Warranty Prediction for Products with Random Stresses and Usages

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SUMMARY & CONCLUSIONS

Making accurate warranty predictions is challenging. It becomes even more challenging when products are operated under random stresses and random usages. Traditional method only uses the average values of these random variables for warranty prediction. The randomness of the variables is ignored, which may result in inaccurate results. This paper presents methods to solve this issue. Solutions for two different situations are discussed. In the first situation, only random stresses are the major concern. In the second situation, both random stresses and random customer usages are considered. Two analytical solutions, the exact and the approximated solution, are provided for each case. The comparison shows that, although they are simple to use, approximated solutions can be very different from the exact results. In this paper, not only the mean value of the warranty prediction, but also the variances and intervals of the prediction are calculated. This is much better because interval estimate provides more information than a simple point estimate. The proposed methods can be applied to many industries such as electronic, automobile and home appliance companies.

1 INTRODUCTION

Warranty prediction is one of the most important issues in reliability engineering. In the prediction of warranty returns, operating stresses and customer usage data must be accounted for [1]. Usually, nominal or average values of the operating stresses are used. However, stresses are often not constant. Instead, they are random and can be described using distributions. For example, not every user accumulates 12,000 miles per year on a vehicle, nor does every user print the same number of pages per week on a printer. Therefore, using a single constant value for a random variable in the calculation is not appropriate. The randomness of the stresses and usage must be considered. By considering the randomness, a confidence interval rather than a single value of the warranty return can be calculated. In this paper, methods for obtaining the confidence interval will be provided.

To accurately predict the warranty returns, the life-stress relationship needs to be established first, mainly through accelerated tests. Once the life-stress relationship is obtained, the effect of the random stresses on the product life can be quantitatively estimated.

In the following sections, the theory of life-stress relationships in accelerated testing is discussed first. Then methods for predicting warranty returns for two different situations are provided. In the first situation, the probability of failure during the warranty period is affected only by random stresses. In the second situation, the failure is a function of both random stresses and random customer usages.

2 THEORY ON ACCELERATED TESTING AND LIFE-STRESS RELATIONSHIPS

The life-stress relationship function explains how stresses affect product life. In this function, life is represented by a percentile of the failure distribution, t_p. In general, the function can be written in a log-linear form:

$$t_p = e^{\alpha_0 + \alpha_1 S_1 + \alpha_1 S_2 + \ldots} \quad (1)$$

S_i is the stress or a transformation of the stress. If we assume there is only one stress, based on different transformations, the life stress relationship in equation (1) can be [2]:

$$\begin{cases} t_p = A e^{\frac{B}{S}} & \textit{Arrhenius} \\ t_p = \dfrac{1}{K \cdot S^n} & \textit{Inverse Power Law} \end{cases} \quad (2)$$

The percentile is selected according to the life characteristic of different life time distributions. Some typical life characteristics are presented in Table 1.

Distribution	*pdf* (Probability Density Function)	Life Characteristic
Weibull	$\frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}}$	Scale Parameter (η)
Exponential	$\lambda e^{-\lambda t}$	Mean Life ($1/\lambda$)
Lognormal	$\frac{1}{t\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\ln(t)-\mu}{\sigma}\right)^2}$	Median (e^{μ})

Table 1 – Typical Life Characteristics

The life-stress relationship can be integrated into a lifetime distribution. For example, assume there are two independent stresses. The life-stress relationship for one stress is Arrhenius and for the other stress it is the inverse power law. The combined life-stress relationship is:

$$t_p = Ae^{\frac{B}{S_1}}\frac{1}{KS_2^n} = Ce^{\frac{B}{S_1}} / S_2^n \tag{3}$$

The above equation can be integrated into a life distribution, such as the Weibull distribution. For a Weibull distribution, $t_p = \eta$. The Weibull model is:

$$f(t,S_1,S_2) = \frac{\beta S_2^n e^{-\frac{B}{S_1}}}{C}\left(\frac{tS_2^n e^{-\frac{B}{S_1}}}{C}\right)^{\beta-1} e^{-\left(\frac{tS_2^n e^{-\frac{B}{S_1}}}{C}\right)^{\beta}} \tag{4}$$

In the above equations (1-4), stress *S* can be either a constant or a random variable.

In order to estimate the parameters in equation (4), failure data are needed, so accelerated life tests are conducted to obtain failure data first. Then, an estimation method such as the maximum likelihood estimation (MLE) method is utilized for estimating the model parameters [3].

In the following sections, we assume that the model parameters have been correctly estimated. We will use the model to predict the probability of failures for a warranty period when the stresses are random.

3 WARRANTY PREDICTION BASED ON RANDOM OPERATING STRESSES

3.1 Theory on Functions of Random Variables

Consider a product with two random stresses: temperature and voltage. Its failure time distribution is given in equation (4). In the traditional method for warranty prediction, the average stress values are used in the calculation. Then, the predicted probability of failure by the end of the warranty period of t_0 is:

$$F(t_0,\bar{S}_1,\bar{S}_2) = 1-\exp\left[-\left(t\bar{S}_2^n e^{-\frac{B}{\bar{S}_1}}/C\right)^{\beta}\right] \tag{5}$$

Instead of using the mean value of each stress, we can use their distributions to obtain the expected probability of failure. Assume the distribution for S_i is $g_i(s_i)$ and all the stresses are independent. The expected probability of failure is:

$$\begin{aligned} &E[F(t_0,S_1,S_2)] \\ &= \int_0^\infty\int_0^\infty \left\{1-\exp\left[-\left(tS_2^n e^{-\frac{B}{S_1}}/C\right)^{\beta}\right]\right\} g_1(S_1)g_2(S_2)dS_1dS_2 \end{aligned} \tag{6}$$

The variance of the probability of failure is:

$$\begin{aligned} &Var[F(t_0,S_1,S_2)] = E[F(t_0,S_1,S_2)^2] - (E[F(t_0,S_1,S_2)])^2 \\ &= \int_0^\infty\int_0^\infty \left\{1-\exp\left[-\left(tS_2^n e^{-\frac{B}{S_1}}/C\right)^{\beta}\right]\right\}^2 g_1(S_1)g_2(S_2)dS_1dS_2 \\ &-(E[F(t_0,S_1,S_2)])^2 \end{aligned} \tag{7}$$

Equation (5) is an approximation of equation (6). This is from the Taylor series expansion. According to the Taylor series expansion, the value of probability of failure can be approximated by:

$$\begin{aligned} &F(t_0,S_1,S_2) = F(t_0,\bar{S}_1,\bar{S}_2) \\ &+\sum_{i=1}^{2}\frac{\partial^{(n)}F(t_0,S_1,S_2)}{n!\partial^{(n)}S_i}(S_i-\bar{S}_i)^n\Bigg|_{\substack{S_1=\bar{S}_1\\ S_1=\bar{S}_2}} + \ldots \end{aligned} \tag{8}$$

If we assume the terms with order of 2 or higher can be ignored, the expected value of the probability of failure at t_0 is:

$$E[F(t_0,S_1,S_2)] = F(t_0,\bar{S}_1,\bar{S}_2) \tag{9}$$

If all the stresses are independent, the variance of the probability of failure at t_0 can be approximated by:

$$Var[F(t_0,S_1,S_2)] = \sum_{i=1}^{2}\left[\frac{\partial F(t_0,S_1,S_2)}{\partial S_i}\right]^2 Var(S_i) \tag{10}$$

where $Var(S_i)$ is the variance of the *i*th stress.

If we assume only the terms with order of 3 or higher can be ignored, the expected value of the probability of failure at t_0 is:

$$F(t_0,S_1,S_2) = F(t_0,\bar{S}_1,\bar{S}_2) + \sum_{i=1}^{2}\left(\frac{\partial^{(2)}F(t_0,S_1,S_2)}{2!\partial^{(2)}S_i}\right)^2 Var(S_i) \tag{11}$$

and the variance is:

$$\begin{aligned} Var[F(t_0,S_1,S_2)] &= \sum_{i=1}^{2}\left(\frac{\partial F(t_0,S_1,S_2)}{\partial S_i}\right)^2 Var(S_i) \\ &+\sum_{i=1}^{2}\left(\frac{\partial^{(2)}F(t_0,S_1,S_2)}{2!\partial^{(2)}S_i}\right)^2 Var\left((S_i-\bar{S}_i)^2\right) \end{aligned} \tag{12}$$

All the derivatives in the above equations are calculated at the mean values of the stresses. In this paper, approximations in equation (9) and (10) are used. The first order derivatives for *S*1 and *S*2 are:

$$\frac{\partial F}{\partial S_1} = \frac{\beta CB}{\eta S_2^n S_1^2} e^{-\frac{B}{S_1}\left(\frac{t}{\eta}\right)^{\beta}}\left(\frac{t}{\eta}\right)^{\beta};$$

$$\frac{\partial F}{\partial S_2} = \frac{\beta nC}{\eta S_2^{n+1}} e^{-\frac{B}{S_1}\left(\frac{t}{\eta}\right)^{\beta}}\left(\frac{t}{\eta}\right)^{\beta}$$

3.2 Example

Consider a component under two stresses: temperature and voltage. The temperature-nonthermal life-stress relationship of equation (3) is used. Accelerated tests are conducted and a portion of the data is given in Table 2.

The life distribution is the Weibull distribution. The estimated parameters using MLE are:

β =1.434; B =1986.038; C=125.962; n = 1.8763

The Weibull probability plot at the test stresses is given in Figure 1.

From the design specifications, it is known that the operating temperature and voltage are random variables following normal distributions. They are assumed to be independent from each another. The distribution parameters are given in Table 3.

Time Failed (hrs)	Temperature (K)	Voltage (V)
108	348	10
116	348	10
27	348	15
48	348	15
51	378	10
85	378	10
138	378	15
148	378	15
…	…	…

Table 2 – Failure Data for the Two Stresses Example

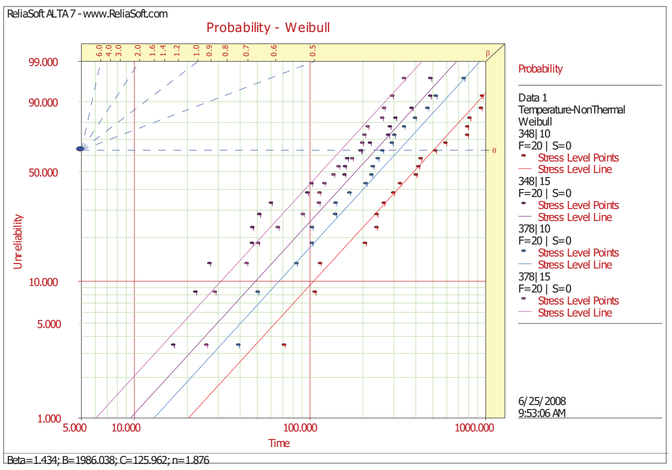

Figure 1 – Weibull Probability Plot of the Test Stresses

Stress	Distribution	Parameters
Temperature	Normal	$N(\mu = 300, \sigma = 10)$
Voltage	Normal	$N(\mu = 8, \sigma = 2)$

Table 3 – Distribution for the Two Random Stresses

Assume the warranty time is 400 hours. The expected probability of failure and its variance can be obtained using equation (9) and (10). The expected value is:

$$E[F(t_0, S_1, S_2)] = F(t_0, \bar{S}_1, \bar{S}_2)$$
$$= 0.101$$

and the variance is:

$$Var[F(t_0, S_1, S_2)] = \sum_{i=1}^{2} \left[\frac{\partial F(t_0, S_1, S_2)}{\partial S_i} \right]^2 Var(S_1)$$
$$= (0.003)^2 \times 100 + (0.032)^2 \times 4$$
$$= 0.005$$

Once the mean and variance of the probability of failure are obtained, its confidence bounds can be easily calculated by assuming that the logarithm of $F(t_0, S_1, S_2)$ is normally distributed [5]:

$$[\frac{\bar{F}}{\bar{F} + (1 - \bar{F})w}, \frac{\bar{F}}{\bar{F} + (1 - \bar{F})/w}] \qquad (13)$$

where $\bar{F} = F(t_0, \bar{S}_1, \bar{S}_2)$, $w = \exp\{z_{1-\alpha/2} \sqrt{Var(F)} / [\bar{F}(1 - \bar{F})]\}$ and $F = F(t_0, S_1, S_2)$. The upper and lower 90% two-sided bounds for this example are [0.030, 0. 289].

To validate whether the approximation results are accurate enough, the exact analytical solutions of the expected probability of failure and its variance are also calculated using the integrals in equation (6) and (7). They are:

$$E[F(t_0, S_1, S_2)] = 0.115; \quad Var[F(t_0, S_1, S_2)] = 0.006$$

As expected, they are slightly larger than the approximated solutions because the high order terms are ignored in equation (9) and (10). The exact analytical solution for the confidence bounds of the probability of failure is [0.036, 0.312]. For this example, the approximated and exact analytical solutions are very close.

In the above analysis, the uncertainty (randomness) of the operating stresses is considered in the calculation. The uncertainly of the model parameters is not considered. The model parameters are estimated from the available failure data. Their uncertainty can be greatly reduced if there is a large enough sample size or enough history information. However, the uncertainty caused by the random stresses cannot be reduced. It is embedded in the product operation. If one wants to integrate the uncertainty of model parameters in the calculation, equation (8) can be expanded by treating model parameters as random variables. For details, please refer to [4, 5].

3.3 Simulation Results

In section 3.2, the exact and approximated analytical solutions are provided for the example. Both solutions require intensive computation. In this section, simulation solutions are given. Using Monte Carlo simulation to solve problems with random stresses is easy and straight forward. The simulation procedure is:

- Generate n set of random number for (S_1, S_2).
- Calculate $F(t_0, S_1, S_2)$ for each set of (S_1, S_2).
- Get the mean and variance for the n $F(t_0, S_1, S_2)$.

Fortunately, it is not necessary to write new simulation code. Simulation software packages such as ReliaSoft's RENO can be used. For this example, 10,000 simulation runs were conducted in RENO, taking about 1 minute to complete the simulation. The mean and variance for the probability of failure at warranty time of 400 are 0.114 and 0.006. These values are very close to the exact analytical solutions and are more accurate than the approximated solutions.

4 WARRANTY PREDICTION BASED ON RANDOM STRESS AND USAGE PROFILE

In section 3, we discussed how to make accurate warranty prediction by considering the randomness of random stresses in the calculation. In some applications, such as washing machines, the warranty return is not only related to a random stress such as load, but is also affected by random customer usage. In this section, a stress-strength based method will be proposed to solve this complicated problem.

4.1 *Theory on Stress-Strength Model*

The stress-strength model is widely used in structural reliability calculation [6-8]. Assume the strength distribution is $F_1(X)$ and stress distribution is $F_2(X)$. The expected probability of failure is defined as:

$$E[F_1(X_2)] = P(X_1 < X_2) = \int_0^\infty P(X_1 < x) f_2(x) dx \qquad (14)$$
$$= \int_0^\infty F_1(x) f_2(x) dx$$

where $F_i(x)$ is the *CDF* (cumulative distribution function) and *pdf* (probability density function). Figure 2 compares a stress distribution and a strength distribution.

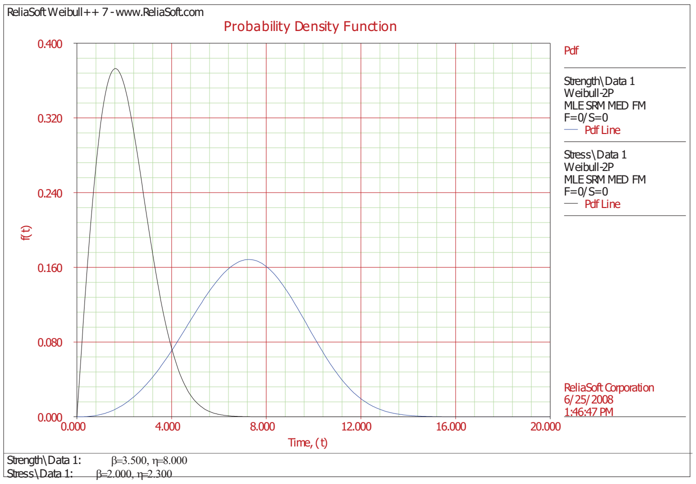

Figure 2 –Comparison of Stress and Strength Distributions

The larger the overlap area in Figure 2 is, the greater the probability of failure.

The stress-strength method is also traditionally used in the automobile industry for warranty prediction [9]. For example, the usage distribution in a 3 year warranty period can be thought of as stress and the strength is the failure distribution in terms of miles. The predicted probability of failure in the warranty period is calculated using equation (14). For the automobile industry, a typical warranty policy is 3 years and 36,000 miles. So equation (14) can be modified to consider only vehicles with mileage less than 36,000. The modified equation is:

$$P(X_1 < X_2 \mid X_2 < 36{,}000) = \int_0^{36{,}000} P(X_1 < x) f_2(x) dx$$
$$= \int_0^{36{,}000} F_1(x) f_2(x) dx$$

where $F_i(x)$ is the probability of failure at mileage of x and $f_2(x)$ is the *pdf* of the usage mileage distribution at x.

For the automobiles, only the random usage is considered in the calculation. For washing machines, the warranty returns are affected not only by the random usage but also by the random load. In section 4.2, a method of solving problems like the washing machine example will be provided.

4.2 *Example*

A washing machine manufacturer conducted a survey on the usage profile of its customers. The average loads and average hours of using the machine were recorded for each user. Since this usage information was available, the company wanted to use it to make more realistic estimates of the failures of the motors used in the washing machine for a 5 year warranty period.

First, accelerated testing was conducted to establish the life-stress (load) relationship. Failures were recorded in hours. A Weibull-IPL (inverse power law) model was used and the parameters were estimated from the failure data. They are:

$$\beta_1 = 2.350;\ K = 1.692\text{E-}5;\ n = 1.520$$

The *pdf* of this failure time distribution is denoted as $f(t)$.

From the survey data, the analyst found the average load is 7.162 lbs and the average usage duration per week is 2.9 hours. Given a 5 year warranty, the total average operating time is 754 hours. Applying these two average numbers to the warranty prediction, the predicted probability of failure is:

$$p(x < 754 \mid S = 7.162) = 1 - \exp\left[-\left(tKS^n\right)^{\beta_1}\right] \qquad (15)$$
$$= 1 - \exp\left[-(754 \times 1.692E - 5 \times 7.162^{1.52})^{2.35}\right] = 0.039$$

However, because more information is available in the customer usage data, instead of simply using the average values, the distribution of the load and the operating hour can be used. The analyst calculated the load distribution from the survey data using a Weibull distribution. The parameters are:

$$\beta_2 = 5;\ \eta_2 = 7.8$$

The *pdf* of the load distribution is denoted as $l(s)$.

It was found that the average hours and average loads are correlated. For the customers with larger average loads, longer operating hours are expected. In order to utilize this information, the analyst applied a Weibull distribution to the operating hours and treated the scale parameter η as a function of load. A general log-linear function was used for the η-load relation, which is:

$$\eta_3 = e^{\alpha_0 + \alpha_1 S}$$

where S is the load. The parameters in the model for the 5 year operating hour are:

$$\beta_3 = 2;\ \alpha_0 = 6.094;\ \alpha_1 = 0.0896$$

This *pdf* operating hour distribution is denoted as $g(x)$.

So far, three distributions (the life distribution of the motor, the load distribution and the usage hour distribution of customers) are available for the warranty return calculation. The expected probability of failure by the end of the 5^{th} year can be calculated using the stress-strength model with the three distributions.

First, for a given load s, the expected probability of failure is:

$$E[F(X \mid s)] = p(T < X \mid s)$$
$$= \int_0^\infty p(T < x \mid s) g(x \mid s) dx \qquad (16)$$
$$= \int_0^\infty F(x \mid s) g(x \mid s) dx$$

Then, treating load as a random variable, the overall probability of failure is:

$$E(F(X,S)) = E(E[F(X \mid s)]) = \int_0^\infty p(T < X \mid s) l(s) ds = \int_0^\infty \int_0^\infty F(x \mid s) g(x \mid s) l(s) dx ds \quad (17)$$

The variance of the probability of failure is:

$$Var[F(X,S)] = E[F(X,S)^2] - (E[F(X,S)])^2 = \int_0^\infty \int_0^\infty [F(x \mid s)]^2 g(x \mid s) l(s) dx ds - (E[F(X,S)])^2 \quad (18)$$

where:

$$F(x \mid s) = 1 - e^{-\left(\frac{x}{\eta_1}\right)^{\beta_1}};$$

$$g(x \mid s) = \frac{\beta_3}{\eta_3}\left(\frac{x}{\eta_3}\right)^{\beta_3 - 1} e^{-\left(\frac{x}{\eta_3}\right)^{\beta_3}};$$

$$l(s) = \frac{\beta_2}{\eta_2}\left(\frac{s}{\eta_2}\right)^{\beta_2 - 1} e^{-\left(\frac{s}{\eta_2}\right)^{\beta_2}};$$

$$\eta_1 = \frac{1}{1.692E-5 \times s^{1.52}};$$

$$\eta_3 = e^{6.094 + 0.0896 s}$$

Equation (17) and (18) can be solved numerically. Commercial software packages such as Mathcad can be used. For this example, the result for the mean value in equation (17) and the variance from equation (18) are:

$$E[F(X,S)] = 0.076; \qquad Var[F(X,S)] = 0.014$$

Using these two values, the 90% confidence interval for the probability of failure is [0.005, 0.568].

Equation (17) can be shown to be similar to equation (6). Therefore, the approximation methods for the mean and variance in section 3 can be extended to use here. However, because of the complexity of the problem, the approximation results are not close to the exact analytical solutions anymore. To use the mean value of the load and usage to calculate the probability of failure, we first need to obtain these two mean values. They are:

$$E(x) = \int_0^\infty \int_0^\infty x g(x,s) l(s) dx ds = 754$$

and

$$E(s) = \int_0^\infty s l(s) = 7.162$$

Using these two values, the predicted probability of failure is 0.039, as given in equation (15). This value is very different from the exact analytical solution of 0.076 obtained by equation (17). Therefore, the approximated analytical solution from the Taylor series expansion is not accurate for this example.

From the above calculation procedure, it can be seen that obtaining an analytical solution for the probability of failure becomes very challenging when multiple random variables are involved. It becomes even more complicated when these variables are correlated. Therefore, simulation becomes an attractive option. In section 4.3, the simulation solutions for the above example are provided.

4.3 Simulation Results

The simulation procedure is:

- Generate a random number for stress S
- Use this S to generate a random number of usage X
- Use S and X to calculate $F(X,S)$.
- Repeat above steps for n times and get n $F(X,S)$
- Get the mean and variance for the n $F(X,S)$.

For this example, 10,000 simulation runs were conducted in RENO, taking about 1.5 minutes to complete the simulation. The mean and variance for the probability of failure at a warranty time of 5 years are 0.075 and 0.014. These results are very close to the exact analytical solutions and much better than the approximation results.

5 CONCLUSION

In this paper, methods for warranty prediction of products with random operating stresses and random customer usages are discussed. Analytical solutions are provided for the case studies. Because of the complexity of the procedure for obtaining the analytical solutions, the use of simulation to obtain the solutions is also illustrated. Unlike the traditional method which can only calculate the mean value of the warranty failures and ignores the randomness of the stresses and usages, the proposed methods can calculate both mean and variance by integrating the randomness of stresses and usage into the calculation. This is much better because interval estimate provides more information than a simple point estimate. Comparisons show that simulation results are very accurate. Consequently, it should be preferred by engineers, given the complexity of obtaining the analytical solutions.

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