THE IMPACT OF AGING ON LIFE CYCLE COST: TECHNIQUES FOR ANALYSIS AND OPTIMIZATION

Mikko I. Jyrkama and Mahesh D. Pandey
Department of Civil Engineering, University of Waterloo
Waterloo, Ontario, N2L 3G1, Canada
mjyrkama@uwaterloo.ca

ABSTRACT

Systems, structures and components in a nuclear power plant are undergoing a variety of age-related degradation mechanisms (ARDMs) due to the severe environmental and operational conditions. Incorporating these recognizable, yet highly uncertain effects into a decision making or asset management process in a methodical way clearly requires a risk-based approach. This paper examines the impact of aging in the context of life cycle cost (LCC) analysis. Aging components generally experience higher failure rates which will have a direct influence on expected costs, and hence on overall system risk. The impact of aging can be modelled using the Weibull distribution, however, it must be modified in the context of life cycle cost analysis for consistent comparison of decision making alternatives. The results of this study demonstrate how age-based failure rates can have a significant influence on the net present value, and should therefore not be ignored, particularly for operational planning and asset management decisions related to end-of-life and refurbishment. The benefits of the developed methodology are demonstrated by integrating it with the life cycle planning of the main generator system.

1. INTRODUCTION

Life cycle management (LCM) involves optimization of both reliability and cost of an asset until its end of life. The optimization is based on various asset management alternatives which are compared on an equivalent economic basis, often the net present value (NPV). In addition to the costs associated with the operation and maintenance of the particular asset, the decision analysis must also account for changes in the assets reliability in the context of the various management alternatives. This is particularly important for aging systems and components which generally experience decreasing reliability and hence increasing maintenance and operating costs over time.

Systems, structures and components (SSCs) in a nuclear power plant operate in a dynamic environment in which wear and damage accumulates over time as a result of various aging related degradation mechanisms (ARDMs) such as corrosion, fatigue and creep. Because of the considerable variability associated with the degradation mechanisms and the influence of other factors, such as material properties, operational stresses, and environmental conditions, the analysis of system or component reliability over time is highly uncertain.

Cost analysis, on the other hand, is generally more straightforward as income and disbursements are carefully tracked and managed by accounting and finance departments. Figures can effectively be compiled for costs associated with, for example, a particular asset's procurement and acquisition, operation, scheduled and unscheduled maintenance, lost production due to forced outages, etc. While operational experience helps to reduce the variability in the cost numbers, estimating costs in the future is often highly uncertain due to the unpredictability of end of life and the need for corrective repair work. Estimating the cost of electricity in the future can also be especially challenging.

It is evident that both the reliability and cost of an asset are subject to various sources of uncertainty which contribute to risk. Accounting for these uncertainties through a risk-informed approach is critical to the success of a life cycle management program. This paper presents methods for quantifying the uncertainty in the asset's reliability due to the influence of aging, and integrating the results into economic decision analysis.

2. BACKGROUND

2.1 *Risk and Economic Analysis*

Risk is simply defined as the probability of an event multiplied by the cost associated with its consequence. The total expected cost, or risk, associated with an event, e.g. failure of an asset, *A*, to provide its intended function, is equal to

$$E[C] = P_A \cdot C_A \tag{1}$$

where P denotes the probability of the event and C is the total cost associated with the occurrence of the event. The expected costs can then be discounted to present value using standard economic formulas, i.e.

$$PV_A = \frac{E[C]}{(1+i)^n} \tag{2}$$

where PV is the present value, i is the discount rate and n is the year of occurrence relative to the reference year (i.e. the present time).

2.2 *Reliability Analysis*

In each year of the life of an asset, there is a chance that the asset will fail to provide its intended function or service. For many engineering components, the rate or occurrence of failures follows the so called "bathtub" shape, as shown in Figure 1. The failure rate is generally high at the beginning of the components life cycle due to manufacturing and design problems. The failure rate then decreases toward a constant level for the bulk of the operating life. Finally, at a certain age, the component reaches the wearout phase where the failure rate begins to increase due to aging related effects.

The assumption of a constant failure rate is widely used in economic decision analysis and life cycle planning (e.g. EPRI, 2003a). This approach seems reasonable for highly reliable and highly maintained systems where replacements and repairs are performed in time to avoid the wearout phase. However, this implies that highly reliable and highly maintained systems, such as those in a nuclear power plant, would not require any aging assessment at all, since they would presumably never reach the age at which the wearout type failures would begin to occur.

For very large and complex systems it has also been argued that the system failure rate is essentially constant due to the interaction of failure rates of numerous individual subcomponents (Abernethy, 2000; EPRI, 2002). The assumption is that because a number of subcomponents will be replaced several times before the wearout phase of other components come into play, the entire system essentially never wears out.

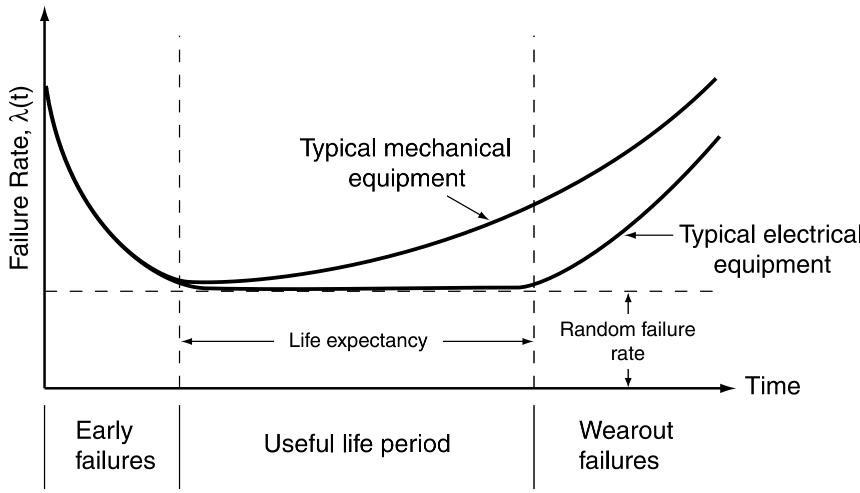

Figure 1: The bathtub failure curve (Dai and Wang, 1992).

Finally, one of the main reasons for using constant failure rates arises from operational experience. Because of the highly reliable and highly maintained systems in the nuclear industry, failures simply have not been observed. This lack of observational data makes it difficult not only to estimate the constant failure rate during the useful life of the asset, but even more challenging to quantify any time-dependent behaviour.

Nuclear fleets around the world are aging, and as stated before, are subject to a host of aging related degradation mechanisms (ARDMs). A great deal of research has been undertaken to understand and mitigate the impact of aging in the industry (e.g. NRC, 2005). The avenue for aging mitigation is through effective maintenance programs, which can greatly attenuate the majority of the wearout phenomena. This is the key factor behind the constant failure rate assumption, which relies on the preventive maintenance (PM) program to avoid entering the wearout failure phase.

Preventive maintenance may not always be effective, however, due to failure mechanisms which are simply not addressed by the maintenance tasks or controlled by any maintenance programs. The impact of ARDMs such as corrosion, fatigue, and creep, accumulates over time and is influenced by highly dynamic operational and environmental factors (e.g. heat and radiation). Predicting the useful life period and failure rates for SSCs subject to these types of degradation mechanisms is subject to a great deal of uncertainty. The wearout phenomena due to ARDMs should therefore not be ignored, especially in economic decision analysis concerning life extension and refurbishment.

2.3 Aging and the Weibull Distribution

As shown in Figure 1, the influence of system or component aging is characterized by an increasing failure rate function. This behaviour can be modeled using, for example, a Weibull distribution with shape parameter greater than one. The Weibull failure rate function (also referred to as the hazard rate function) is given as

$$h(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} \quad for\ t \geq 0 \tag{3}$$

where t represents time, α is the scale parameter, and β is the shape parameter. The scale parameter controls the amount of dispersion by stretching or compressing the distribution, while the shape parameter defines the shape of the distribution. The Weibull survival function is defined as

$$S(t) = \exp\left\{-\left(\frac{t}{\alpha}\right)^{\beta}\right\} \tag{4}$$

The Weibull density and lifetime distribution functions are

$$f(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} \exp\left\{-\left(\frac{t}{\alpha}\right)^{\beta}\right\} \tag{5}$$

and

$$F(t) = 1 - \exp\left\{-\left(\frac{t}{\alpha}\right)^{\beta}\right\} \tag{6}$$

respectively. It is evident that the failure rate function can also be expressed as the ratio of the probability density function to the survival function

$$h(t) = \frac{f(t)}{S(t)} \tag{7}$$

while the survival function is simply equal to

$$S(t) = 1 - F(t) \tag{8}$$

Figure 2 illustrates the various functions for a range of Weibull scale and shape parameters. The Weibull failure time distributions, shown in Figure 2a, represent probability densities of lifetimes. For aging SSCs with $\beta > 1$, the shape of the density function indicates only few failures initially, with increasing numbers of failures with time, and finally, fewer failures later on as most of the items will have already failed.

The Weibull distribution can be used to model not only increasing failure rates, but also various stages of the component life as shown in Figure 2d. For a shape parameter

- $\beta < 1.0$ the failure rate is decreasing (infant failures)
- $\beta = 1.0$ the failure rate is constant (operating life)
- $\beta > 1.0$ the failure rate is increasing (wearout phase)

For component aging with a shape parameter greater than 1

- $1.0 < \beta < 2.0$ the failure rate is increasing at a decreasing rate
- $\beta = 2.0$ the failure rate is increasing at a constant rate
- $\beta > 2.0$ the failure rate is increasing at an increasing rate

The Weibull distribution, therefore, provides a versatile model for simulating different types of failure behaviour.

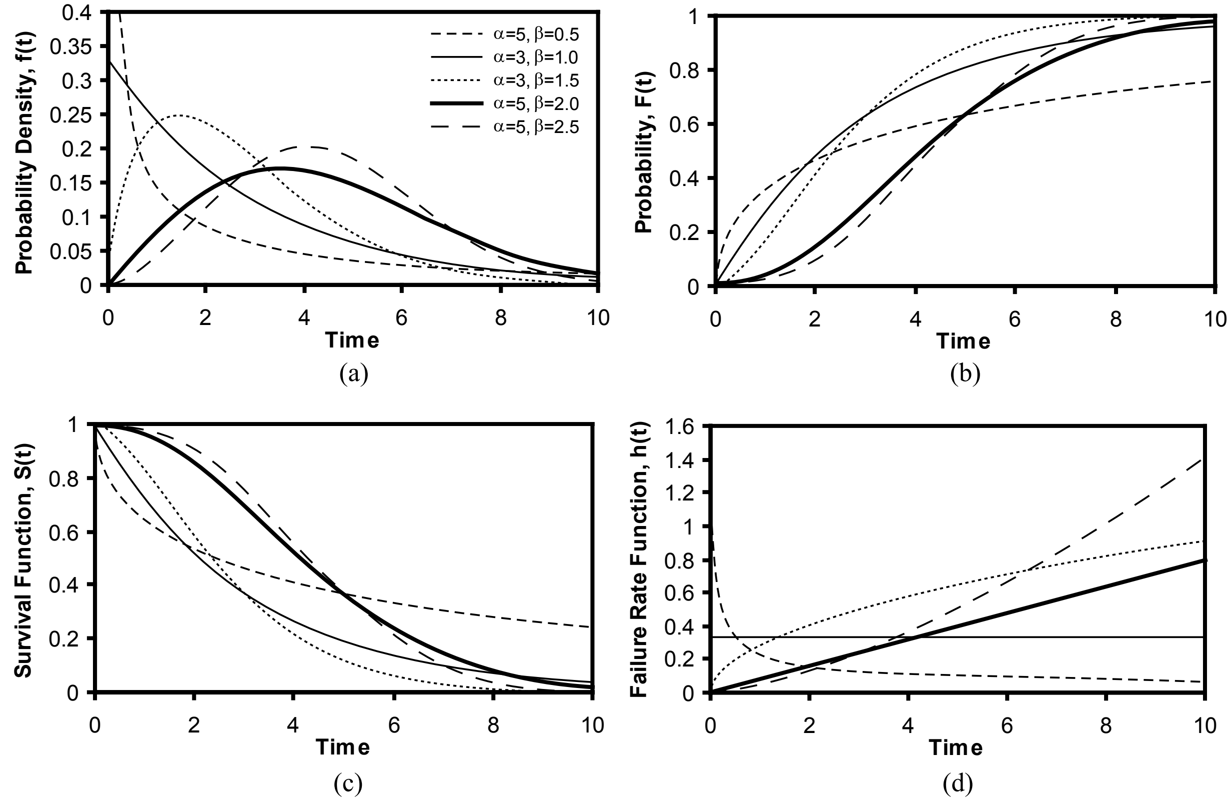

Figure 2: Weibull (a) probability density functions, (b) probability distribution functions, (c) survival functions, and (d) failure rate functions for various scale and shape parameters.

2.4 Estimating Failure Rates using Simulation

As shown in Equation (1), the expected cost in a given time period is computed simply as the product of the probability of failure and the associated cost. Failure rate or hazard rate is defined as an instantaneous rate that represents the probability that a component or system of age t will fail in a small interval of time $t + \Delta t$. In the case when the failure rate is constant, the probability of failure is the same in each time period, making the economic analysis straightforward. When the failure rate is changing over time, however, computing the probability of failure is more complicated, requiring methods such as Monte Carlo simulation.

Using simulation, the frequency or probability of failure in a given time period is estimated by sampling failure times from the lifetime distribution repeatedly, and then computing the frequency of failures in each time period. For the Weibull distribution, the failure times can be simulated using the inverse transform method, by solving the lifetime distribution in Equation (6) for time resulting in

$$t = \alpha \ln\left(\frac{1}{1-p}\right)^{\frac{1}{\beta}} \tag{9}$$

where p is the probability, which also corresponds to a random number from the standard uniform distribution U(0,1).

The above method is then used with the strategy of restoring a failed component to as-good-as-new condition, which is illustrated in Figure 3. Each iteration involves a number of Monte Carlo trials, whereby individual failure times or lifetimes (t_1, t_2, t_3,… t_n) are drawn randomly from the lifetime distribution and added cumulatively over the total analysis period. The objective is to simulate all the failures expected to occur within the economic analysis period. The random failure times can be generated, for example, by using the RAND( ) function in Excel to return a uniformly distributed random number between zero and one for p in Equation (9).

As an example, consider the operation period of 10 years and the assumed distribution parameters as shown in Figure 3. Starting at time zero, we generate the first random time to failure, t_1, which happens to be 4.7 years. This means that the component has now suffered a failure and needs to be fixed or replaced. Following the fix-when-broken strategy, the component is fixed and we continue operating and draw the next random time to failure, t_2, which is equal to 3.8 years. The concept of fixing to as-good-as-new condition means that we continue sampling from the same lifetime distribution with the same distribution parameters. We now have a failure at 4.7 + 3.8 = 8.5 years of operation which is fixed and a new trial is conducted. The next random time from the same Weibull distribution, t_3, is equal to 3.1, which would occur at 8.5 + 3.1 = 11.6 years of operation. Because the operation period is only 10 years, we can discard this failure and begin the next iteration cycle, starting at time zero.

In the end, the probability of failure can be estimated after N number of iterations by computing the frequency of failures in each time period of interest, for example, in each year within the 10 year operating period. The failure rate (and probability of failure) is simply the number of simulated failures within each time period divided by the total number of iterations.

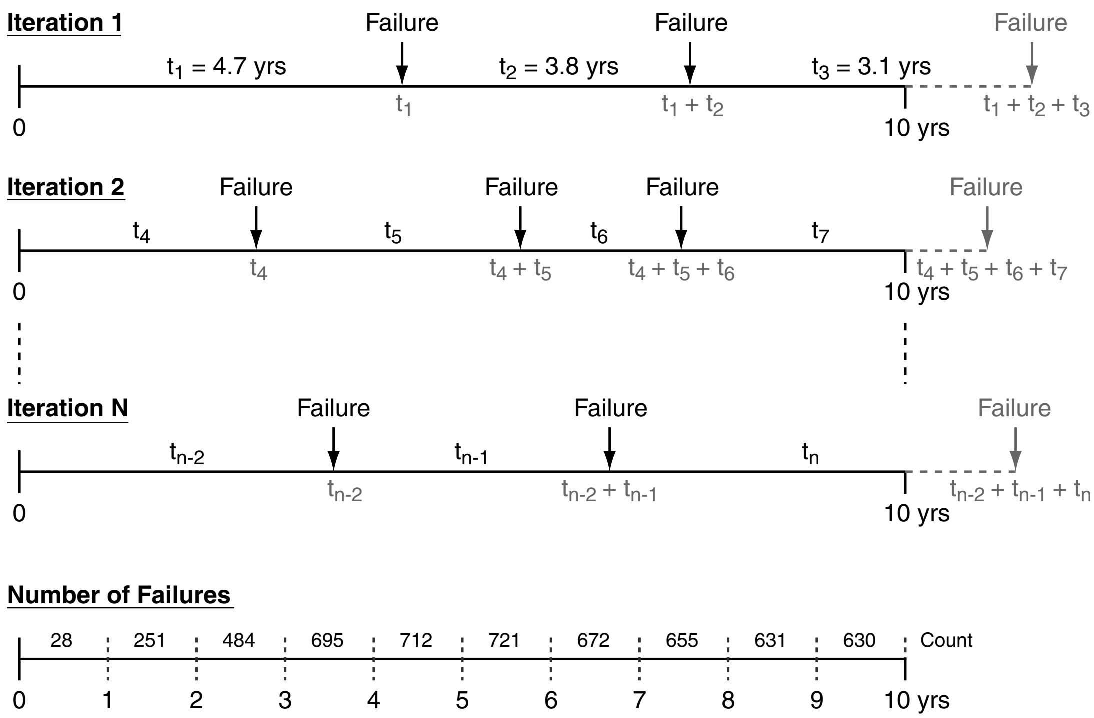

Figure 3: Simulating failure times from the Weibull distribution with scale parameter $\alpha = 6$ and shape parameter $\beta = 2.5$.

3. LIFE CYCLE COST ANALYSIS

The objective of economic decision analysis is to maximize business objectives in the face of limited resources. Life cycle cost (LCC) analysis is a critical component of the decision making process. It involves a detailed analytical study to estimate the total costs experienced during the life of a particular asset or project. The main benefit of LCC is that it identifies the most cost effective approach from a series of alternatives such that the lowest long term cost of ownership or operation is achieved (Barringer and Weber, 1996). When the analysis is conducted in terms of expected costs involving probabilities, this also corresponds to the lowest overall risk.

The key concept in life cycle cost analysis is the reduction of the decision making alternatives to a common base while taking into consideration the time value of money. Time value of money simply refers to the fact that the investment of money can result in economic gain over time. Because prospective cash flows occur at different points in time for different alternatives, it is essential to reduce them to an equivalent basis for accurate comparison. The most commonly used measure is the net present value (NPV), although other factors can also be used such as annual equivalent, or net future worth (Fabrycky et al., 1998).

3.1 Example Problem: LCC of Main Generator and Auxiliaries

The operation of the turbine/generator system is second in criticality only to the operation of the reactor itself. Generator components require long repair times and failures are significant contributors to lost power generation and plant trips. The goal of generator life cycle management is not only to maintain the generator at high reliability and availability for power generation, but also to ensure the life expectancy of the generator meets or exceeds the life of other critical components such as the steam generators and reactor components. The generator system represents a very large and critical capital investment, which must be carefully managed to maximize the economic benefits for the operator.

In simple terms, the main generator converts mechanical energy into electrical energy. The operation is based on electromagnetic induction, whereby voltage is induced into the stationary stator iron (i.e. coils of wire) by the rotating magnetic field created in the rotor by the exciter. The auxiliary systems consists of the

- Exciter System - supplies and regulates DC current to the generator rotor field windings,
- Stator Cooling Water System - cools the stator windings and terminal bushings,
- Hydrogen Gas Cooling System - removes heat from the rotor and stator iron, and
- Seal Oil System - provides lubrication and an oil seal between the generator shaft and the generator end shields.

The main generator and auxiliaries therefore consist of five major systems which in turn are composed of a number of sub-components that contribute to overall system functionality.

A process for LCM of the main generator is given in an Electric Power Research Institute (EPRI) sourcebook (EPRI, 2003a). The document contains generic information, data, and references, industry wide generator issues and ways to ensure that they are addressed at the plant, generator component aging mechanisms together with the maintenance activities to manage them, generator, exciter and voltage regulator obsolescence issues and available management options, and alternative LCM plans that can be considered during long-term planning for the generator critical components. Main generator LCM plans for six U.S. nuclear plants are also available from EPRI (EPRI, 2003b).

The most critical generator components that contribute 90-95% of the generator failure rates and associated repair and outage costs have been identified as the stator winding, the stator core, the rotor, the exciter, and the voltage regulator (EPRI, 2003a). Clearly, these components should be maintained and managed at a very high level, and should play a central role in any economic decision analyses. However, there are also other components whose failure will directly result in the functional failure of the generator, and should therefore not be overlooked.

The preceding example highlights one of the main challenges of economic decision analysis, which is its scope. The risk attributed to the main generator is directly dependent on the probability of failure of a number of sub-systems and components as well as the associated repair costs. The failure of the generator itself to provide power will also contribute to the overall risk, regardless of the cause, due to costs associated with lost gross margin, potential regulatory intervention and penalties, erosion of morale and public opinion, etc. A comprehensive life cycle cost analysis should consider all possible costs and sources of failure for a consistent evaluation of net present value. As discussed before, however, both costs and particularly the failure rates are subject to high uncertainty due to scarce data.

Due to the lack of plant specific failure data for the main generator and auxiliaries, we will consider the components and associated industry average values presented in the EPRI generator sourcebook (EPRI, 2003a) as guidance. The components considered in the analysis are shown in Figure 4, while the associated (assumed) data is presented in Table 1. Figure 4 illustrates how the system can be thought of as a fault tree, as the failure of any one component (or sub-system) will result in the failure of the system to perform its intended function.

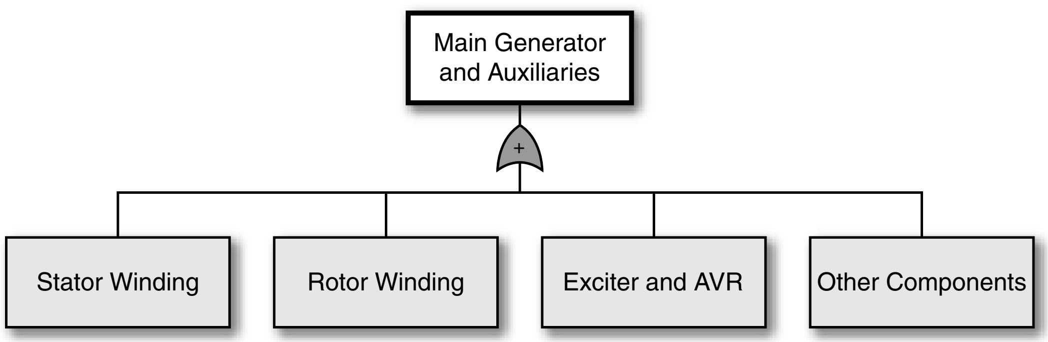

Figure 4: The components used in the life cycle cost analysis of the main generator and auxiliaries.

Table 1: Assumed outage duration (OD) and corrective maintenance (CM) data used for the generator components.

Component	**Outage Duration*** (*hours*)	**Corrective Maintenance / Repair Cost** (*$K*)
Stator Winding	720	800
Rotor Winding	480	500
Exciter and AVR	48	20
Other Components	24	10

* The outage duration is the expected time to repair the failed component to as-good-as-new condition.

Besides the reliability estimates, as discussed before, there are many uncertainties involved with cost estimates, especially in the future. While the economic calculations are clearly defined, factors such as the discount rate can also be highly uncertain. Because the objective of this paper is to investigate the risk associated with the time-dependent failure rates, we consider all other parameters to be constant in time. These parameters are summarized in Table 2.

Table 2: Other parameters used in the life cycle cost analysis.

Parameter	Value
Generator output	600 MW
Price of electricity	\$ 0.0495 / KWh
Labour cost	\$ 54 / hour
Annual PM costs	\$ 200 K / year
Interest (discount) rate	8 %
Analysis period	25 years

Based on the generator output and assumed (fixed) price of electricity, the cost of lost production is equal to

$$C_{LP} = 600\ \text{MW} \cdot \$0.0495\,/\,\text{KWh} \cdot 1000\ \text{KW}\,/\,\text{MW} = \$29,700\ /\ \text{hour} \qquad (10)$$

For simplicity, assume that the present maintenance program will continue for the 25 year operating period without major upgrades or replacements, i.e., only repair to as-good-as-new condition.

3.1.1 Constant Failure Rate Model

Following the industry approach, we first consider the case where the component failure rates are assumed to be constant in time. The assumed failure rates are again based on the EPRI generator sourcebook (EPRI, 2003a) and are shown in Table 3.

The system failure rate is the sum of the individual failure rates, therefore, in this case the failure rate for the entire main generator and auxiliaries system is equal to 0.06 + 0.03 + 0.035 + 0.02 = 0.145 failures/year, which is equivalent to one failure in every 6.9 years (assuming a constant failure rate). It is interesting to note that, because there is no redundancy in the system (see Figure 4), the system failure rate is much higher than the individual component failure rates. As a reference, the industry average generator failure rate is 0.092 failures/year, or one failure every 10.9 years (EPRI, 2003a).

Table 3: Assumed constant failure rates for the generator components.

Component	Failure Rate (*failures/year*)
Stator Winding	0.06
Rotor Winding	0.03
Exciter and AVR	0.035
Other Components	0.02

Adopting the expected cost approach, computation of net present value is straightforward, as the failure rates are the same every year. The expected annual lost gross margin is computed as

$$E[C_{LGM}] = \sum_{k=1}^{4} OD_k C_{LP} P_k \tag{11}$$

where OD is the outage duration, C_{LP} is the cost of lost production, P is probability of failure (i.e. annual failure rate), and the subscript k denotes each of the four components. The expected annual cost of corrective maintenance (including labour cost) is computed similarly. The results are summarized in Table 4.

Table 4: The expected annual costs associated with the generator components.

Component	**Expected Annual Lost Gross Margin** (*$K/year*)	**Expected Annual Cost of Corrective Maintenance** (*$K/year*)	**Total Expected Annual Cost** (*$K/year*)
Stator Winding	1,283.0	50.3	1,288.3
Rotor Winding	427.7	15.8	443.5
Exciter and AVR	49.9	0.8	50.7
Other Components	11.9	0.2	12.1
Totals	1,772.5	67.1	1,839.6

The cost of annual PM can be also viewed as an expected cost with probability of occurrence equal to one. The total expected annual cost is then equal to

$$A = E[C_{LGM}] + E[C_{CM}] + E[C_{PM}] = 1,772.5 + 67.1 + 200 = \$2,039.6 \text{ K/year} \tag{12}$$

It is evident that the cost of lost power production is the biggest contributor to the average annual cost. As expected, stator winding is the largest cost contributor out of the four components, since it has the highest failure rate, the longest associated outage duration, and the highest CM/repair cost.

Because the costs are the same in each year, the net present value can be computed using the equal-payment-series present-worth factor as

$$NPV = A\left[\frac{(1+i)^n - 1}{i(1+i)^n}\right] \tag{13}$$

where A represents a series of equal annual costs. For an annual interest rate of 8 % and a 25 year study period, the NPV is equal to $21,772.5 K.

3.1.2 Aging Failure Rate Model

Aging of generator components occurs within normal system operating conditions over time. This is referred to as normal aging, because it is acknowledged and expected to occur during the operating life of the generator. Due to operational and environmental stresses, many generator systems and components suffer from thermal degradation, mechanical wear and fatigue, electrical and voltage related stress, and chemical changes and contamination (EPRI, 2003a). The degree or rate of the degradation is not only affected by the operating conditions, but also by initial design and fabrication.

While all generator components are traditionally designed for a life expectancy of 30 years, actual in-service experience of large generators has indicated that the actual life may be significantly different (EPRI, 2003a). There is a great deal of uncertainty in the life expectancy of the generator, which requires careful consideration, especially for power utilities considering life extension and refurbishment.

Consider the preceding example of the main generator system with the constant failure rate assumption. Suppose that the generator has been in operation for close to its design life of 30 years and company management is now considering extending the life of the plant by another 25 years. The decision for plant life extension will naturally be based on not only the main generator, but on careful assessment of all the systems and components at the plant. In the end, the ultimate decision will be influenced by a jumble of engineering, safety, economics, and politics, a topic which is clearly beyond to scope of this paper.

The decision to operate the main generator for another 25 years can be addressed through life cycle cost analysis. Depending on the condition of the generator and its components, decision alternatives may be proposed that involve component replacements, introduction of new and improved monitoring systems, etc. The basic alternative, however, is to continue operating the system for another 25 years under the existing conditions. Because the generator will now be asked to operate beyond its useful design life, it is reasonable to assume that aging may begin to influence the failure rate (refer to Figure 1).

The increased risk due to aging can be quantified methodically by incorporating age-based failure rates into the life cycle cost analysis. The analysis allows the net present value (i.e. risk) of both the constant failure rate assumption and the aging failure rate assumption to be compared on an equivalent basis. While judging which assumption is more appropriate may be challenging, the key point here is that it is reasonable to assume that the failure rate may be increasing due to aging, and should therefore not be ignored.

The problem with using the standard Weibull distribution to model the impact of increasing failure rates in economic decision analysis is that it assumes the failure rate is equal to zero initially. As shown in Figure 1, the failure rate for the wearout phase of an asset does not begin at zero, but continues from the rate observed during the useful life period. Therefore, the Weibull distribution must be modified to account for this inherent failure rate of the system.

To model both the constant and the wearout part of the bathtub curve, a constant term, λ, is introduced to the standard Weibull failure rate function shown in Equation (3) as

$$h(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} + \lambda \quad for\ t \geq 0 \tag{14}$$

Solving for the new density function results in

$$f(t) = \left(\frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} + \lambda\right)\exp\left\{-\left(\frac{t}{\alpha}\right)^{\beta} - \lambda t\right\} \tag{15}$$

which is essentially a combination of the Weibull and Exponential distributions. The shape is a mixture of the two distributions, where the degree of influence of each distribution is controlled by the distribution parameters. The lifetime distribution for this model is

$$F(t) = 1 - \exp\left\{ -\left(\frac{t}{\alpha}\right)^{\beta} - \lambda t \right\} \tag{16}$$

Rearranging the above equation as

$$\left(\frac{t}{\alpha}\right)^{\beta} + \lambda t + \ln(1-p) = 0 \tag{17}$$

shows that the adjusted model cannot readily be used to simulate failure times using the inverse transform method. However, Equation (17) can be solved for time explicitly when $\beta = 2$ as

$$t = \frac{\lambda \pm \sqrt{\lambda^2 - \dfrac{4\ln(1-p)}{\alpha^2}}}{2}\alpha^2 \tag{18}$$

where the negative root is inadmissible. The adjusted Weibull model can therefore be used to simulate failure times when $\beta = 2$ using the methods described in Section 2.4.

The assumption of a linearly increasing failure rate has been used in the nuclear industry (NRC, 1987) and seems reasonable due to the lack of evidence to support an increasing rate that is changing with time. The adjusted Weibull model can naturally be used with a combination of any shape or scale parameters, however, this would require a different simulation approach, such as the acceptance/rejection method, for generating the random failure times.

Because the new parameter, λ, is equal to the constant failure rate in the original example and the shape parameter is fixed at 2, the only unknown in the adjusted Weibull model is the parameter α. Substituting $\beta = 2$ into Equation (14) results in

$$h(t) = \frac{2}{\alpha^2}t + \lambda \quad for\ t \geq 0 \tag{19}$$

which is the equation of a line with slope $2/\alpha^2$ and intercept λ. The slope of the failure rate line is therefore directly controlled by the parameter α, which can be specified to correspond to some proportional increase in the failure rate, e.g. 1 %, per year.

Table 5 summarizes the parameters used when the failure rate is assumed to increase linearly by 1 % per year for all components over the 25 year period. Based on these distribution parameters, the failure rates for each year are computed by simulation using Equation (18). The total expected annual costs are then computed similar to the previous example. For an annual discount rate of 8 %, the NPV is equal to \$23,002.8 K in this case, an increase of 6 % as compared to the constant failure rate assumption.

Table 5: Adjusted Weibull parameters for the generator components when $\beta = 2$.

Component	λ	α
Stator Winding	0.06	57.74
Rotor Winding	0.03	81.65
Exciter and AVR	0.035	75.6
Other Components	0.02	100

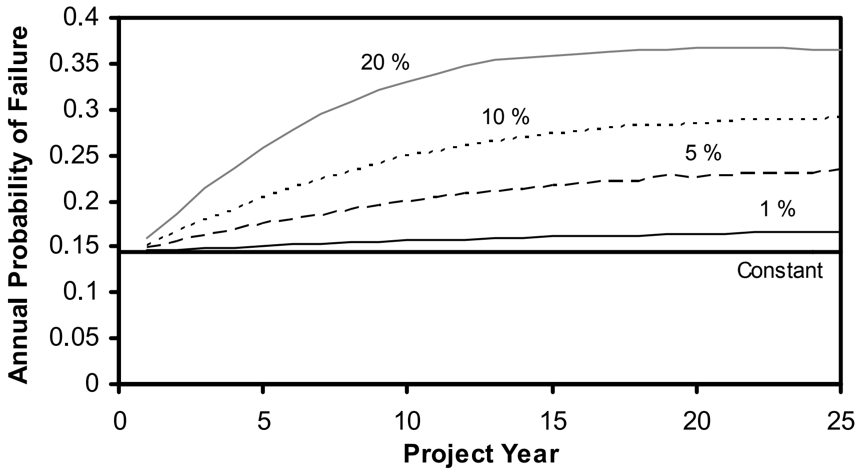

Figure 5: Annual probability of failure for various rates of increase in the component failure rates.

Figure 5 shows the annual probability of failure for various rates of increase in the component failure rates, based on one-million Monte Carlo iterations for each component. It is evident that even a small increase in the component failure rates due to aging can result in a significant increase in the annual probability of failure for the generator. Figure 5 also shows an interesting result of the fix-when-broken repair strategy, where the system probability of failure approaches a constant value over time, even though the component failure rates are increasing linearly in time.

The shape of the probability of failure curve in Figure 5 is directly related to the Weibull scale parameter, α. In the standard Weibull distribution, the scale parameter, α, is referred to as the characteristic life, which represents the time at which 63 % of the components will fail. The mean or expected life, refers to the time at which 50% of the components will fail. During simulation, the random failure times drawn from the lifetime distribution will follow the shape of the density function defined by the given scale and shape parameters. Initially, starting at time zero, most of the failure times will naturally be near the mean or expected life, and hence, also near the scale parameter. In subsequent trials, most of the simulated failure times will again be around the mean value, however, in the fix-when-broken strategy, the new failure times are added to the previous ones to obtain the time of failure in terms of operation time (refer to Figure 3). This addition of random failure times results in increasing scatter over operational time, eventually converging towards a constant value. The number of expected failures is therefore lower initially, while approaching a constant value after the mean lifetime.

As shown in Table 5, the scale parameters for the various generator components are well beyond the operating life of 25 years assuming an increase of 1 % per year in the failure rates. Therefore, the probability of failure would be expected to be increasing for the duration of the operating period, which is confirmed by the results in Figure 5. As shown in Equation (19), the percent increase in the failure rate (i.e. the slope of the failure rate line) is inversely proportional to the scale parameter, therefore, assuming a higher increase in the failure rates will result in smaller (earlier) component mean lifetimes. As expected, Figure 5 shows how the annual probability of failure curves increase more rapidly and converge earlier for higher rates of increase in the component failure rates.

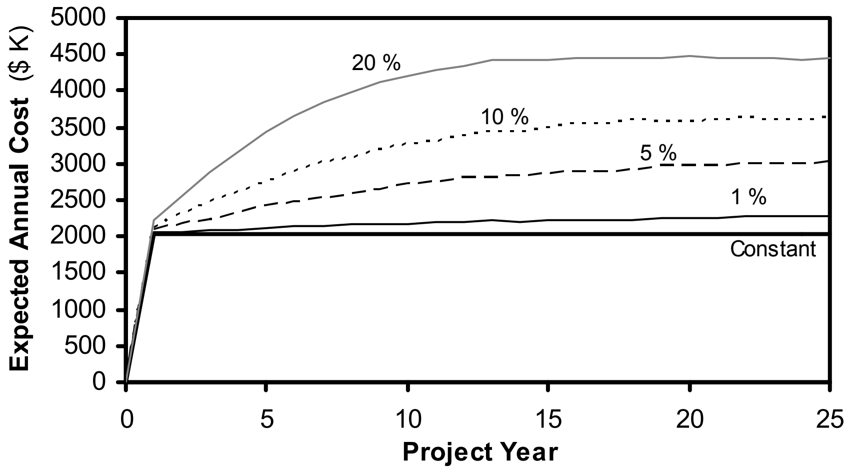

Figure 6: Total expected annual cost for the adjusted Weibull model for various rates of increase in the component failure rates.

Figure 6 shows the total expected annual costs for the various cases of increasing failure rates. As expected, the results look identical to Figure 5, since expected cost is simply equal to the probability of failure multiplied by the associated cost (see Equation 1). It is evident that aging can have a significant impact on the annual costs. The expected annual costs are also related to the individual component failure rates and their relative rates of change. For example, the results are more sensitive to the increase in the stator winding failure rate than the other components since it has the highest constant failure rate and the highest associated repair time and cost.

Figure 7 shows the impact of increasing failure rates on the change in net present value as compared to the constant failure rate assumption. The effect of different discount rates is also included. As illustrated by the results, the NPV can increase substantially due to even a small increase in the assumed failure rates. For example, assuming a 5 % increase per year in the component failure rates will result in a 26 % increase in the NPV using an 8 % discount rate.

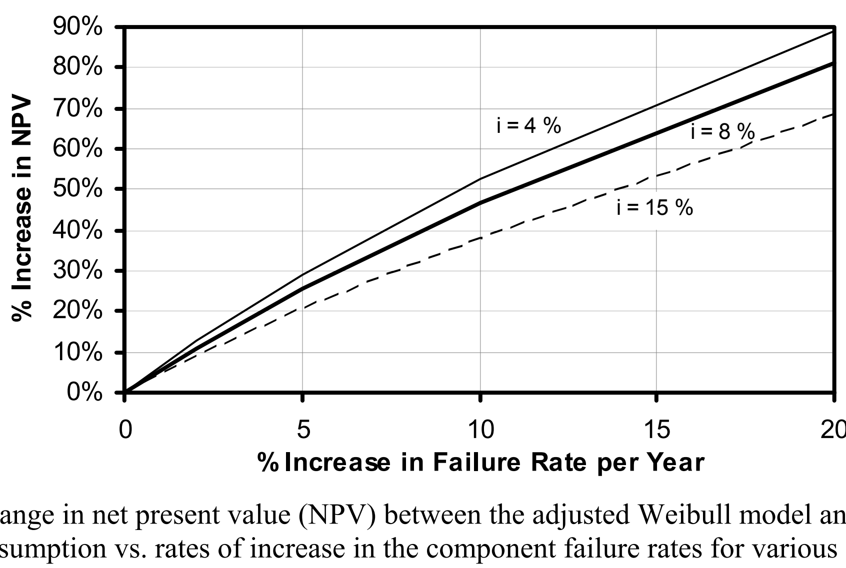

Figure 7: Change in net present value (NPV) between the adjusted Weibull model and the constant failure rate assumption vs. rates of increase in the component failure rates for various discount rates.

Figure 7 also shows the impact of discount rate on the net present value in the context of the aging failure rates. As expected, a lower discount rate will always result in a higher net present value, however, the impact increases with the rate of increase in the failure rates. The results therefore demonstrate not only the increased risk associated with aging in terms of net present value, but also the increased sensitivity of the economic analysis to the assumed discount rate.

4. SUMMARY AND CONCLUSIONS

Life cycle management (LCM) involves optimization of both reliability and cost of an asset until its end of life. A risk-informed approach to asset management is an essential part of the LCM process due to high uncertainties associated with the cost and reliability estimates which contribute to risk. The most cost effective asset management scenario can be identified through life cycle cost (LCC) analysis, which compares a series of alternatives on an equivalent economic basis, such that the lowest long term cost of ownership or operation is achieved. When the analysis is conducted in terms of expected costs involving probabilities, this will also correspond with the alternative having the lowest overall risk.

Systems, structures and components (SSCs) in a nuclear power plant are exposed to dynamic operational stresses and environmental conditions. Over time, these factors contribute to a host of aging degradation mechanisms (ARDMs), such as corrosion, fatigue, and creep, making the prediction of failure rates and end of life highly uncertain. The increased risk due to ARDMs should not be ignored, especially in economic decision analysis concerning life extension and refurbishment, where the SSC is asked to operate beyond its useful design life.

Aging components generally experience higher failure rates which will have a direct influence on expected costs, and hence on overall system risk. This behaviour can be modeled using the Weibull distribution, however, computing the probability of failure requires methods such as Monte Carlo simulation. The standard Weibull distribution must furthermore be modified in the context of life cycle cost analysis for consistent comparison of decision making alternatives.

The main generator system represents a large capital investment and is one of the critical components in a nuclear power plant. Due to operational and environmental stresses, many generator systems and components are exposed to a variety of ARDMs. In this study, the influence of aging was integrated into the life cycle cost analysis of the main generator and auxiliaries and compared to the results obtained using the constant failure rate assumption.

The results of the study revealed that even a small increase in the component failure rates due to aging can result in a significant increase not only in the annual probability of failure, but also in the expected annual costs, and hence risk. The net present value may also increase substantially, making a particular asset management scenario economically unattractive due to the increased overall risk. The results also illustrated the sensitivity of the analysis to the assumed discount rate, especially when aging is taken into consideration. The impact of the discount rate was shown to increase with the degree of increase in the aging failure rates.

ACKNOWLEDGEMENTS

This work is part of the Industrial Research Chair program at the University of Waterloo funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) in partnership with the University Network of Excellence in Nuclear Engineering (UNENE).

REFERENCES

Abernethy, R.B. 2000. *The New Weibull Handbook*, 4th Edition.

Barringer, H.P. and D.P. Weber. 1996. *Life Cycle Cost Tutorial*. Proceedings of the Fifth International Conference on Process Plant Reliability, Houston, TX.

Dai, S.-H. and M.-O.Wang. 1992. *Reliability Analysis in Engineering Applications*. Van Nostrand Reinhold, New York.

Electric Power Research Institute (EPRI). 2002. *Reliability and Preventive Maintenance: Balancing Risk and Reliability*. EPRI Technical Report 1002936. EPRI, Palo Alto, CA.

Electric Power Research Institute (EPRI). 2003a. *Life Cycle Management Sourcebooks – Volume 5: Main Generator*. EPRI Technical Report 1007423. EPRI, Palo Alto, CA.

Electric Power Research Institute (EPRI). 2003b. *Main Generator and Exciter Life Cycle Management Plans at STARS Nuclear Plants*. EPRI Technical Report 1007960. EPRI, Palo Alto, CA.

Fabrycky, W.J., G.J. Thuesen and D. Verma. 1998. *Economic Decision Analysis*. Prentice Hall, New Jersey.

U.S. Nuclear Regulatory Commission (NRC). 1987. *Risk Evaluations of Aging Phenomena: the Linear Aging Reliability Model and Its Extensions*. NUREG/CR-4769.

U.S. Nuclear Regulatory Commission (NRC). 2005. *Generic Aging Lessons Learned (GALL) Report*. NUREG-1801.