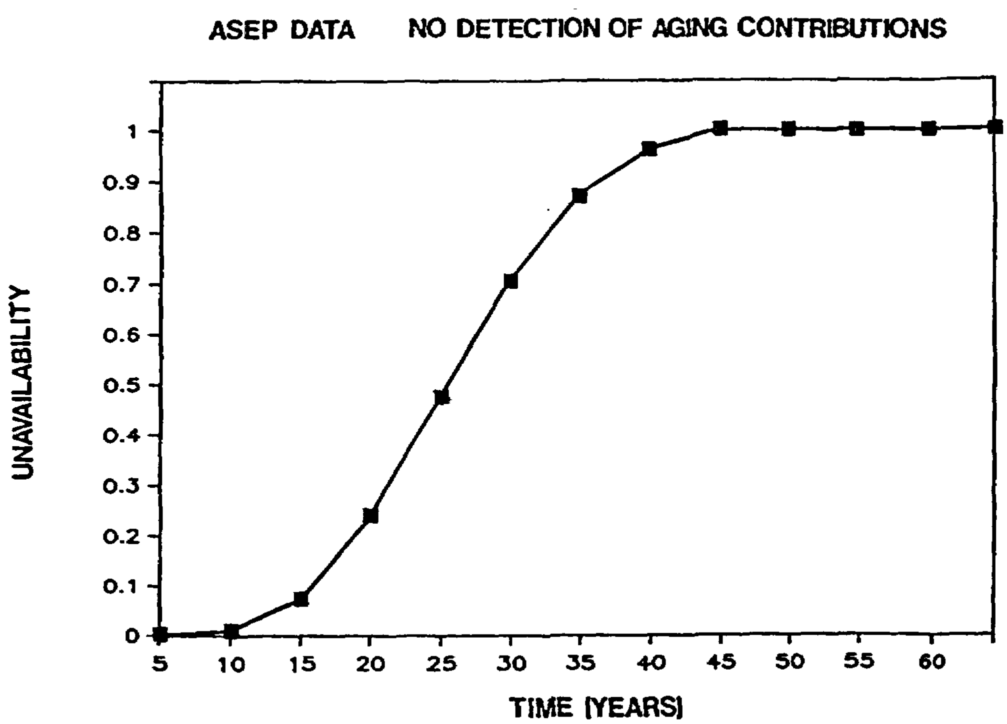


Figure 16. System unavailability versus age (ASEP data, no detection of aging contribution).

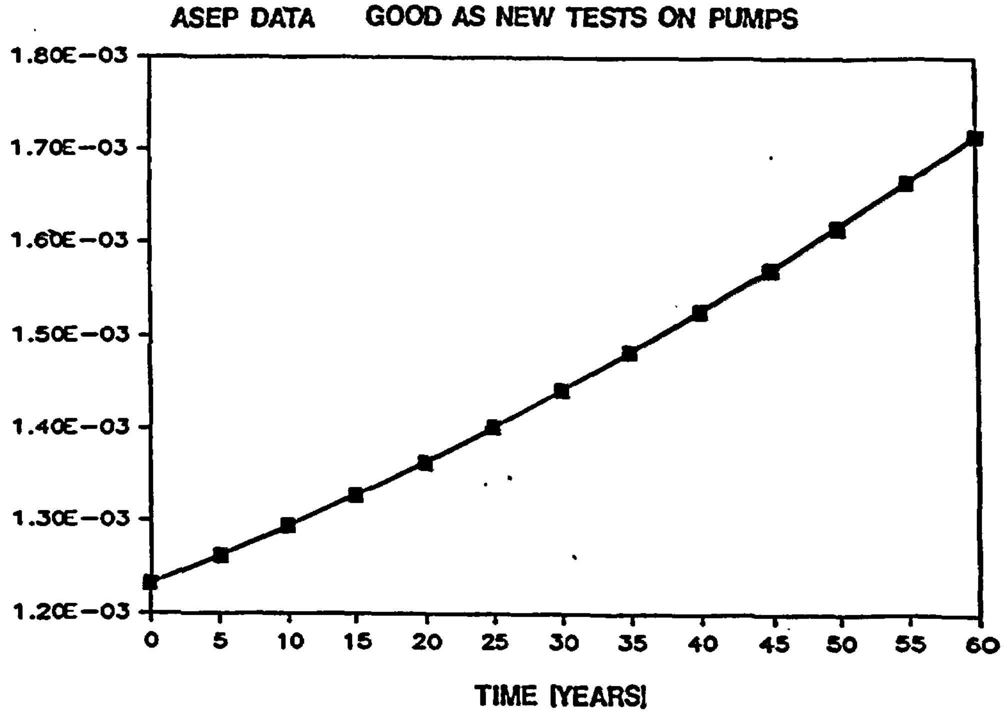


Figure 17. System unavailability versus age (ASEP data, good as new tests on pumps).

and a factor of nearly 1000 increase with completely ineffective testing shown in Figure 16.

As a sensitivity study, Figure 18 shows the system unavailability versus plant age for the piping total failure rate increased by a factor of 10. The other data are the same as Figure 14, with good as old testing on the pumps and valves and no effective testing on the piping. The system unavailability now increases by approximately 25% (a factor of 1.25) over that shown in Figure 14 at 40 and 60 years. This is a small but discernible effect. Figure 19 shows the minimal cut set contributions for this case. As seen, the piping contribution now increases and surpasses the motor-operated valve and pump contribution after approximately 50 years.

Because of the larger piping failure contribution, performing effective testing and corrective maintenance on the pumps will have less overall system impacts. Figure 20 shows the case where the piping failure rate is increased by a factor of 10 and good as new tests are performed on the pumps. As observed, the system unavailability still increases by close to a factor of 2 after 40 years and by nearly a factor of 2.5 after 60 years.

Finally, Figure 21 shows the case where WASH-1400 failure rates are used instead of the ASEP failure rates. The same aging fractions and exposure times (average ages at failure) are used, but WASH-1400 failure rates are used to calculate the aging rates [using Equation (64)]. This case, therefore, corresponds to having more reliable components with the same aging fractions and average age at failure due to the aging mechanisms.

As observed from Figure 21, the overall system unavailabilities are decreased, but the effects of aging are increased significantly. The aging causes the unavailability to increase by approximately a factor of 9 in 40 years and a factor of 15 in 60 years. The piping failure contribution significantly contributes to these large effects because of the lower failure rates of the other components and the assumption that no effective tests are performed on piping. This calculation thus shows that aging in structures and piping can increase significantly and even dominate system unavailability when tests and corrective maintenances on structures and piping are ineffective in detecting and correcting aging degradations. Appendix C contains additional plots for the above different cases that were examined to demonstrate system unavailability evaluations using the linear aging model.

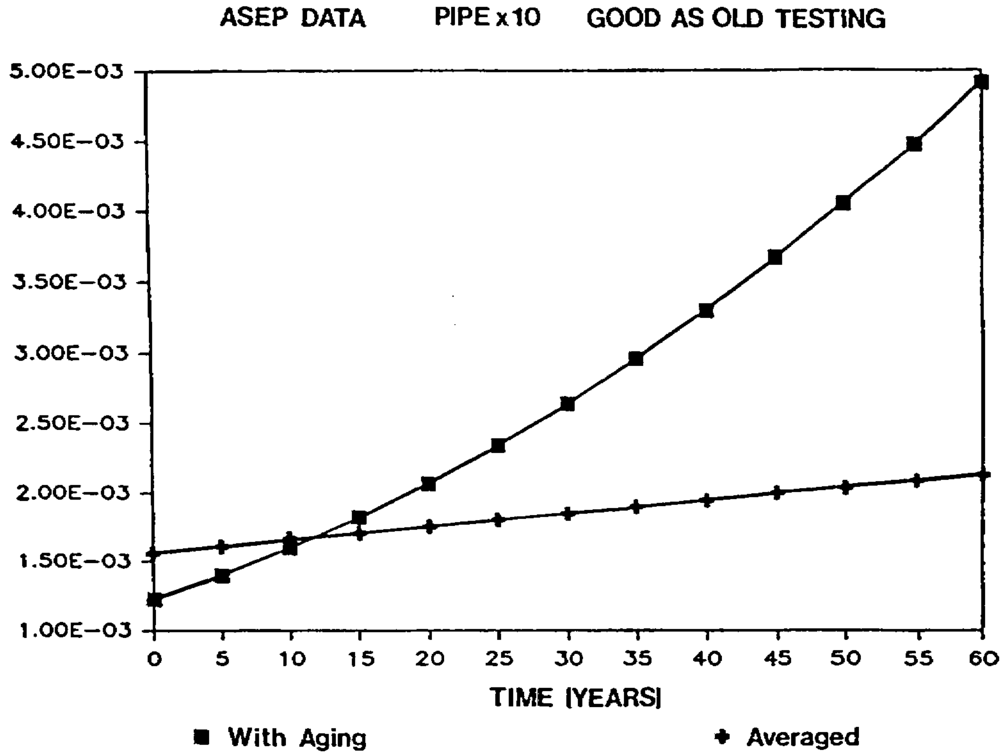


Figure 18. System unavailability versus age (ASEP data, pipe x 10, good as old testing).

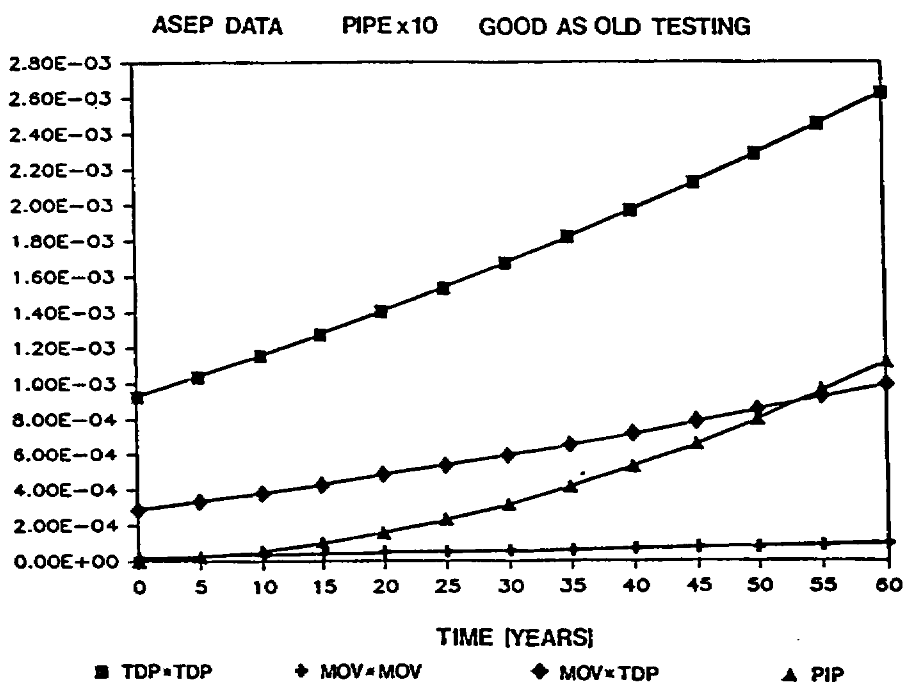


Figure 19. Minimal cut set unavailabilities (ASEP data, pipe x 10, good as old testing).

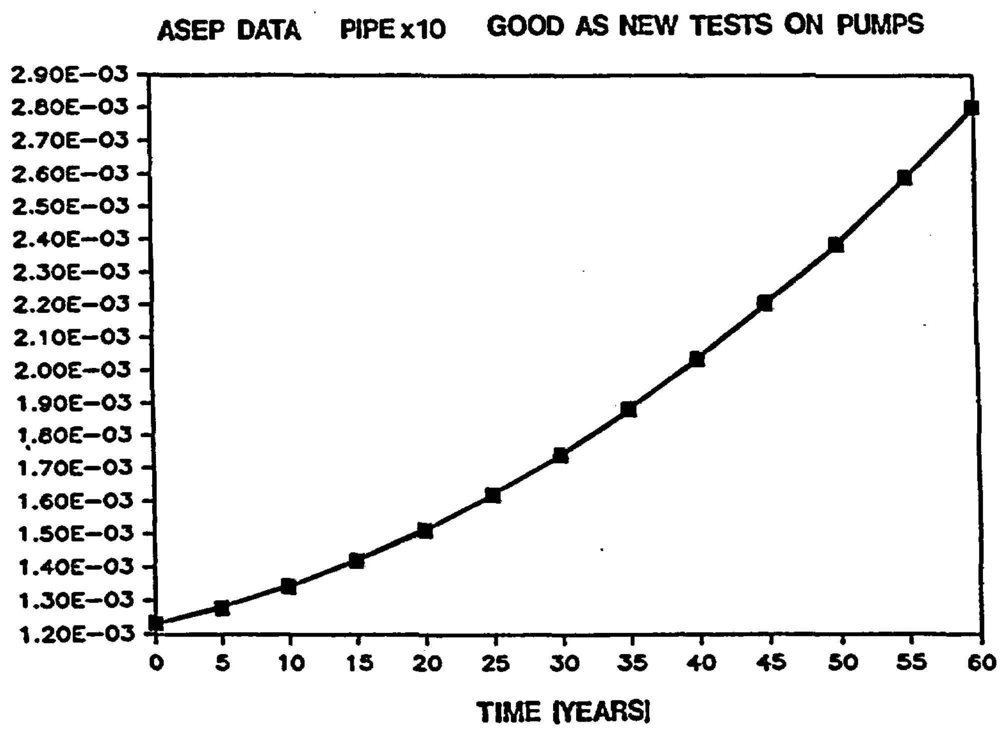


Figure 20. System unavailability versus age (ASEP data, pipe x 10, good as new tests on pumps).

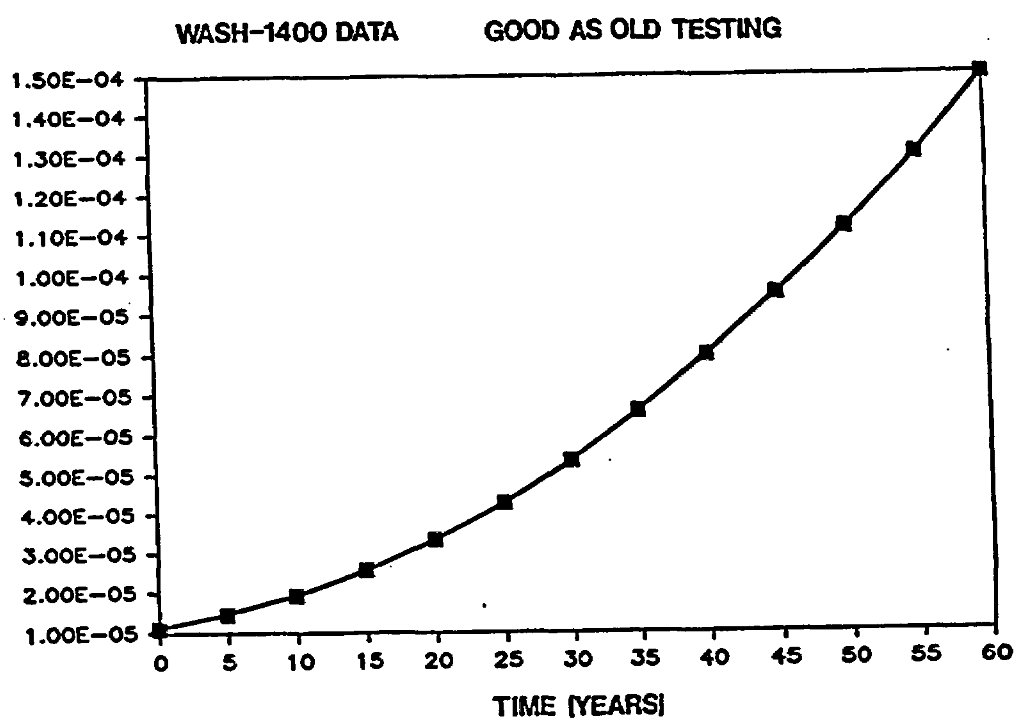


Figure 21. System unavailability versus age (WASH-1400 data, good as old testing).

12. SUMMARY AND CONCLUSIONS

The linear aging model is an attractive model for evaluating the reliability implications of aging because of its phenomenological basis and its ease of implementation. Engineering information on the aging mechanisms and their behavior can be utilized to complement available data in utilizing the linear aging model in its macroscopic form. Less detailed data is required and even gross data can be used for exploratory evaluations.

For more detailed evaluations involving load conditions, environmental effects, and material properties, the linear failure rate can be decomposed into its constituent factors. This decomposition offers the opportunity for directly tying condition monitoring information to failure rate and reliability implications. The linear aging model can also be extended to cover nonlinear and dependent aging mechanisms when data are available to differentiate these effects.

The ease of implementation of the linear aging model is demonstrated by applying it to the gross aging data collected in the NRC NPAR Program. The demonstrations show the significant effects that aging mechanisms can have on component failure probabilities if the aging is not detected and corrected by testing and maintenance. The linear aging model is also applied to a model of the auxiliary feedwater system for Arkansas Nuclear Unit 1 to demonstrate the handling of aging contributions in calculating system unavailability. Depending upon the types of testing performed, it is shown that aging can either have a small effect on system unavailability or can cause the system unavailability to increase significantly with plant age. If the testing is completely ineffective in detecting and correcting aging-related failure modes, then the system can become essentially unavailable for any accident.

The work that has been done represents a good first step in determining the risk and reliability effects of aging phenomena. The linear aging model needs to be applied to more specific aging mechanism data to obtain more precise aging rates. Operating effects, environmental effects, and plant-specific effects on aging rates need to be evaluated. More comprehensive statistical analyses need to be performed to more accurately estimate aging rates and their associated uncertainties. Where available, time-dependent data should be collected to test more thoroughly the linear aging model and to identify aging mechanisms where the model extensions better describe the phenomena.

With regard to applications of the aging models to determine aging effects on system unavailabilities, core melt frequencies, and public risks, the accurate modeling of testing and maintenance effects is important. The tests and maintenances that are presently performed need to be evaluated for the proper models to use to describe their effects on aging contributions. Good as old and good as new assumptions are only two extremes and there are many other, more realistic treatments. More effective testing and maintenance strategies can, furthermore, be evaluated as part of these studies.

In order to utilize the aging models to identify risk effects, systematic procedures need to be developed to translate present knowledge on aging into equivalent aging rates. This does not only involve determining statistical estimates of aging rates, but, in addition, translating engineering knowledge of aging mechanisms to aging rates and uncertainties. Engineering knowledge can be especially important where data are lacking. In these evaluations, the identification and propagation of uncertainties is important in quantifying the uncertainties that are associated with aging and their resulting impacts on risk uncertainties.

Finally, work needs to be started to investigate explicitly relating load conditions, environmental effects, and material properties to component aging rates. It is through these relationships that information from condition monitoring and other similar activities can be directly translated to reliability and risk implications. Damage and deterioration can, thereby, be corrected before actual failures occur and accidents are initiated.

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APPENDIX A

EVALUATION OF LER DATA FOR AGING PATTERNS

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EVALUATION OF LER DATA FOR AGING PATTERNS

Overview

As a supplementary effort to the model development, License Event Reports (LERs) from 1981 to 1986 were analyzed to obtain additional information on aging contributions and aging patterns. The effort involved was relatively minor and, because of the grossness of the data analyzed, only summarized information was obtainable from the data. However, the information obtained provided useful insights on aging contributions and aging patterns, as measured by the fraction of LERs that were caused by aging-related mechanisms.

The information obtained showed that aging is an important and often dominant contributor of LERs. The components most affected by aging included bistables and switches, heat exchangers, relays, power supplies, indicators and recorders, as well as piping, valves, controllers, and pumps. All the systems examined showed significant contributions from aging, with the Engineered Safety Features Actuation System, the Reactor Protection Trip System, and the Component Cooling Water System having the highest aging contributions.

Significant system effects on component aging contributions were observed. Depending on the system in which the component was located, the aging contribution to a component could be insignificant or could be the dominant cause of LER-associated failures. Bistables and switches, controllers, indicators and recorders, piping and valves showed the largest system effects.

Aging-related failures of components were observed to sometimes cause system failures; the consequences of aging-related failures depended strongly on the component and system involved. Aging contributions to piping were observed to increase linearly with plant age, helping to validate the linear aging failure rate model. The following figures and short associated descriptions provide the bases for the above information, as well as other highlights that were obtained from the data analyses.

Analysis Description

In response to a request by the Nuclear Plant Aging Research (NPAR) Program, Oak Ridge National Laboratory (ORNL) categorized the LERs from 1981 to 1986 using the Sequence Coding and Search System (SCSS). That information is contained in Appendix D. The LERs were categorized for the following BWR and PWR systems as follows:

- Reactor Protection Trip System (RPTS)
- Engineered Safety Features Actuation System (ESFAS)
- High Pressure Coolant Injection System (HPIS)
- Class 1E Electrical Power Distribution System (EPDS)
- Service Water System (SWS)
- Component Cooling Water System (CCWS)
- Low Pressure Coolant Injection System (LPIS).

The LERs were categorized according to the component involved, system involved, general cause of the LER, general severity of the LER, and the general age of the plant when the LER occurred. For the general cause of the LER, the following four broad cause categories were defined:

- Design and installation
- Aging and service wear
- Test and maintenance
- Human related.

For the severity classification, the following six severity categories were defined:

A. Loss of system function
B. Potential loss of system function (if demanded)
C. Degraded system performance
D. Potential degraded system function
E. Loss of redundancy (train failure)
F. Potential loss of redundancy.

Finally for the plant age classifications, the following four plant age categories were defined:

- 0 to 5 years
- 6 to 10 years
- 11 to 15 years
- Greater than 15 years.

The LERs were classified according to these categorizations, and tables were constructed of the categorized LERs. Table A-1 is an example of the tables that were produced; the complete set of tables is contained in Appendix D.

This appendix summarizes the results that were obtained from analyses of the ORNL tables. The tables were specifically analyzed to identify patterns and trends in the LERs that were associated with aging-related causes. This effort was done to provide insights for the Risk Evaluation of Aging Phenomena (REAP) Project being conducted at INEL. The effort also served as a test for some of the data analysis and presentation approaches that are being evaluated in REAP. The involved effort was relatively minor because the analyses were performed on a personal computer (PC) using commercial PC programs. Because the LER data categorizations were rather gross, detailed or sophisticated data analysis approaches did not yield many results. However, top level, summarized information was obtainable and this yielded interesting insights on aging contributions and aging patterns. Highlights of the LER analyses that provided useful information are presented in the following figures and associated discussions.

Aging Contributions by Component

Figure A-1 shows the percentage of LERs for given types of components that are due to aging-related causes. The figure gives the average importance of aging in causing LERs for a given component. The component aging percentage in the figure can be termed the component aging importance based on LERs. The spreads on each bar in the figure indicate the associated standard deviation of the estimated percentage contribution. The horizontal line across the figure is the average aging contribution for all components.
The figure indicates the following:

- On an average, aging is an important cause of component LERs, causing 42% of the LERs.
- There is a wide deviation in the importance of aging in causing LERs when specific components are examined. For some components, aging is the dominant cause of LERs; for other components, it is a minor cause.
- The components whose LERs are dominated by aging include bistables, switches, and heat exchangers. The components for which aging is a minor cause of failure include conductors, filters, and strainers.

Aging Contributions by System

Figure A-2 shows the percentages of LERs for given systems that are aging related. The figure thus gives the average importance of aging in causing LER-related failures for different systems. The system aging percentages shown in Figure A-1 can be termed the system aging importance based on LERs.
The figure indicates the following:

- Aging is, in general, an important cause of LERs for all the systems that were examined.
- The aging contributions ranged from a high of 53% for the Engineered Safety Features Activation System (ESFAS) to a low of 28% for the Electrical Power Distribution System (EPDS), which was still significant.

System Effects on Component Aging Contributions

Figure A-3 shows how the system environment can affect the importance of aging in causing LERs for a given type of component. The figure plots the range of aging contributions for a given type of component across the different systems that contain the component. The width of the range is a measure of the system effect on the component aging importance.
The figure indicates the following:

- System effects on aging contributions to components can be very large. Depending on the system in which the component is located, the contribution of aging can be insignificant or can be the dominant cause of failure.
- The components that show the greatest system effects include controllers, bistables, switches, indicators and recorders, and valves.
- The components that show more moderate system effects include pumps and motors; however, even for these components, the system effects can change the aging contributions from 25% to 45%.

Table A-1. High pressure coolant injection system, age of plant at time of failure versus categories of failure, 0 to 5 years

SCSS CODE	COMPONENTS	NUMBER of LERs	NUMBER OF FAILURES	DESIGN & INSTALLATION A	B	C	D	E	F	OTHER	AGING & SERVICE WEAR A	B	C	D	E	F	OTHER	TEST & MAINTENANCE A	B	C	D	E	F	OTHER	HUMAN RELATED A	B	C	D	E	F	OTHER
350	Valves	22	43							2							11							1		1				1	27
360	Valve Operators	6	6	2				2							1											1				1	
290	Pumps	15	19					4							3		3								2	1			9	1	
211	Circuit Breaker	0																													
150	Filters/ Strainers	1	1	1				1																							
250	Motors	2	2																						1				2		
815 219	Bistables/ Switches	16	20	1				1		3							14														1
215 216	Indicators/ Recorders	4	5							1							1														3
200	Piping	18	29	2				3	1	4	2				2		3														12
310	Pipe Supports	7	13														4														9
213	Controllers	3	3														2												1		
217	Relays	1	1							1																					
HX	Heat Exchangers	0																													
212	Integrators\ Power Supplies	0																													
JX UJX	Electronic Power Supplies	0																													
30	Annunciators	0																													
110	Conductors	2	2																										3		
214	Isolation Device	0																													

[a] Age of plant is calculated from date of operating license (OL). Individual components may have been placed in service 5 to 10 years prior to OL or may have been replaced at some time after OL date.

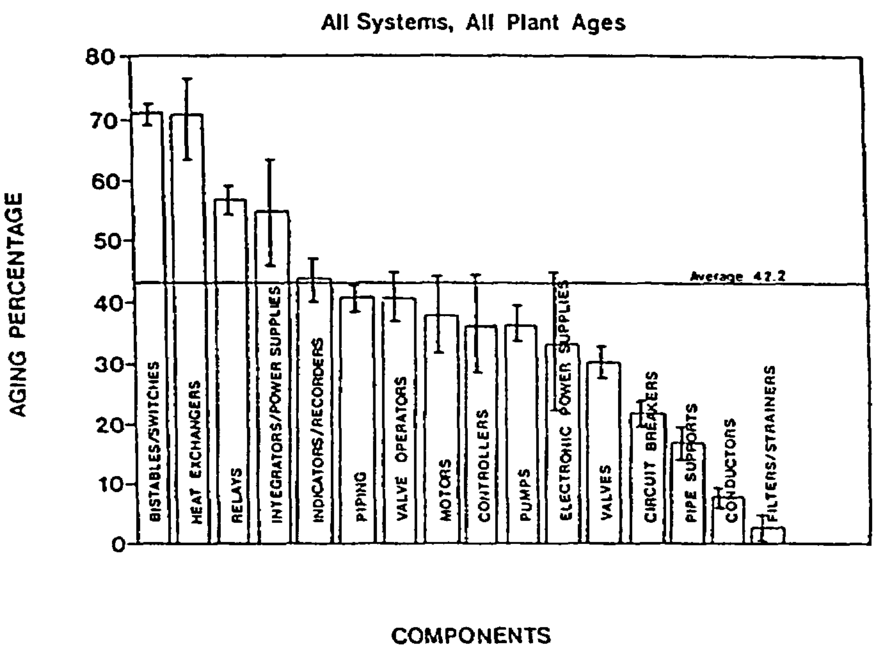

Figure A-1. Aging contributions by component.

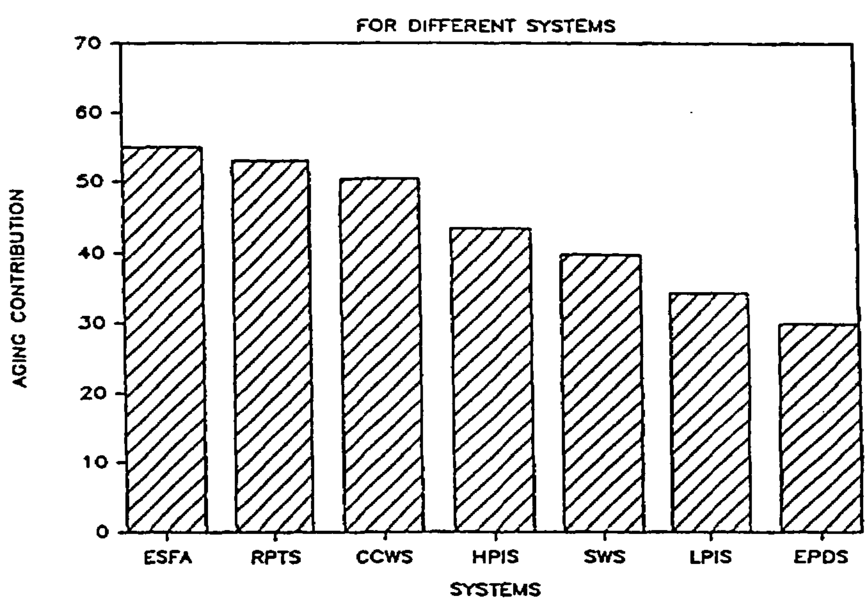

Figure A-2. Aging contributions by system.

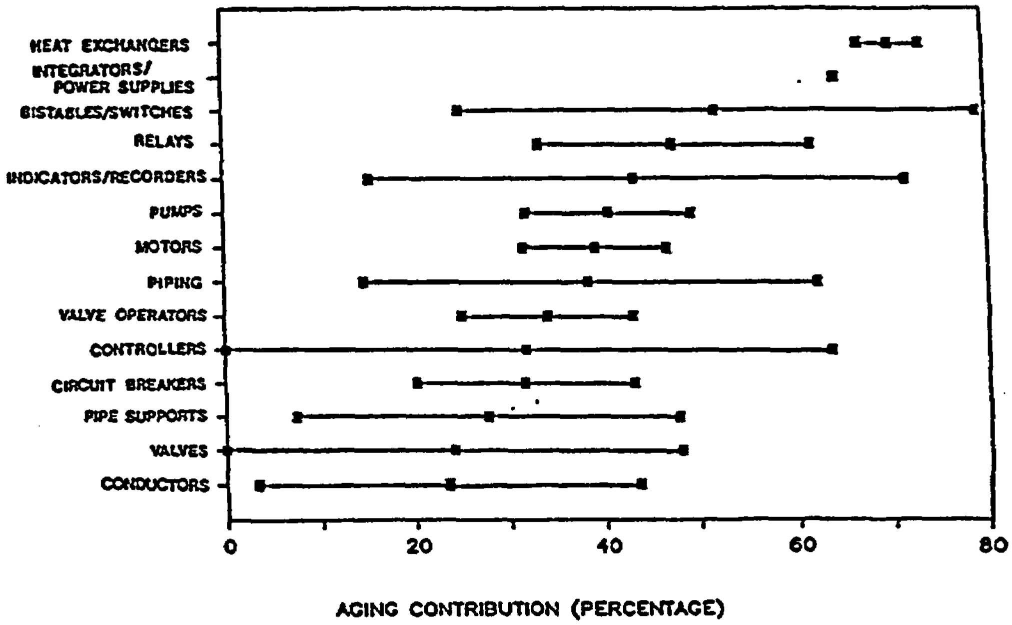

Figure A-3. System effects on component aging contributions.

- The components that show almost no system effects are heat exchangers, which always have a dominant aging contribution (65%) regardless of the system in which they are located. Integrators and power supplies show no system effects, however, they are not in different systems (for the data analyzed).

- For all the components in the High Pressure Injection System (HPIS) and the Component Cooling Water System (CCWS), aging is a moderate-to-significant contributor of LERs. Even for the components with the lowest aging contribution, there is still at least a 20% contribution from aging.

Component Effects on System Aging Contributions

Figure A-4 shows how the type of component can affect the importance of aging in causing LERs for a given system. The figure plots the range of aging percentages for different components within a system. The width of the range is a measure of the component effect on the system aging importance. The figure indicates the following:

- The importance of aging within a system can vary significantly depending upon the component examined in the system.

Component Aging Contributions Versus System

To provide more detail on the system effects on component aging contributions, Figures A-5 through A-17 plot the LER aging percentages for a given type of component across the different system containing that type of component. The figures are generally ordered in terms of decreasing system effects, with the initial figures showing the components whose aging contributions vary the most for different systems. The figures clearly point out the systems where specific components experience the most aging, as measured by the percentage of LERs that are aging related.

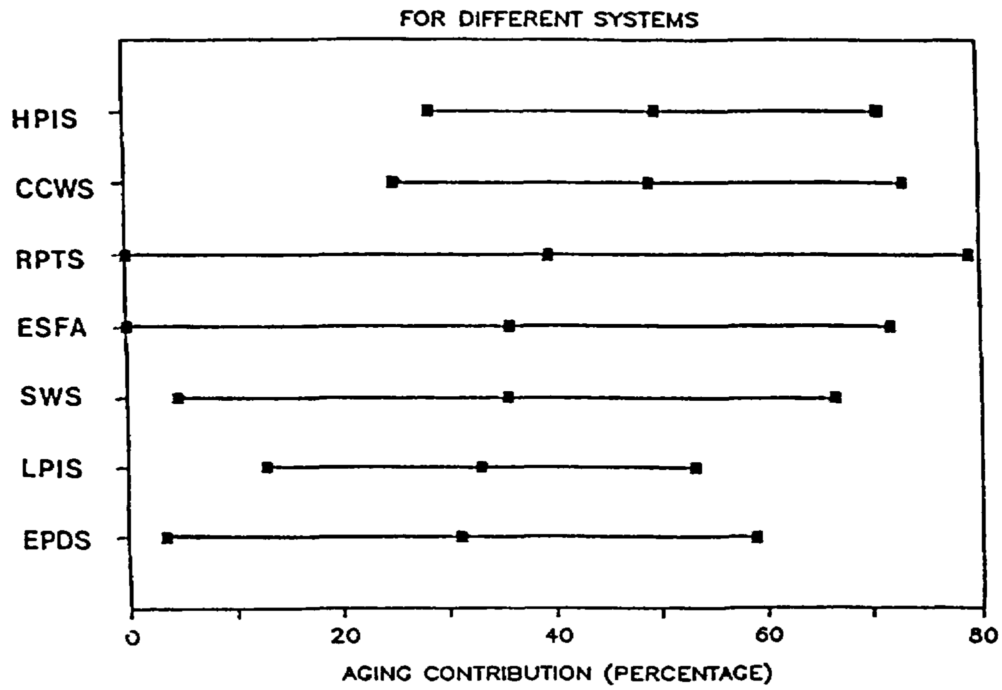

Figure A-4. Component effects on system aging contributions.

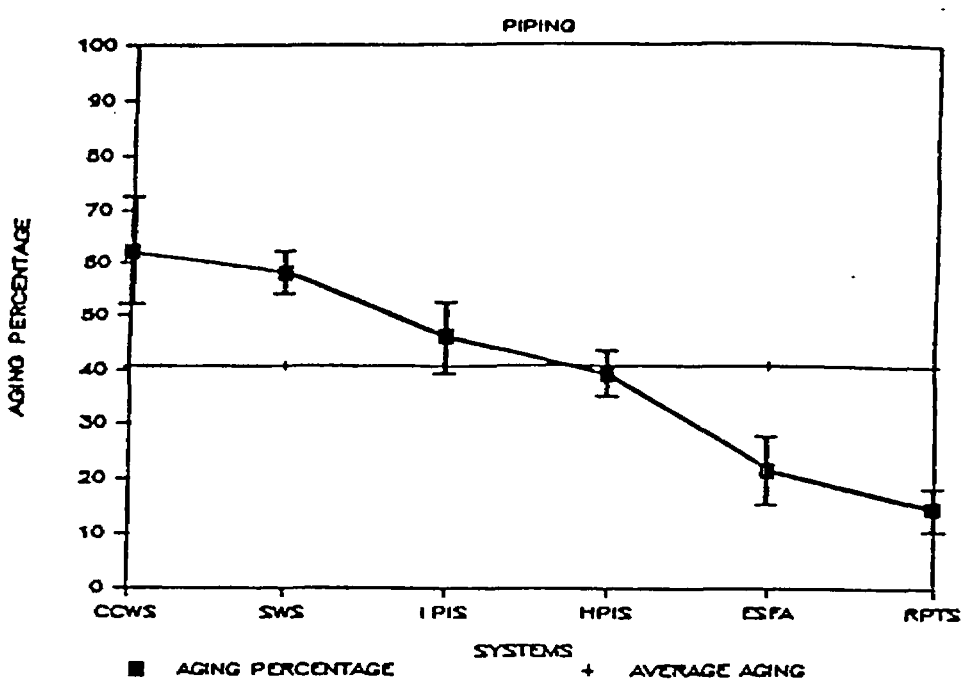

Figure A-5. Component aging contributions versus system for piping.

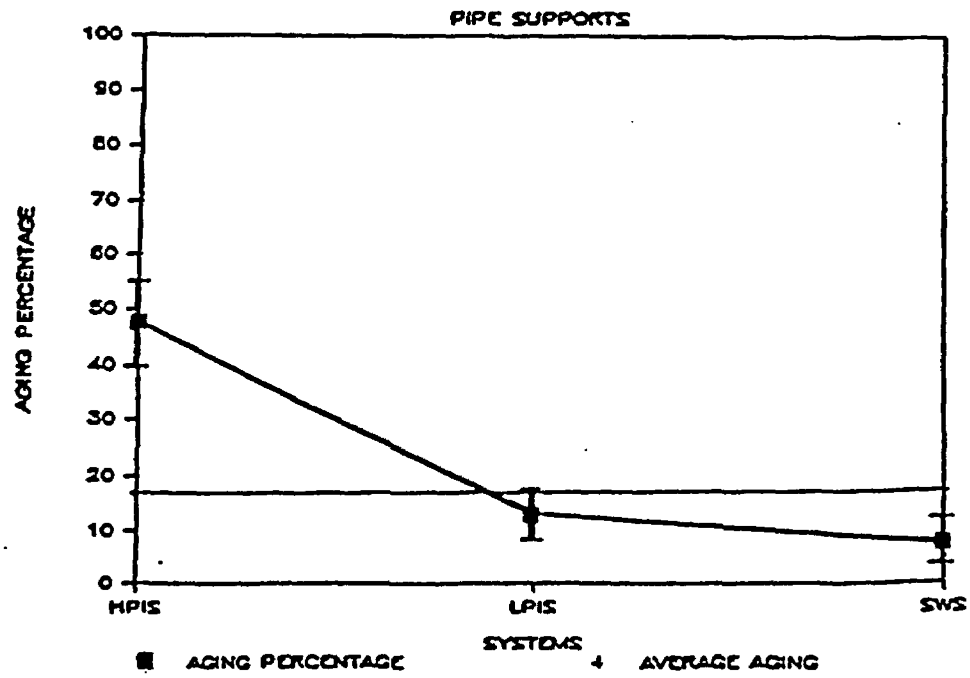

Figure A-6. Component aging contributions versus system for pipe supports.

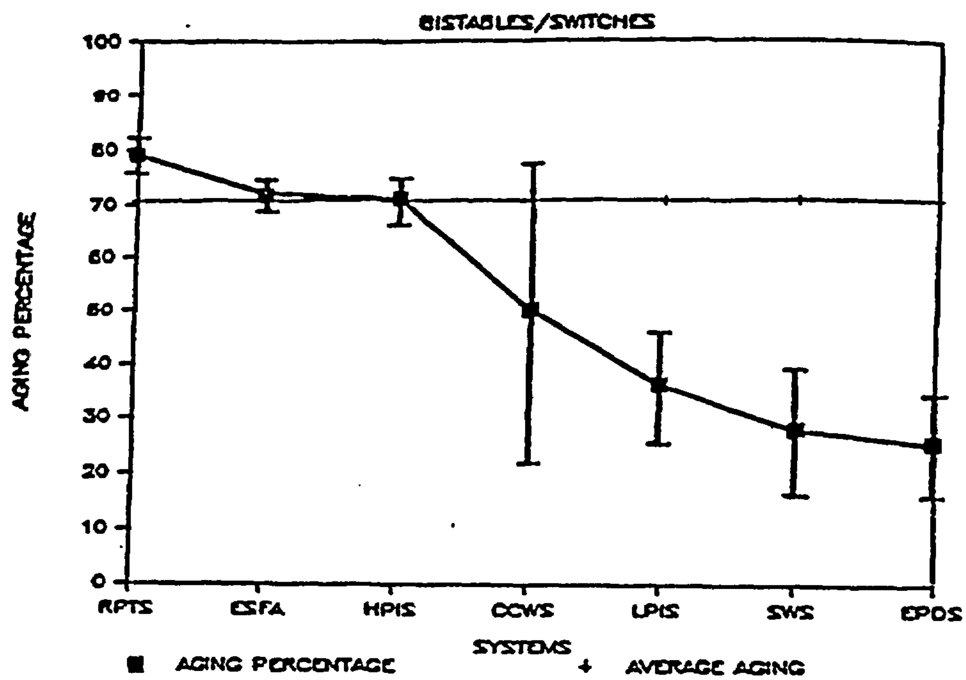

Figure A-7. Component aging contributions versus system for bistables/switches.

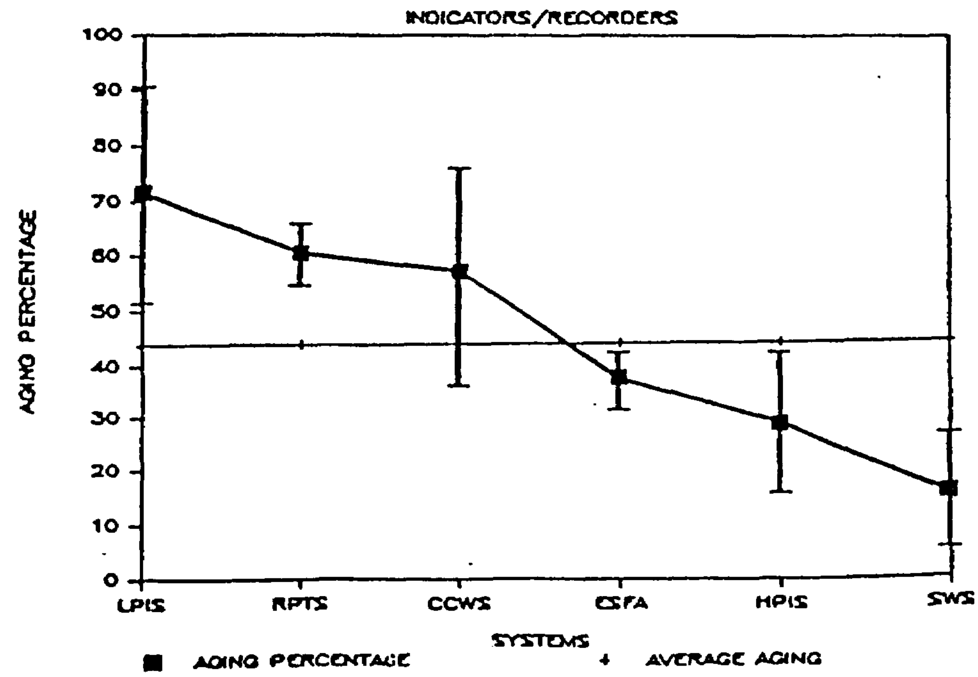

Figure A-8. Component aging contributions versus system for indicators/recorders.

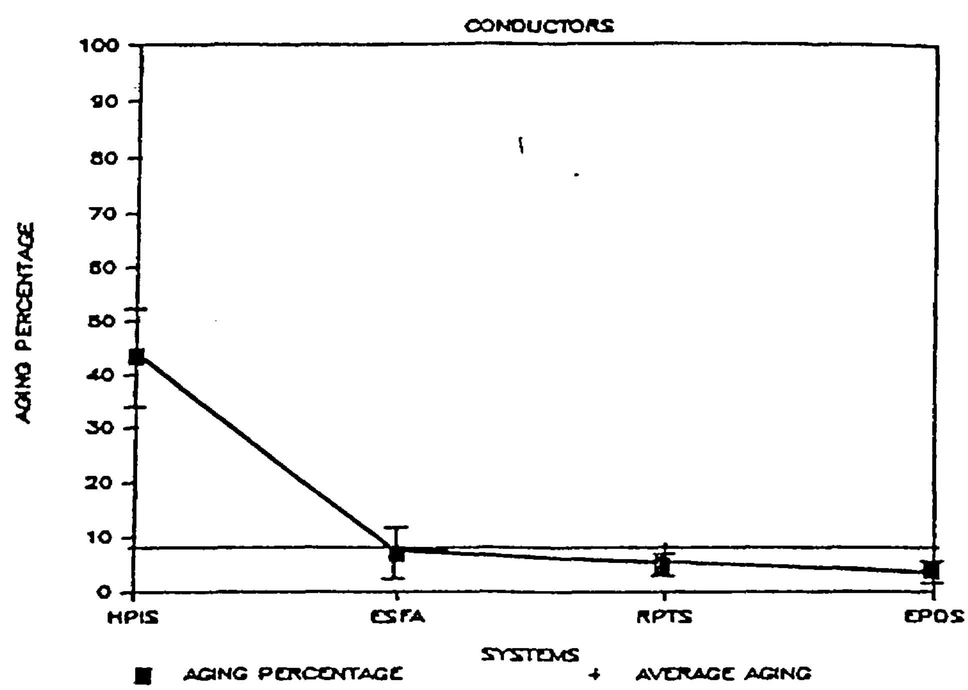

Figure A-9. Component aging contributions versus system for conductors.

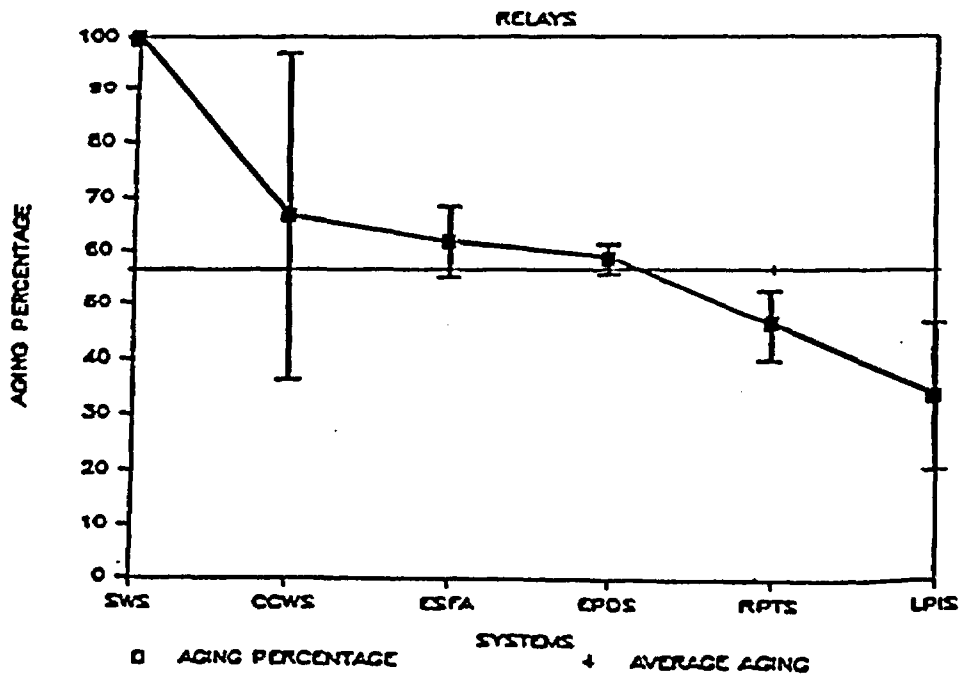

Figure A-10. Component aging contributions versus system for relays.

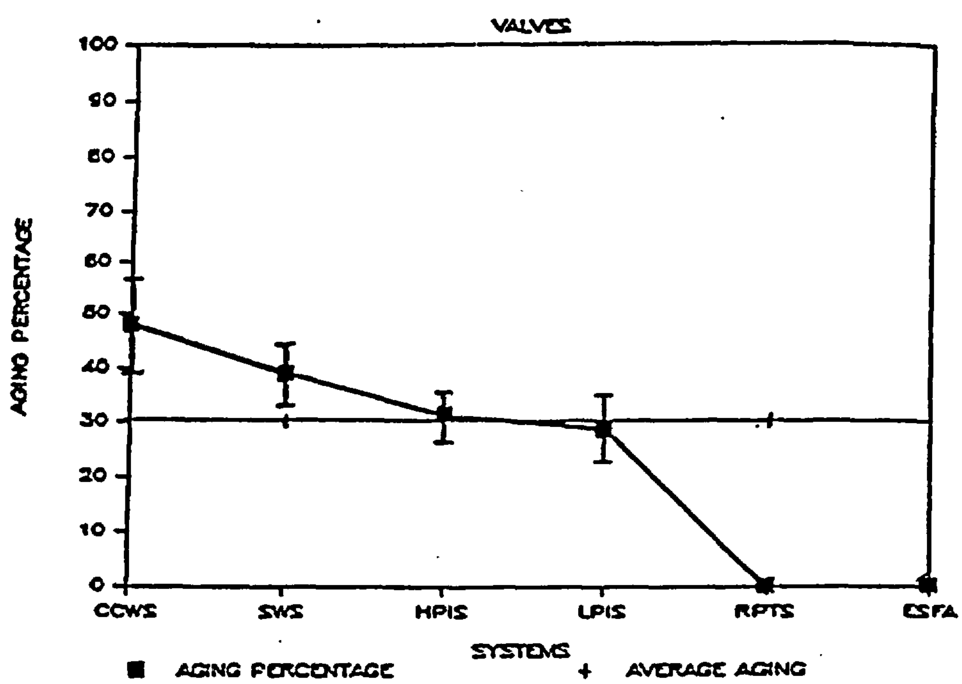

Figure A-11. Component aging contributions versus system for valves.

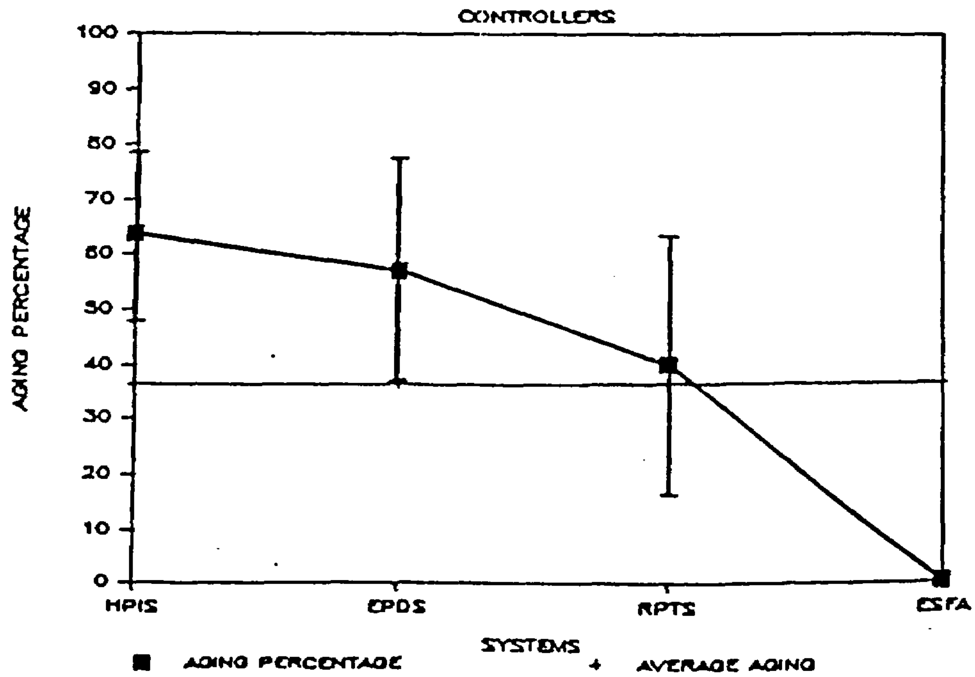

Figure A-12. Component aging contributions versus system for controllers.

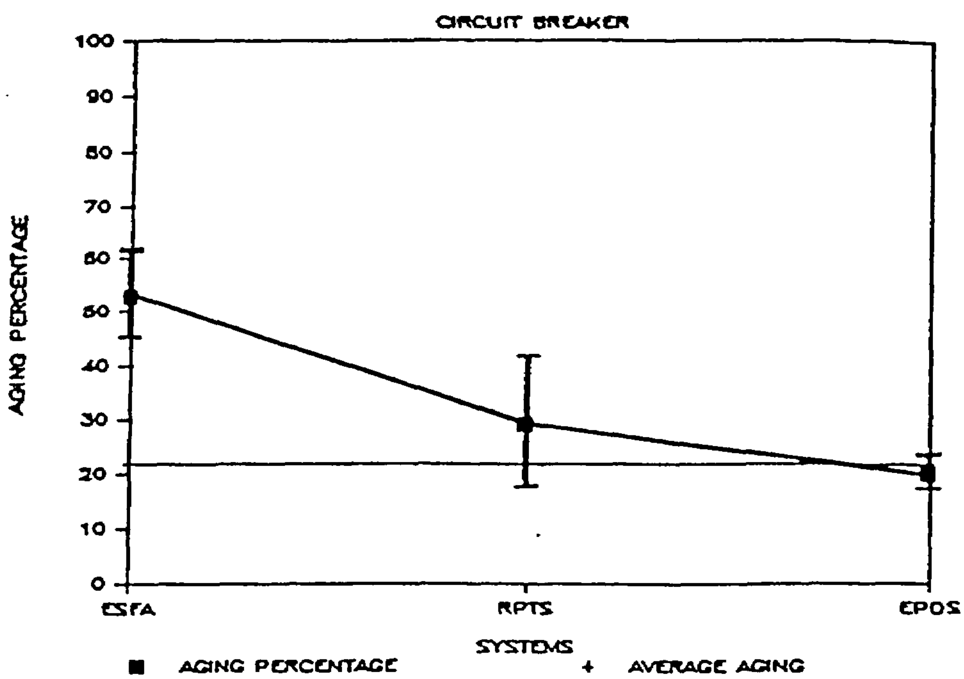

Figure A-13. Component aging contributions versus system for circuit breaker.

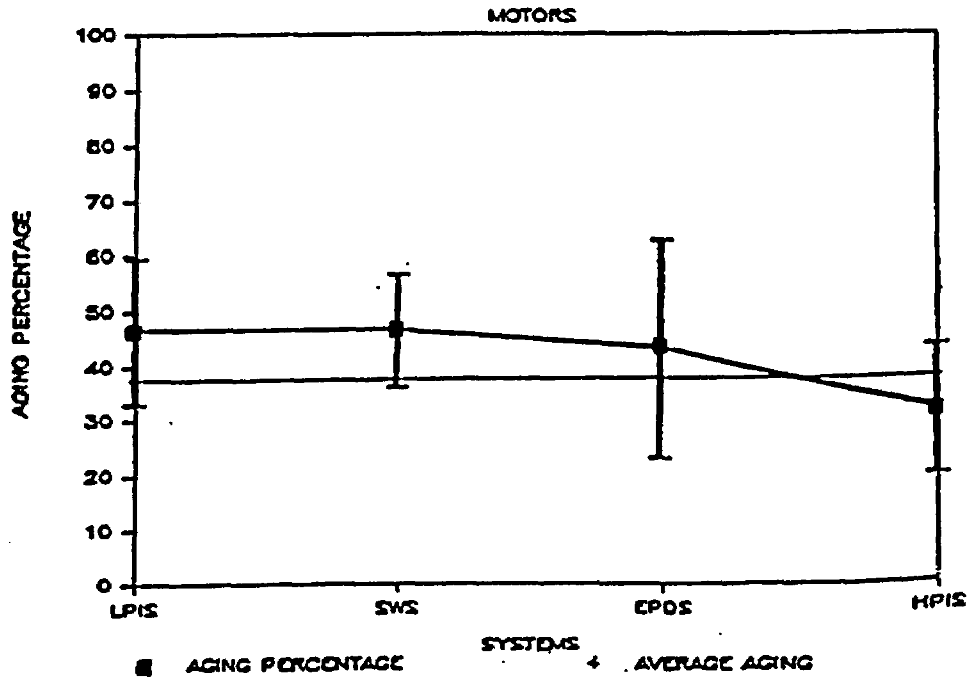

Figure A-14. Component aging contributions versus system for motors.

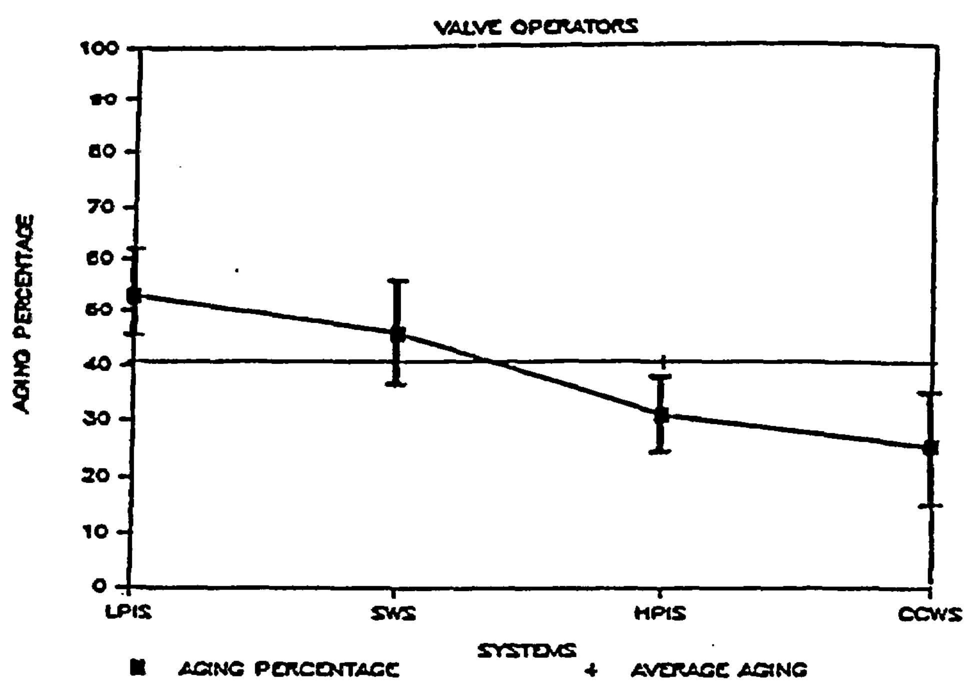

Figure A-15. Component aging contributions versus system for valve operators.

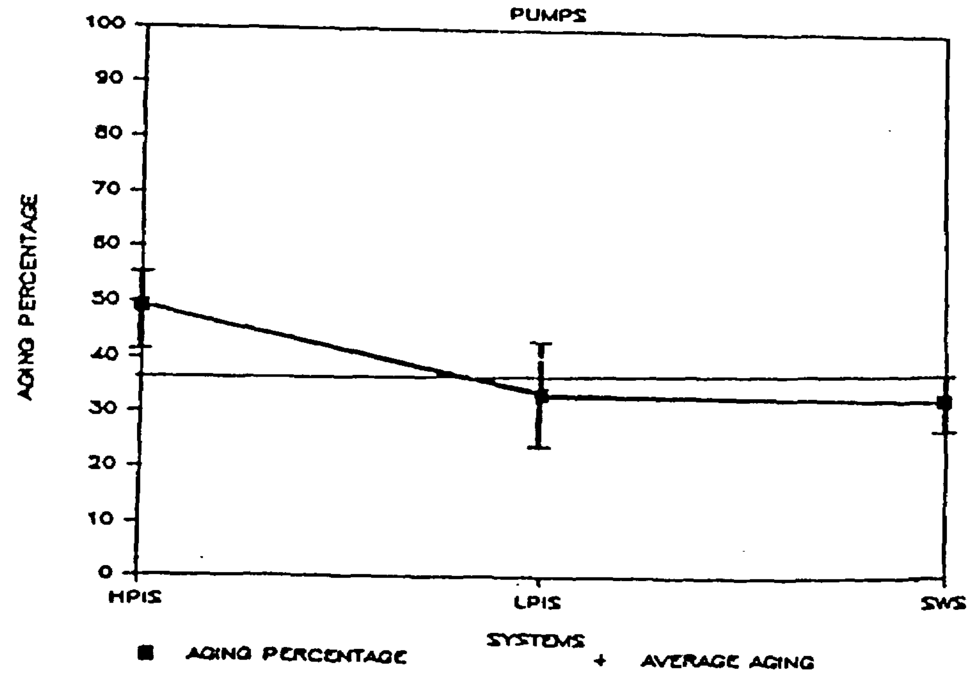

Figure A-16. Component aging contributions versus system for pumps.

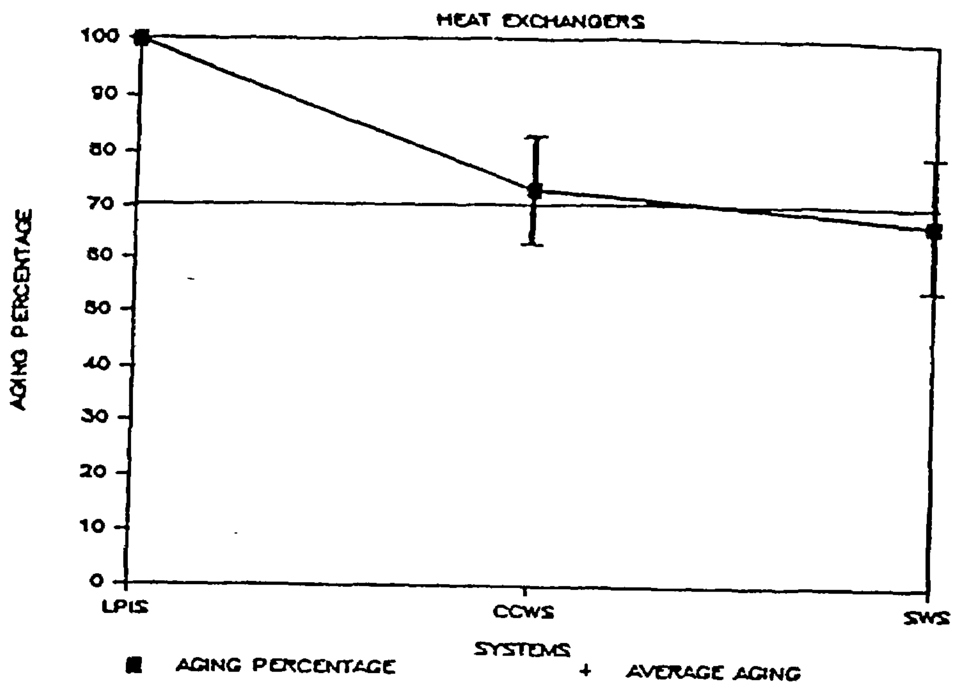

Figure A-17. Component aging contributions versus system for heat exchangers.

Severity Consequences of Aging-Related LERS by Component

Figure A-18 gives the percentage of aging-related LERs for a component that result in severe system effects. Severe system effects are defined to be either Category A or B in the severity classification (i.e., the LER results in loss of system function or in potential loss of system function if the system were demanded). The percentage for a component in Figure A-18 can be interpreted as the probability that an LER associated with the comment will result in severe system effects. The component severity percentages thus rank the components in terms of the system consequences that result from an aging-related LER occurring for that component.

The figure indicates the following:

- Aging-related LERs for pipe supports are significantly more likely to have severe system effects than LERs for any other component. Approximately 41% of aging-caused LERs in pipe supports result in severe system effects.
- For the remaining components, the likelihood of aging-related LERs having severe system effects ranges from 15% for motors to 2% for bistables and switches.

Severity Consequences of Aging-Related LERS by System

Figure A-19 gives the percentage of aging-related LERs for a given system that have severe system effects. The percentage for a given system is the probability that an aging-related LER associated with that system will result in severe system effects.

As observed, an aging-related LER associated with the High Pressure Injection System (HPIS) has the highest likelihood of resulting in severe system effects; the severity percentage being approximately 10%. The Component Cooling Water System (CCWS) follows with a 6% severity percentage. Then, the Low Pressure Injection System (LPIS) comes next with a 3% severity percentage. The systems with the highest severity percentages are those that have critical components most likely to be affected by aging.

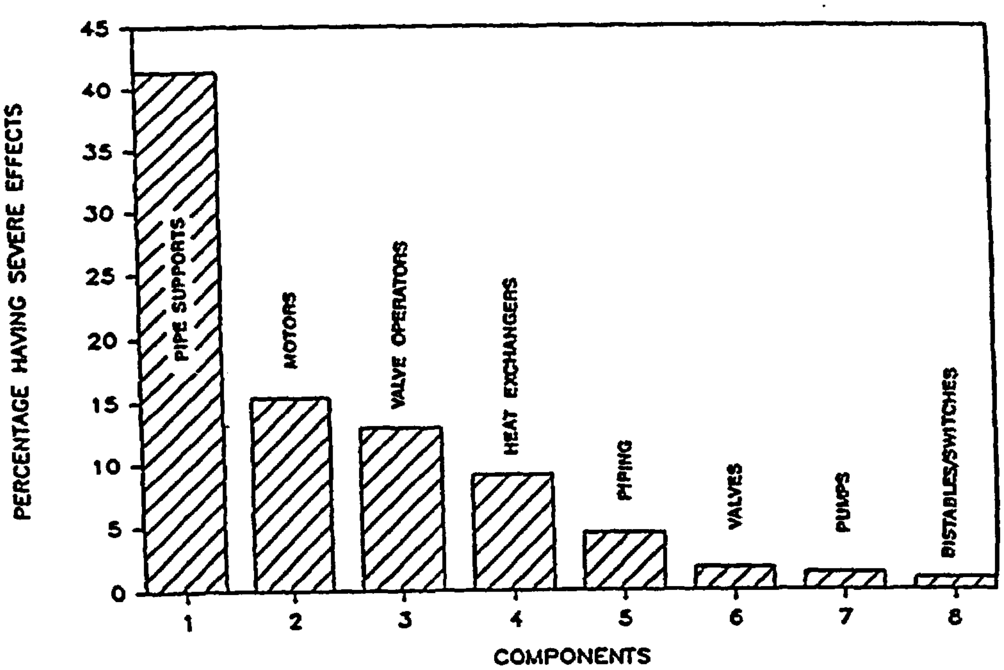

Figure A-18. Severity consequences of aging-related LERS by component.

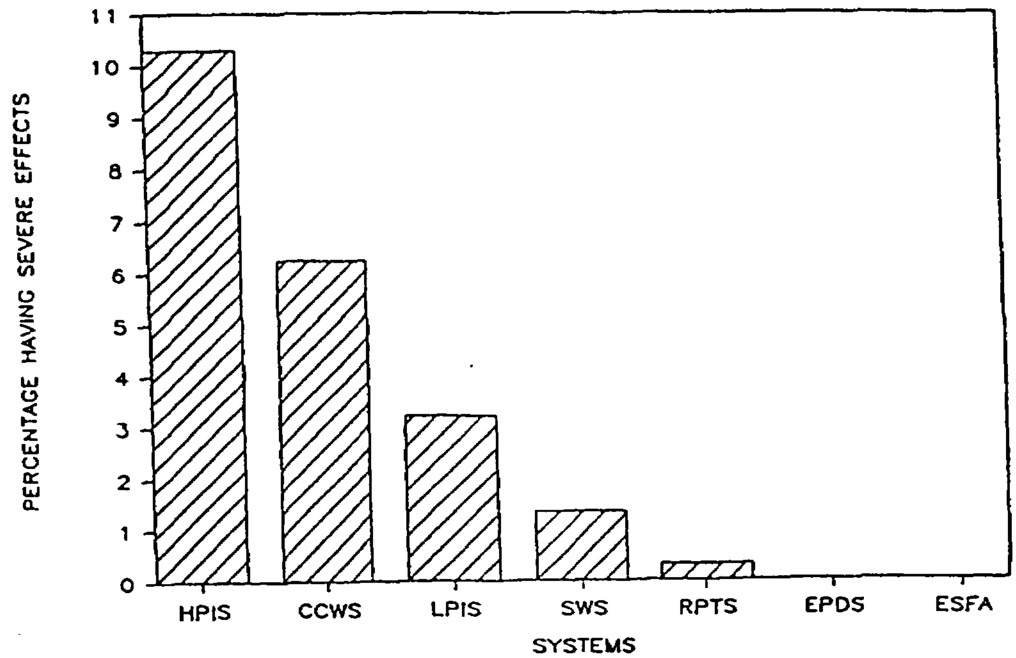

Figure A-19. Severity consequences of aging-related LERS by system.

System Effect on Aging Severity Consequences for a Component

Figure A-20 shows how the severity consequences for an aging-related LER varies, depending upon the system in which the component is located. The figure plots the range of severity percentages for a given type of component across the different systems containing that type of component. The width of the range effectively measures the variation in the importance of the component to the functioning of the systems.

As observed, pipe supports and valve operators have the largest ranges, reflecting their widely varying importance to the functioning of a system. To determine the consequences of aging-related LERs for these components with wide ranges, the specific systems must also be defined. The components whose aging-related LERs have essentially zero system consequences, such as relays and circuit breakers, generally are redundant components in which a single failure does not result in system consequences. Common cause aging failures resulting in multiple components failing would have severe system effects, however, no such common cause failures were contained in the data analyzed.

Component Effect on Aging Severity Consequences for a System

Figure A-21 plots the range of severity consequences of aging-related LERs for different components in a system. The systems with the widest ranges are those having components that vary the most in terms of their importance to the systems functioning. To determine the consequences of aging-related LERs associated with the systems having wide ranges such as the High Pressure Injection System (HPIS), or even systems with moderate ranges such as the Service Water System (SWS), the specific components must be examined. The Reactor Protection Trip System (RPTS), the Emergency Power Distribution System (EPDS), and the Engineered Safety Features Actuation System (ESFAS) generally have zero severe percentages because of the redundancies built into these systems, which result in individual components and associated LERs having no direct, severe system consequences.

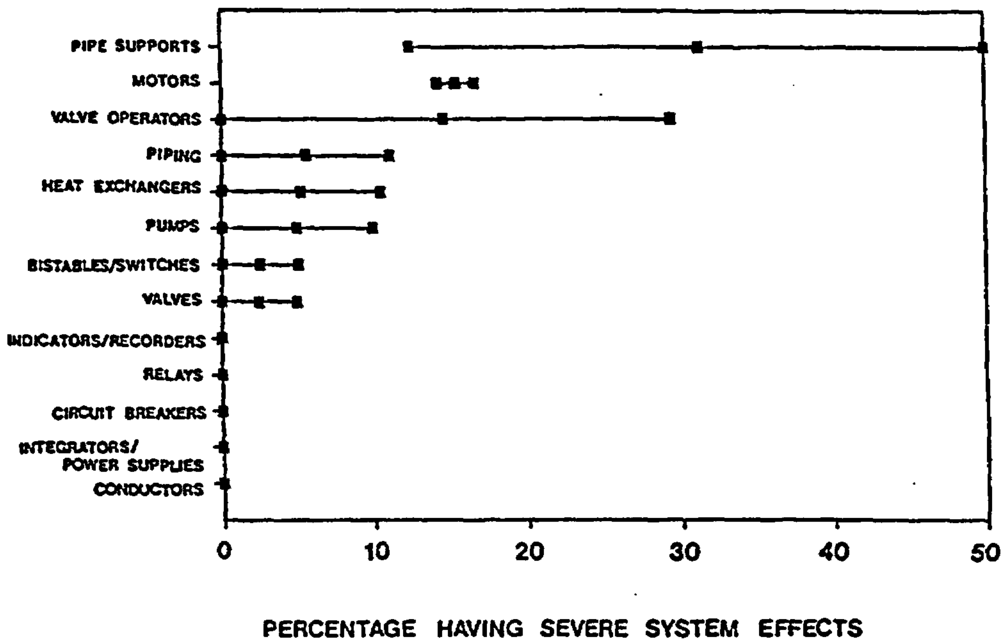

Figure A-20. System effect on aging severity consequences for a component.

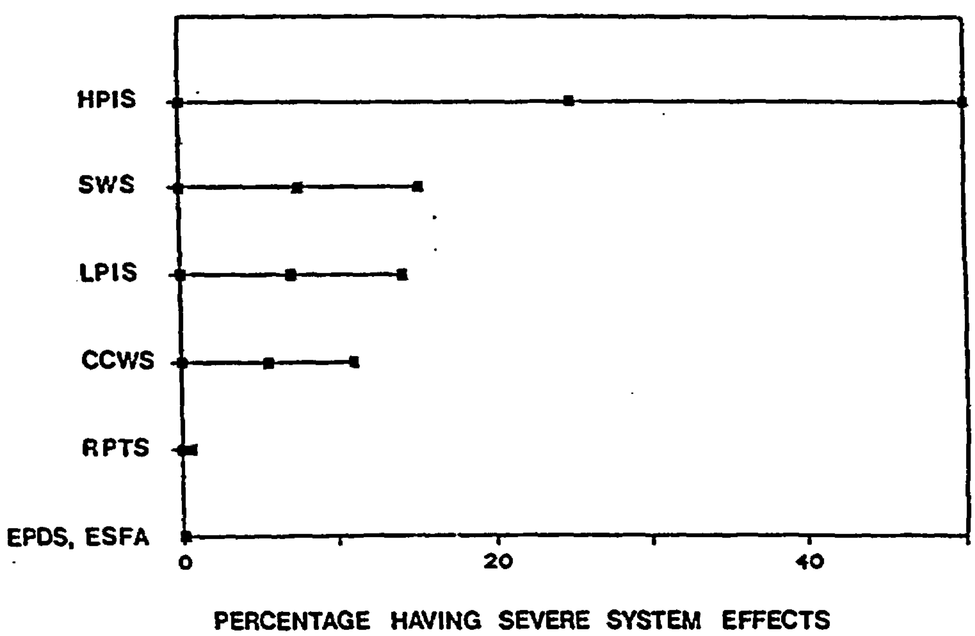

Figure A-21. Component effect on aging severity consequences for a system.

Aging Contribution Versus Plant Age for Piping

As part of the analyses, the data were examined to determine any trends in the aging contributions versus plant age. The only component showing an apparent trend was piping, as shown in Figure A-22. Figure A-22 indicates a strong linear trend with plant age in the percentage of LERs associated with aging, starting at approximately 28% for plants 0 to 5 years in age and linearly increasing to approximately 67% for plants greater than 15 years in age. The piping failures covered the range from minor cracks to more severe breaks. (The testing and maintenance performed on the other components with the accompanying replacement of parts tends to complicate any time trends due to aging, while piping generally does not have this complication.) The linear trend indicates an increasing failure rate for aging failures in piping relative to other failures.

Aging Contributions Versus Plant Age for Piping in Different Systems

Figure A-23 shows the aging contribution in piping versus plant age for different systems containing piping. As observed, all systems show an approximately linear trend in the aging contribution as the plant age increases. The rate of increase of LERs due to aging appears to be approximately the same for the different systems after 5 years. However, the aging contributions vary significantly for the first 5 years (resulting in different intercept values on the vertical axis). The time trends indicate that the probability of a piping failure can be systematically increasing with plant age due to aging mechanisms.

Aging Contribution Versus Plant Age for the Service Water System

Finally, one system exhibited trends in the aging contribution as a function of plant age; that system was the Service Water System (SWS). Figure A-24 shows the percentage of LERs associated with aging for the SWS as a function of plant age. The percentage systematically increases with plant age due to the strong contributions coming from the piping in the SWS. This time trend indicates that the availability of the SWS can be systematically degrading as the plant ages due to aging mechanisms.

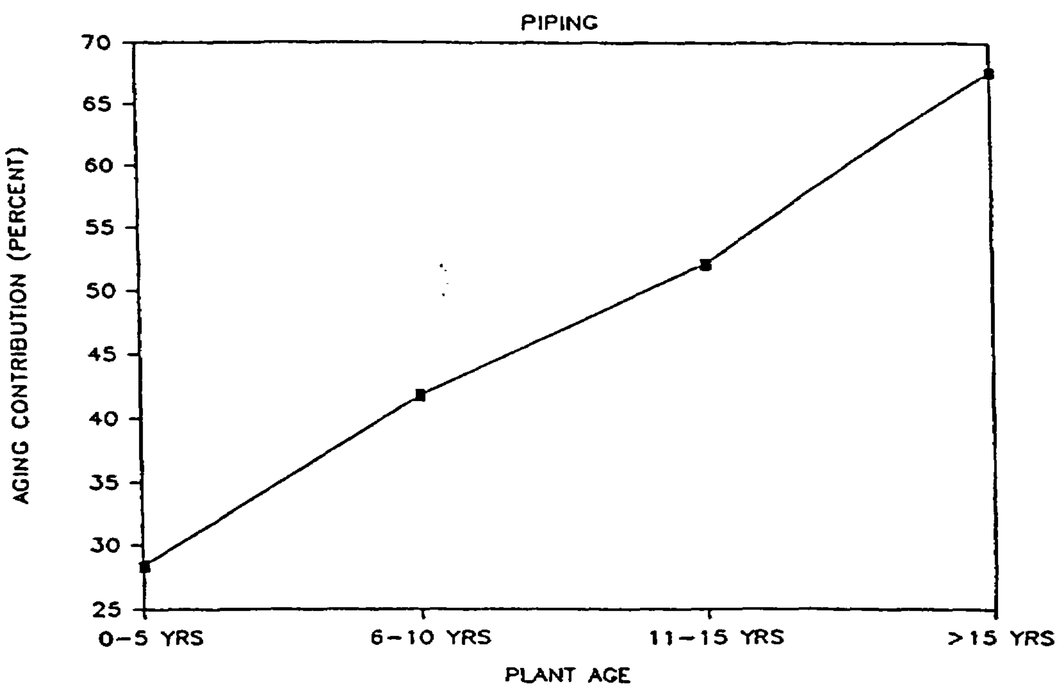

Figure A-22. Aging contribution versus plant age for piping.

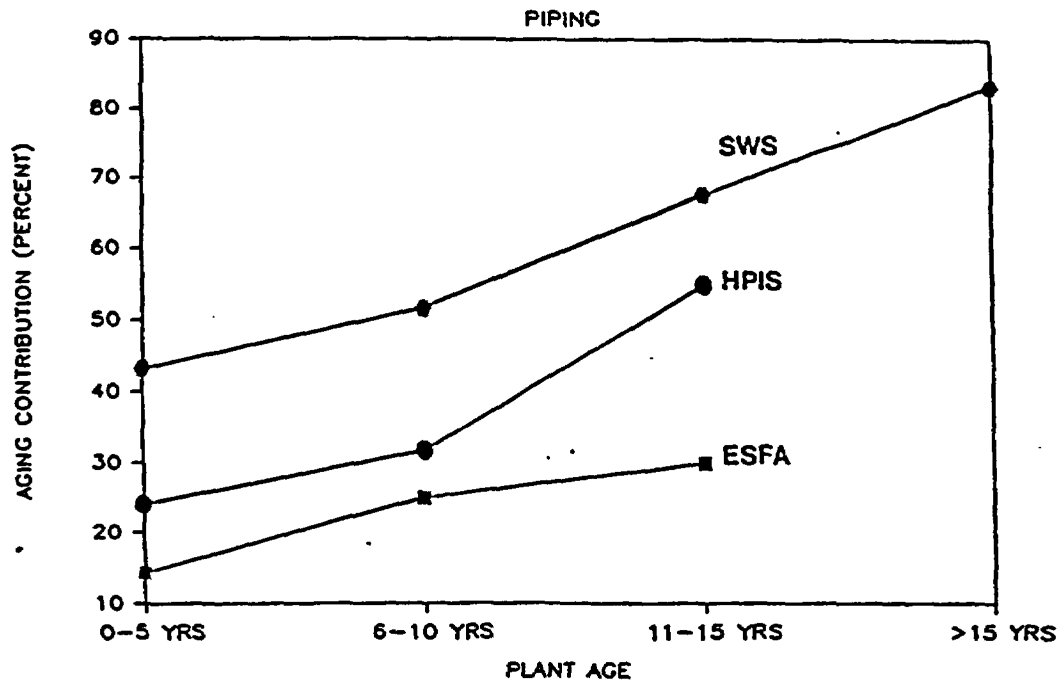

Figure A-23. Aging contributions versus plant age for piping in different systems.

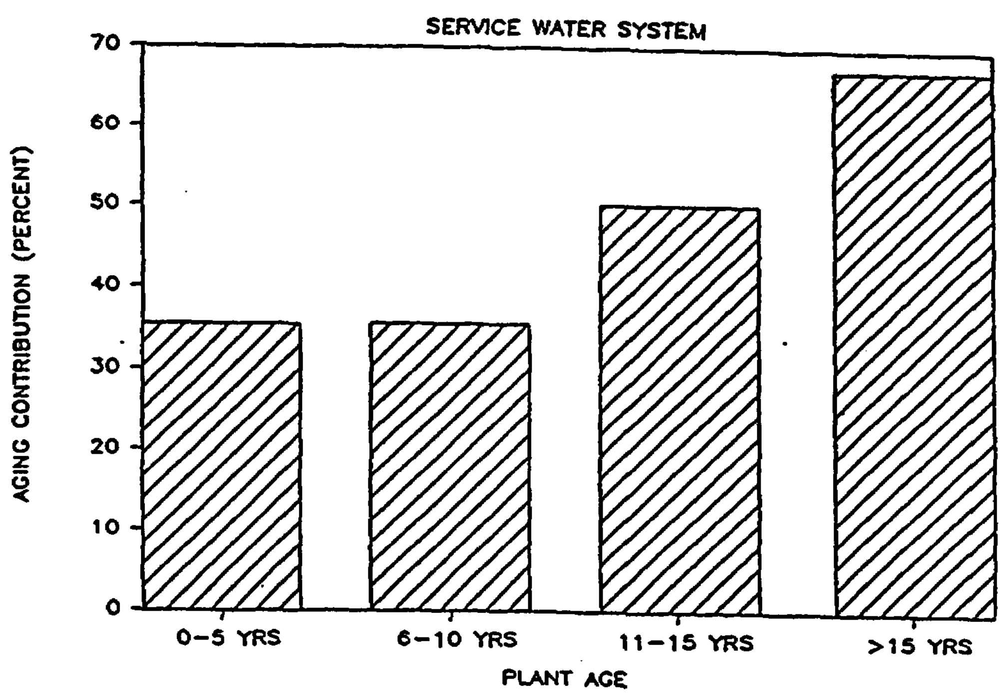

Figure A-24. Aging contribution versus plant age for the service water system.

APPENDIX B

ADDITIONAL PLOTS OF THE COMPONENT FAILURE PROBABILITY FOR AN AVERAGE EXPOSURE TIME (AGE AT FAILURE) OF TWO YEARS

APPENDIX B

ADDITIONAL PLOTS OF THE COMPONENT FAILURE PROBABILITY FOR AN AVERAGE EXPOSURE TIME (AGE AT FAILURE) OF TWO YEARS

(Appendix B is on microfiche attached to the inside back cover)

APPENDIX C

ADDITIONAL PLOTS OF THE UNAVAILABILITY OF THE AUXILIARY FEEDWATER SYSTEM MODEL VERSUS PLANT AGE

APPENDIX C

ADDITIONAL PLOTS OF THE UNAVAILABILITY OF THE AUXILIARY FEEDWATER SYSTEM MODEL VERSUS PLANT AGE

(Appendix C is on microfiche attached to the inside back cover)

APPENDIX D

COMPONENT AGING FAILURE DATA TABLES

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COMPONENT AGING FAILURE DATA TABLES

(Appendix D is on microfiche attached to the inside back cover)

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A model for light water reactor safety system component failure rates due to aging mechanisms has been developed from basic phenomenological considerations. In the treatment, the occurrences of deterioration are modeled as following a Poisson process. The severity of damage is allowed to have any distribution, however, the damage is assumed to accumulate independently. Finally, the failure rate is modeled as being proportional to the accumulated damage. Using this treatment, the linear aging failure rate model is obtained. The applicability of the linear aging model to various mechanisms is discussed. The model is also extended to cover nonlinear and dependent aging phenomena. The implementation of the linear aging model is demonstrated by applying it to the aging data collected in the U.S. Nuclear Regulatory Commission's Nuclear Plant Aging Research Program.

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