## 3.1 INTRODUCTION

In this chapter, the method of assessing the reliability or probability of fracture mechanics assessment methods will be discussed in depth. In section 3.2, theoretical approach to analyze the reliability of linear elastic fracture mechanics (LEFM) to be used in this study will be discussed. Monte Carlo simulation method (MCS) in reliability analysis is discussed in section 3.3 and section 3.4, an important sampling technique (CI), which is one of variance reduction techniques (VRT) is popular for modified Monte Carlo simulation methods are discussed. Chapter III concludes with a summary.

## 3.2 Fatigue Reliability Analysis using Linear Elastic Fracture Mechanics (LEFM)

Fatigue reliability analysis using linear elastic fracture mechanics approach, which considers the existence of the original crack in an engineering structure or component are used in this study. The method of reliability analysis tools used is based on the principles of the approach of linear elastic fracture mechanics, critical stress intensity factor threshold and Paris law to describe the failure by fatigue cracking. In this section, the limit state function for fatigue reliability analysis, random variables such as size of initial crack and the crack will be discussed critically.

### 3.2.1 Limit state function

Some of the engineering component, the crack propagation is not allowed because it would weaken the strength of an engineering system and the subsequent failure by fracture mechanics. Then a maximum limit state function associated with both these random enablement should be issued and limit state function is as equation 3.1;

$$g(K_{I_C}, K) = K_{I_C} - K \tag{3.1}$$

and

$$K = F(a)\sigma_\infty \sqrt{\pi a} \tag{3.2}$$

where $F(a)$ is a function that characterizes the geometry of the crack in a specimen geometry used, $\sigma_\infty$ is the average stress exerted on the material and the size of the original crack.

For large engineering systems such as bridges, cargo ships, and pipelines on the seabed that is exposed to cyclic loading in the long run, a reliability analysis method should be used to determine the reliability of the system of tenure, then Paris and Erdogan (1963), the relationship between crack growth rate with stress intensity factor can be described as equation 3.3;

$$\frac{da}{dN} = C(\Delta K)^m \tag{3.3}$$

and

$$\Delta K = F(a) S_{RE} \cdot \sqrt{\pi a} \tag{3.4}$$

where $N$ is the number of stress cycles imposed and $C$ and $m$ the mechanical properties of materials used and it is determined in Zone II, and $S_{RE}$ is the equivalent stress range.

Derived by substituting equation 3.5 from equation 3.4;

$$\int_{a_o}^{a_f} \frac{da}{\left[F(a)\sqrt{\pi a}\right]^m} = CS_{RE}^m \left(N_f - N_0\right) \tag{3.5}$$

where $a_0$ and $a_f$ is the original crack size and final crack size, $N_0$ and $N_f$ is the number of stress cycles required for crack $a_0$ and the number of stress cycles required for crack $a_f$.

According to Chung (2004), equation 3.5 can apply to the fatigue limit state function with the approach proposed by Madsen et al. (1985) as equation 3.6;

$$g(X) = \int_{a_0}^{a_c} \frac{da}{\left[F(a)\sqrt{\pi a}\right]^m} - CS_{RE}^m \left(N - N_0\right) \tag{3.6}$$

Equation 3.6 can also be simplified to;

$$g(X) = \int_{a_0}^{a_c} \frac{da}{\left[F(a)\sqrt{\pi a}\right]^m} - CS_{RE}^m N \tag{3.7}$$

where $N$ adalah is the total number of stress cycles given.

### 3.2.2 Random variables in the limit state function

#### 3.2.2.1 Initial crack size, $a_0$

Non-Destructive Testing methods included ultrasonic testing, radiographic testing, magnetic particle testing, acoustic emission testing and thermography tests are tests used to determine the size of the initial crack in the environment and the special material. The selection of NDE methods is essential to estimate the size of the initial crack . Because of the uncertainty that always exists in measurement for each method, the initial crack size will usually give different results. Mean and constant variance of the number of resources are shown in Appendix C.

#### 3.2.2.2 Critical Crack Size / Threshold, $a_c$

Critical crack size or crack size threshold is that the fatigue failure is estimated to have occurred. According to Chung, 2004, the critical crack size is usually determined by the approach of fracture mechanics or service approach.

With fracture mechanics based approach used in this study, critical crack size is directly proportional to the critical stress intensity factor of a material. critical stress concentration factor is the mechanical properties of materials are usually determined by tests using Impact Charpy V-notch (CVN). Because of the existence of uncertainty in the CVN tests, the critical stress intensity factor is a random variable. Appendix D shows some data for steel A36, A588 and A514.

#### 3.2.2.3 Fatigue Crack Parameter, *C* and *m*

Because there is a very high variance in many fatigue experiments, the random nature of two-parameter fatigue crack propagation in the Paris equation to be considered in the analysis of reliability of this fatigue crack. Statistical properties of these two parameters can be determined by performing regression analysis on the data available. Appendix E and F reflect the randomness of the two parameter crack growth from many aspects and it shows that the environmental conditions, types of metals and metal manufacturing methods (heat treatment) will affect these two parameters of fatigue crack.

#### 3.2.2.4 Load cycle

Load cycle is a cause of fatigue in a material. Materials can be classified into the load cycle amplitude and variable amplitude. At the maximum amplitude of the load, the stress imposed is the maximum, $\sigma_{\max}$ and instead produce a minimum amplitude of the stress minimum, $\sigma_{\min}$ which can be described in Figure 3.1;

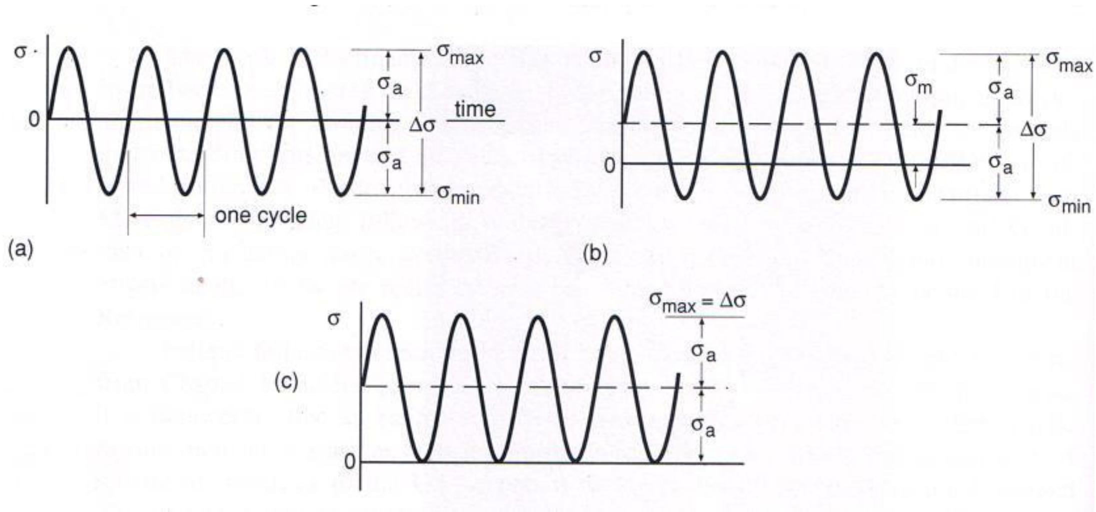


Figure 3.1 Load cycles with maximum and minium stress (Dowling 1999)

Then,

$$\text{Average stress, } S_m = \frac{\sigma_{\max} + \sigma_{\min}}{2} \tag{3.8}$$

$$\text{Stress amplitude, } S_a = \frac{\sigma_{\max} - \sigma_{\min}}{2} \tag{3.9}$$

$$\text{Stress Range, } \Delta S = \sigma_{\max} - \sigma_{\min} \tag{3.10}$$

$$\text{Stress Ratio, } R = \frac{\sigma_{\max}}{\sigma_{\min}} \tag{3.11}$$

Typically, to load completely reversible, the ratio of the stress is -1.

### 3.2.3 Fatigue Reliability Evaluation

The probability of fatigue crack and failure of the reliability index can be determined using equations 3.1 and 3.6 to calculate the probability of bringing $g(X) \leq 0$ with some methods of reliability analysis. Monte Carlo simulation methods and Modified Monte Carlo simulation will be used in this study and will be discussed in the next section.

## 3.3 MONTE CARLO SIMULATION METHOD (MCS)

MCS method is one of the methods used to conduct the reliability assessment of engineering structures and it is one of the most popular methods among researchers in the works or structural reliability assessment of engineering components. The six main steps in the method or element of this MCS will be discussed in depth.

### 3.3.1 Problem Statement

The intial stages of the MCS method is to identify the random variables involved in an engineering problem. When the random variable is identified, an equation that connects all these random variables can be issued in the form of the equation and thus the value of the parameter that determines the rigidity of a structural engineering calculations can be performed and failure criteria can be calculated based on the specific performance of the equation involves the use of a random variable.

Uncertainty that always exists in the world of engineering and it cannot be reduced scientifically. Uncertainty, it is meant as the mechanical properties of engineering materials, properties and structural geometry of loading conditions is introduced. Mechanical properties such as elastic modulus and fracture toughness critical properties, geometry such as position fracture and loading conditions that cause random probability analysis that takes into account the statistical properties of random variables and hence, the nature of these statistics will be used as input values the performance equation, $g(X)$.

Fracture toughness values can be calculated based on the input values have been obtained and will be compared with the critical fracture toughness value. Structural failure will occur if the equation is less than the nature of performance that is, $g(X) < 0$. Because the fracture toughness value depends on the random variables generated and self-critical fracture toughness value is a random variable so comparisons cannot be carried out in determinately.

### 3.3.2 Probability Characteristic of Random Variables

A mathematical representation of the performance equation using a stochastic random variable is one important element in the assessment of reliability of engineering structures. This representation reflects the real situation prevailing in the structural engineering that has always existed in a stochastic.

As an example, the modulus of elasticity of a material engineering is one of the random variable that has always existed naturally, then the probability of assessment should be conducted on the material. To carry out the quantization properties of the probability of a random variable, the information on each random variable should be known in advance and this information is usually obtained from the experiments were carried out repeatedly. If the experiments in determining the elastic modulus of a material carried over engineering and it will always give a different modulus of elasticity. The information obtained can be quantified mathematically.

If the sample $X$ is one of the random variable that has undergone n time monitoring of the population. A method of measuring the central tendency of data, or better known as the mean or the forecast of $X$, also known as the first central moment is represented by the symbol $E(X)$ can be calculated as;

$$E(X) = \mu_X = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3.12}$$

Measurement method which measures the spread of the data from the mean *X* is known as a variance or second central moment is represented by symbols *Var*(*X*) can be calculated as;

$$Var(X) = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu_X)^2 \tag{3.13}$$

or by using the standard deviation is represented by a symbol which can be calculated as;

$$\sigma_X = \sqrt{Var(X)} \tag{3.14}$$

However, the standard deviation or variance was used to characterize the data distribution of the mean, but it does not explain the orderly distribution of random variables without reference to the mean value, then a parameter without units as the ratio between the standard deviation of the average value of the introduced a constant variance that provides symbols, *COV*(*X*) or $\delta_X$, ie;

$$COV(X) = \delta_X = \frac{\sigma_X}{\mu_X} \tag{3.15}$$

For the variable conditions, *COV* (*X*) is zero for deterministic calculation. The value of *COV* (*X*) is smaller meaning smaller uncertainty in the random variable. According, Haldar and Mahadevan (2000), the value of *COV* (*X*) is between 0.1 to 0.3 for most engineering problems.

The calculation of the probability characteristics of a random variable is easy. The main problems or challenges faced by many researchers and engineers are in the process of determining a suitable probability distribution of random variables that deed to be characterize. Typically, the determination of the probability distribution is based on data available and it requires a mathematical proof.

Method of mathematically proving that the method proposed here is a statistical test called the Kolmogorov-Smirnov tests (K-S). The selection method is based on the convenience of this method is not necessary to divide the data into a narrow range, the error range of sizes and selection can be avoided.

K-S experiments are based on a comparison between the cumulative frequency with the theoretical cumulative distribution function of the type proposed distribution. Then the data is arranged in ascending order and the maximum range between the two cumulative functions can be approximated by equation 3.16,

$$D_n = \max\left|F_X(x_i) - S_n(x_i)\right| \tag{3.16}$$

where $F_X(x_i)$ is the cumulative distribution function of the theoretical observations to $i$ in samples $x_i$ and $S_n$ is the cumulative distribution function of the corresponding stages of the data obtained from monitoring and when arranged in ascending order. The value of $S_n(x_i)$ can be estimated,

$$S_n(x_i) = \left\{\begin{array}{ll} 0, & x < x_i \\ \dfrac{m}{n}, x_m & \leq x \leq x_{m+1} \\ 1, & x \geq x_i \end{array}\right\} \tag{3.17}$$

K-S concepts can be shown in Figure 3.2 below,

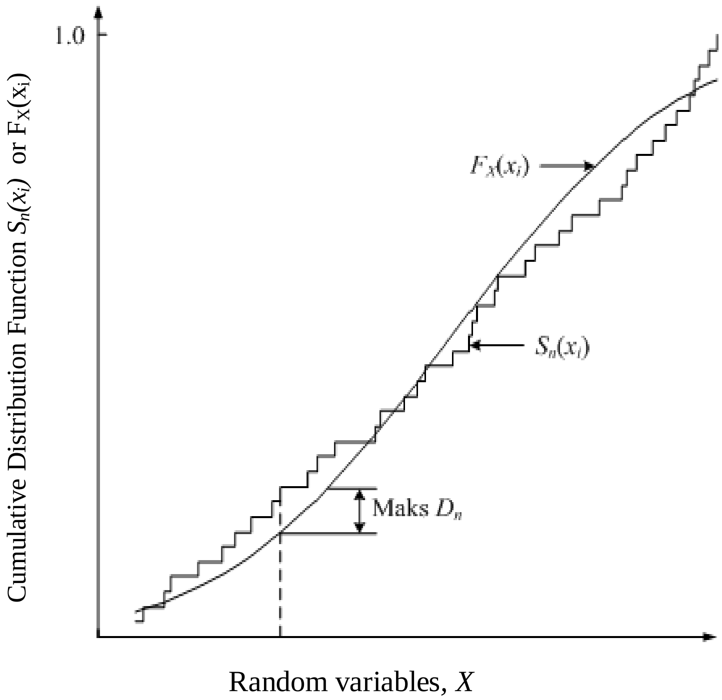


Figure 3.2 Experimental K-Q for the random variable X

Mathematically, $D_n$ is a random variable and its distribution is dependent on sample size, n. Cumulative distribution function of $D_n$ may be associated with the $\alpha$ with,

$$P\left(D_n \leq D_n^{\alpha}\right) = 1 - \alpha \tag{3.18}$$

where the $D_n^{\alpha}$ value at various levels can be obtained from standard mathematical tables in Appendix A. According to the KS tests, if the maximum range $D_n$ is less than or equal to the value $D_n^{\alpha}$ that appear in Appendix A, the type of distribution can be estimated initially received at $\alpha$ .

### 3.3.3 Random Number Generation

Random number generation performed for each variable identified in the section 3.3.1 according to the nature of the probability of each random variable is defined in section 3.3.2. Generation of *N* sets of random numbers for each variable performed according to the nature of probability. The generation of random numbers according to certain distribution is at the heart of the Monte Carlo simulation.

In general, all modern computers have the ability to generate a uniform random number between 0 and 1 in bits or binary digital. Based on the source, the generator will generate random numbers uniformly distributed between 0 and 1. By changing the source, a different set of random numbers will be generated. Depending on the capabilities of computers, random numbers are generated may be repeated, but usually it will happen after the process of generating random numbers as large as $10^9$ random numbers. Random numbers generated in such a manner called Pseudo Random Number.

After generating a uniform random number between 0 and 1, the random numbers should be transformed to the true values of random variables according to their probability nature. The process of transformation of random numbers to the actual value of the random variable can be shown graphically in figure 3.2 and the transformation technique is known as the inverse transformation technique or method of the inverse cumulative distribution probability.

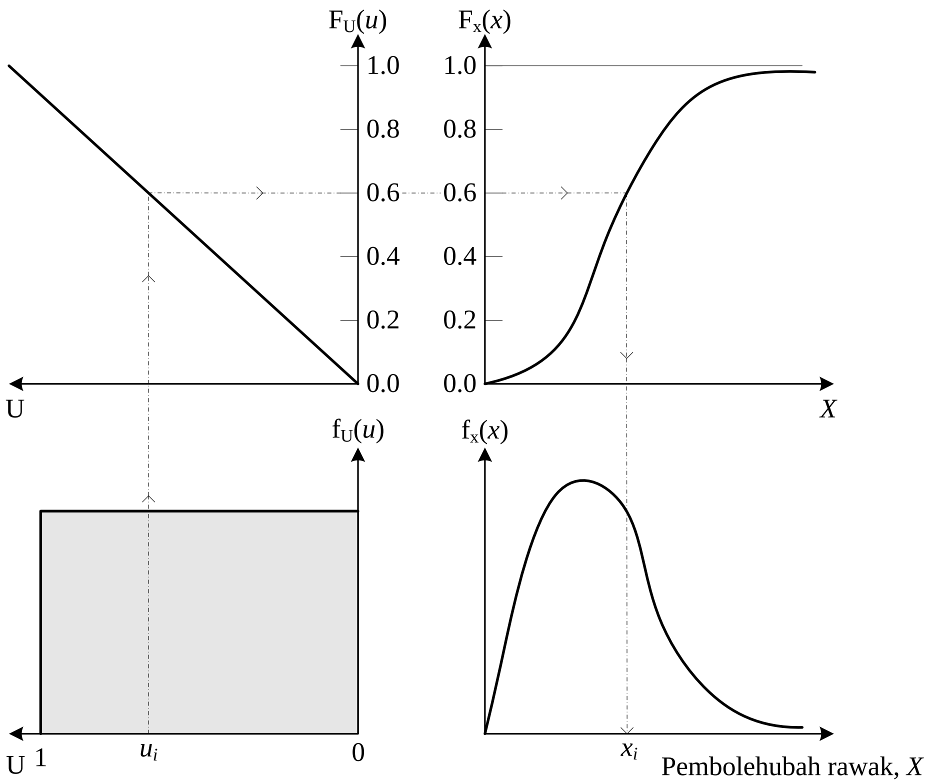


Figure 3.3 Random Number Transformation Process. (Haldar & Mahadevan, 2000)

In this transformation method, a random variable for the cumulative distribution function is equivalent to the random number, $u_i$ generated by the equation

$$F_{X_i}(x_i) = u_i \tag{3.19}$$

and solutions to equations $x_i$ is;

$$x_i = F_X^{-1}(u_i) \tag{3.20}$$

For example, if a random variable, $X$ is normally distributed with mean and standard deviation is $N(\mu_X, \sigma_X)$ the value $S = (X - \mu_X)/\sigma_X$. This equation can be shown by

$$u_i = F_X(x_i) = \Phi(s_i) = \Phi\left(\frac{x_i - \mu_X}{\sigma_X}\right) \tag{3.21}$$

or,

$$s_i = \frac{x_i - \mu_X}{\sigma_X} \tag{3.22}$$

the actual value of the random variable, $x_i$ is;

$$x_i = \mu_X + \sigma_X s_i = \mu_X + \sigma_X \Phi^{-1}(u_i) \tag{3.23}$$

where $s_i = \Phi^{-1}(u_i)$, dan $\Phi^{-1}$ is inverse to the cumulative distribution function for the normal variables.

If the random variable $X$ is lognormal distributed, the average value in the form of lognormal, $\lambda_x$ and standard deviation in lognormal, $\zeta_x$ should be calculated in advance using the following equation.

$$\lambda_X = \ln \mu_X - \frac{1}{2}\zeta_X{}^2 \tag{3.24}$$

and,

$$\zeta_X{}^2 = \ln(1 + \mathrm{COV}(X)^2) \tag{3.25}$$

If $\mathrm{COV}(X) \leq 0.3$ therefore $\zeta_X \approx \mathrm{COV}(X)$. Then a random number, $x_i$ for the -$i$ lognormal distribution can be generated by using the following equation

$$u_i = \Phi\left(\frac{\ln x_i - \lambda_X}{\zeta_X}\right) \tag{3.26}$$

or

$$x_i = \exp[\lambda_X + \zeta_X \Phi^{-1}(u_i)] \tag{3.27}$$

Each transformation of random variables will be used as input to the response equation is derived from the performance of 3.3.2 and it will be discussed in detail in the next section.

### 3.3.4 Numerical Computation

The *N* generation of random numbers for each random variable in engineering problems will produce a set of *N* random numbers that represent the actual engineering problem of uncertainty of random variables. Problem solving in terms of *N* times using equations that have been published in sections 3.3.1 to generate N sample points that represent the output response of the engineering problems. With the release response to *N* samples, statistical analysis such as probability density functions and probability distribution can be carried out. Numerical accuracy would be improved if the number of simulations *N* increased.

### 3.3.5 Computation of Failure Probability

Assuming all the random variables identified in the performance equation that affects the structure of fracture mechanics are statistically independent. MCS method of generating random variables based on probability density functions will give the response characteristics of engineering structures on the uncertainty of this random variable. The properties of this response to describe the probability of failure of the structure.

The probability of failure of engineering structures can be calculated by equation 3.28, ie;

$$P_F = \frac{N_F}{N} \tag{3.28}$$

where $N_F$ is the number of simulations that provide value of *g(X)* < 0 and *N* is the number of simulations that were carried out. The high probability of failure, $P_F$ would mean the engineering structure will crack and vice versa.

### 3.3.6 Determining the Accuracy and Efficiency Simulations

The ability of equation 3.17 to give an accurate estimate of the probability of failure of engineering structures should be considered. As discussed in section 3.2.4, the accuracy of the estimated probability of failure is dependent on the number of simulations that were carried out. For a very small probability of failure or a small number of simulations that will bring an error. For real accuracy, the simulation is an infinite number.

The accuracy of equations 3.28 can be studied by several methods. One method is to measure the variance or $COV(P_F)$ of each simulation is assuming Bernoulli trials, the number of failures in *N* simulation is a Bernoulli distribution, then $COV(P_F)$ can be calculated as;

$$COV(P_F) = \delta_{P_F} \approx \frac{\sqrt{\dfrac{(1-P_F)P_F}{N}}}{P_F} \tag{3.29}$$

the small $\delta_{P_F}$ is required. From equation 3.29, can be observed $\delta_{P_F}$ is almost zero if *N* is infinite.

Equation 3.28 show the number of simulations required to achieve a level of accuracy depends on the probability of failure is not known. The probability of failure is worth $10^{-5}$ may exist in engineering problems. This means that the 100 000 simulations have calculated to estimate the behavior of the structure. Typically, millions of simulations required to produce results acceptable to the researchers. For engineering structures which have *n* random variables, *N* million simulations required to accurately estimate the probability of failure.

## 3.4 MODIFIED MONTE CARLO SIMULATION - IMPORTANT SAMPLING

### 3.4.1 Introduction to Importance Sampling (IS)

The weakness of MCS calculation is a takes computer time and a lot of computer memory space. This section will discuss a technique that will be used and it is also popular among researchers, the importance sampling method (IS).

The basic principle is an important sampling method attempts to focus on the distribution of sampling points in all important areas, namely the area that most contributions, $f^{'}(X)$ the structural failure of the fatigue crack of the overall consideration of random variables in the sample space of random variables. In other words, an important area, $f^{'}(X)$ should be estimated from the sample that has a high potential for failure. This principle can be demonstrated by reference to the figure 3.5 below. Reduction of the effective variance of the simulation process is carried out only in areas potential failures only.

With consideration of the mathematical definition of the basic equations for the probability of failure of;

$$P_F = \int_{g(X)\leq 0} f(X)dx = \int_{g(X)\leq 0} I_F(X) f(X)dx \tag{3.30}$$

For this important sampling method, cumulative distributions function for $f^{'}(X)$ which represents the most important thing is to be used and $f^{'}(X)$ is known as a function of sampling density. Thus, the probability of failure will be as common 3:31;

$$P_F = \int_{g(x)\leq 0} \left[ I_F(X) \frac{f(X)}{f^{'}(X)} \right] f^{'}(X)dx \tag{3.31}$$

and equation 3.30 can be written more briefly as the equation 3:32;

$$P_F = \frac{1}{N} \sum_{i=1}^{N} I_F(x_i) \frac{f_X(x_i)}{f^{'}(x_i)} \tag{3.32}$$

The accuracy of this important sampling method depends on the choice of sampling density function, $f^{'}(X)$ and variance for the probability of failure is as follows;

$$Var(P_F) = \frac{1}{N} Var\left[ I_F(X) \frac{f(X)}{f^{'}(X)} \right] \tag{3.33}$$

$$Var(P_F) = \frac{1}{N} \left( \int_{g(x)\leq 0} I_F(X) \frac{f^2(X)}{f^{'2}(X)} f^{'}(x)dx - P_F^2 \right) \tag{3.34}$$

Selection of sampling density function, $f^{'}(X)$ the optimum can be observed from equation 3:33 with $Var(P_F)$= 0, ie;

$$f_{opt}^{'} = \frac{I_F(X)f(X)}{P_F} \tag{3.35}$$

The optimal functions can not be applied directly because it depends on the goals or objectives of the study, the probability of structural failure. But some types of techniques have been developed by researchers for the purpose of estimating the density function of this important sampling. Among the proposed technique is the method of kernel density function by Ang et al. (1992), the method of support vector machines by Sanseverno and Moreno (2002) and Hurtado (2007), Fission and roulette method of Hong and Wang (2002), descriptive sampling method by Kalman (1995) and the design point method by Fan and Wu (2007).

Design point method developed by Fan and Wu (2007) will be used in determining the importance sampling density function. According to his method of kernel density functions are developed is not suitable in view of difficulties to obtain the optimal sampling density function and this method is only focused on a small area of the entire area may be menpengaruhi failure reliability analysis results.

In the next section, an important sampling method proposed by Fan and Wu (2007) will be discussed and used in reliability analysis of engineering structures.

### 3.4.2 Determination of Most Probable failure Point (MPP)

Important first step sampling method proposed by Fan and Wu is to determine the likely high titk (MPP), also known as the design point. To determine the MPP point, all the random pemboleubah required to transform the standard normal space is called the space U. Then the mean and standard deviation equal to estimated by the method or methods Fiesseler Rackwitz-Chen-Lind.

After changes to the equivalent normal space, there are many techniques and methods can be used to determine the point of which is the method of MPP FORM, SORM and the rules pengotimuman. For this study, the method Rackwitz-Fiessler-FORM will be used to determine the MPP point, as shown in Figure 3.4;

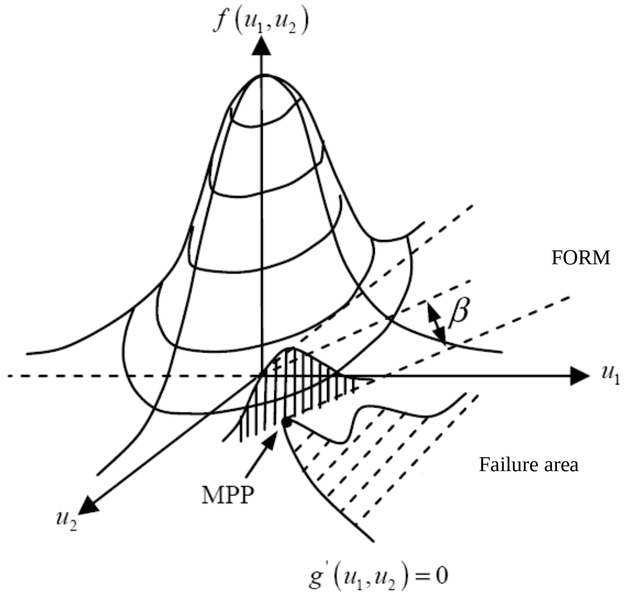


Figure 3.4 First Order Reliability Analysis Method (FORM)

### 3.4.3 The tendency of Random Variables Around MPP

With reference to Figure 3.6 (a), after the transformation of all random variables is equivalent to the normal space, every variable that has transformed the standard normal distribution, then all space-U is a normal distribution multivarians. As shown, the distance from the origin to the MPP point is $\beta$, and a circle of radius $\beta$ and drawn centered at the origin and the normal distribution multivarians divided into two parts.

It is believed that the inside of the circle would not exist any failure of it and this area can be removed or disposed of the entire space. This can be explained by showing the figure 3.5;

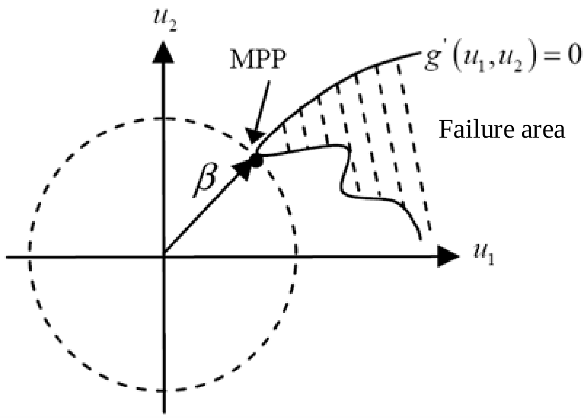


Figure 3.5 A circle with center origin and radius $\beta$

### 3.4.4 Determination of important sampling density function

After all the random variables tend to be around the MPP point, to run the simulation, an important sampling density function (the left) should be determined and this can be done to re-unite the left as shown in Figure 3.6 (c). It should be noted that this important sampling density function is normally distributed as the original functions are normally distributed.

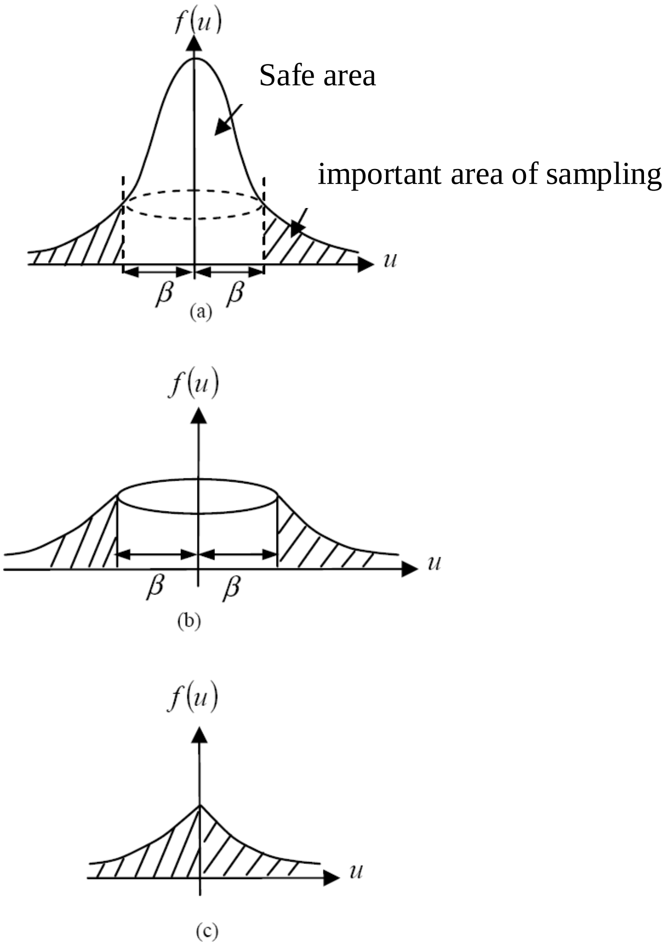


Figure 3.6 Significant sampling method proposed by Fan and Wu (2007)

### 3.4.5 Simulation

Because all variables have tended to point around the MPP, the cause of the failure rate will increase and thus the number of simulation will be reduced drastically compared to the original Monte Carlo simulation methods with a very menyaknikan resolution.

According Shakarayev and Krashanitsa (2005), the probability of failure for each component in the plane is in the range $10^{-10}$ to $10^{-5}$. The proposed method can drastically reduce the number of simulation because it will reduce the number of samples required for the guilty of the simulation. According to Fan and Wu, according to the method applied to systems with high reliability index.

## 3.5 Conclusions

The theoretical analysis of the reliability of fatigue cracking in Zone I and Zone II to consider all random variables involved in this study are discussed. Engineering structural reliability assessment method with Monte Carlo simulation method that has six key elements are discussed.

The probability of failure of engineering structures can be determined by the ratio between the number of simulations with the number of simulations are carried out. The efficiency of Monte Carlo simulation methods can be improved by using variance reduction techniques, the method of sampling is important to focus key areas in which the samples it has the potential to cause structural failure. The next section will discuss the results of failure probability using Monte Carlo simulation method of renovation so the efficiency of this method compared with Monte Carlo simulation methods are discussed.

## 4.1 Introduction

In this chapter, the results of failure probability and reliability index for various crack geometries commonly found in engineering problems are discussed with a view to display the concept of fatigue reliability analysis using linear elastic fracture mechanics approach (LEFM) by weighing the nature of random or stochastic nature of all the variables involved .

The concept of fatigue reliability analysis is applied by using the modified Monte Carlo simulation (MMCS) and the results are compared with Monte Carlo simulation method (MCS). The purpose of this comparison is to determine the effectiveness of the modifications are developed. The effects of such statistical properties of random variables on the efficiency of the MMCS is examined to determine the extent to which the statistical properties will affect the efficiency of the MMCS and the probability of failure.

Finally, the concept of fatigue reliability analysis is used to determine the reliability index of the bridge structure is modeled and Implemented the concept of fatigue reliability analysis is to determine the length of service and optimal inspection period for engineering structures will be discussed.

## 4.2 Material Model

Table 4.1 statistical variables for specimens Cracks

| Random Variables | Average Value | *COV* [c] | Probability Distribution |
|---|---|---|---|
| Fracture Intensity, $K_{Ic}$ | 44 MPa $\sqrt{m}$ | 0.15 [a] | Normal [b] |
| Crack Size, $a$ | 0.01 m | 0.15 [a] | Normal [b] |
| Tension stress, $\sigma_\infty$ | 100 MPa | 0.15 [a] | Normal [b] |
| Specimen Width, $w$ | 0.05 m | - | - |

## 4.4 CENTRE CRACK TENSION (CCT)

Analytical function for stress intensity factor;

$$f(a/W) = 1 + 0.128(a/W) - 0.288(a/W)^2 + 1.525(a/W)^3 \tag{4.3}$$

### 4.4.1 Probability of Failure

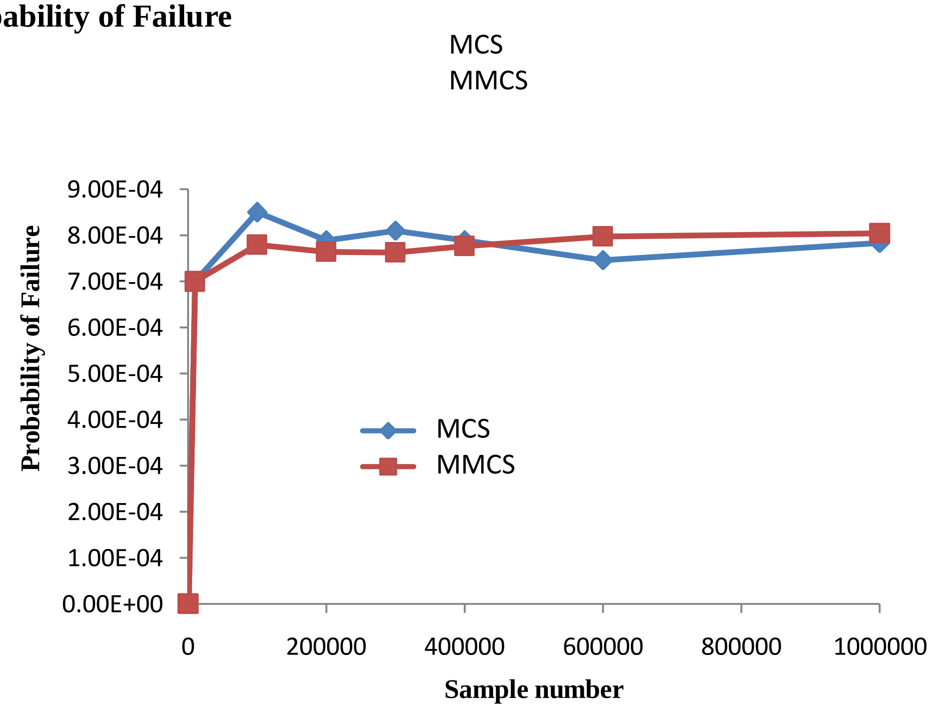


Figure 4.9 The probability of failure of specimens CCT

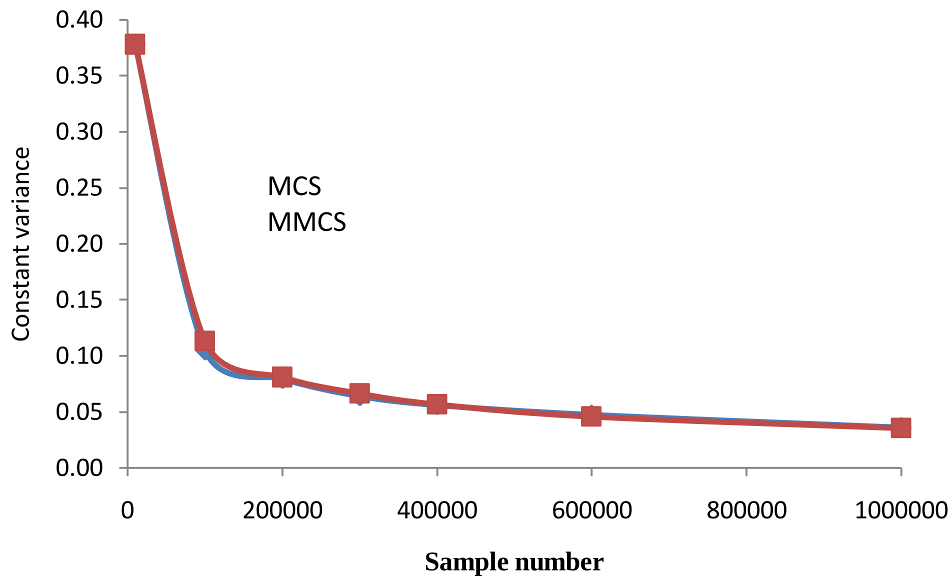


Figure 4.10 Effects of Number of Samples Used to Constant Variance

### 4.4.2 The efficiency of Modified Monte Carlo Simulation Method

Table 4.3 Comparison of methods for MCS with MMCS Method CCT specimens

| Number of Samples | Number of Simulations (MCS) | Number of Simulations (MMCS) | Percentage Reduction Simulations (%) |
|---|---|---|---|
| 10,000 | 10,000 | 185 | 98.2 |
| 100,000 | 100,000 | 1,793 | 98.2 |
| 200,000 | 200,000 | 3,617 | 98.2 |
| 300,000 | 300,000 | 5,312 | 98.2 |
| 400,000 | 400,000 | 7,188 | 98.2 |
| 600,000 | 600,000 | 10,953 | 98.2 |
| 1,000,000 | 1,000,000 | 18,097 | 98.2 |

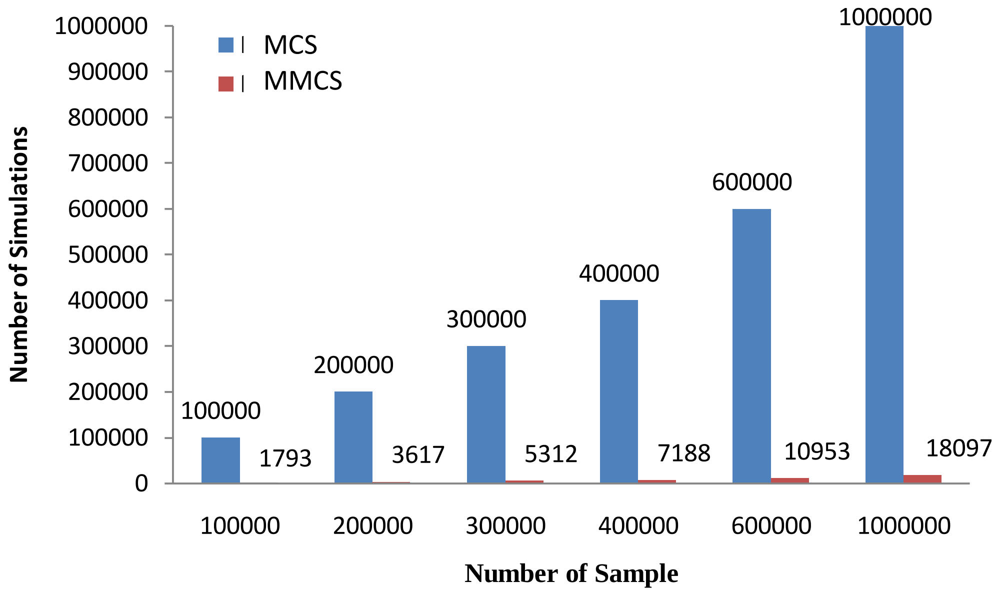


Figure 4.11 Comparison of Number of Simulations conducted by the MCS and MMCS

### 4.4.3 Factors Affecting Efficiency of Modified Monte Carlo Simulation

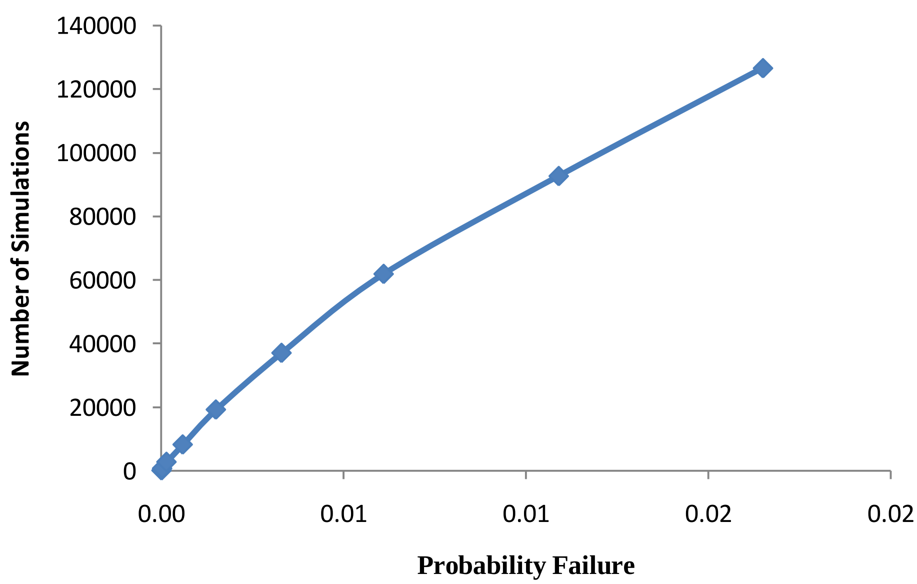


Figure 4.12 Effects of failure probability to the number of simulation methods for Modified Monte Carlo Simulation

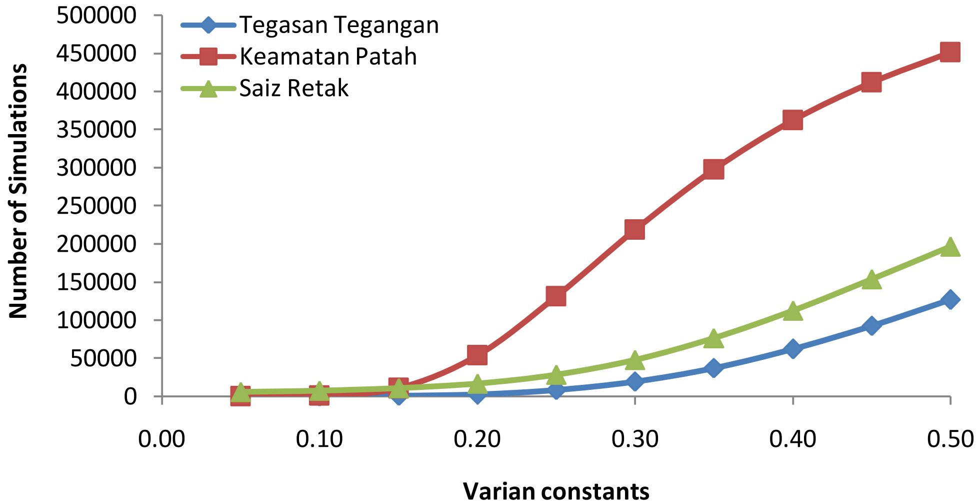


Figure 4.13 Effects of constant variance to the number of Simulations Conducted for Modified Monte Carlo Simulation

### 4.4.4 Sensitivity Analysis of Random Variables

#### 4.4.4.1 loading conditions

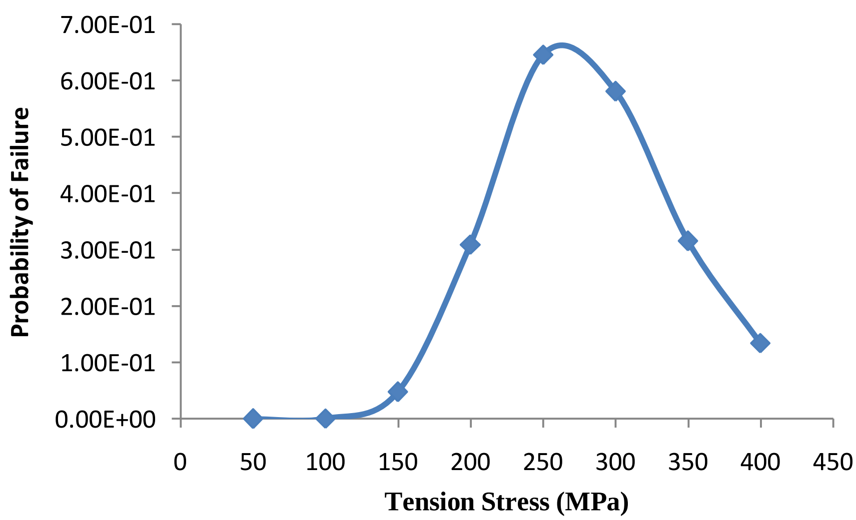


Figure 4.14 Effects of Stress Stress to Failure Probability

#### 4.4.4.2 Crack Size

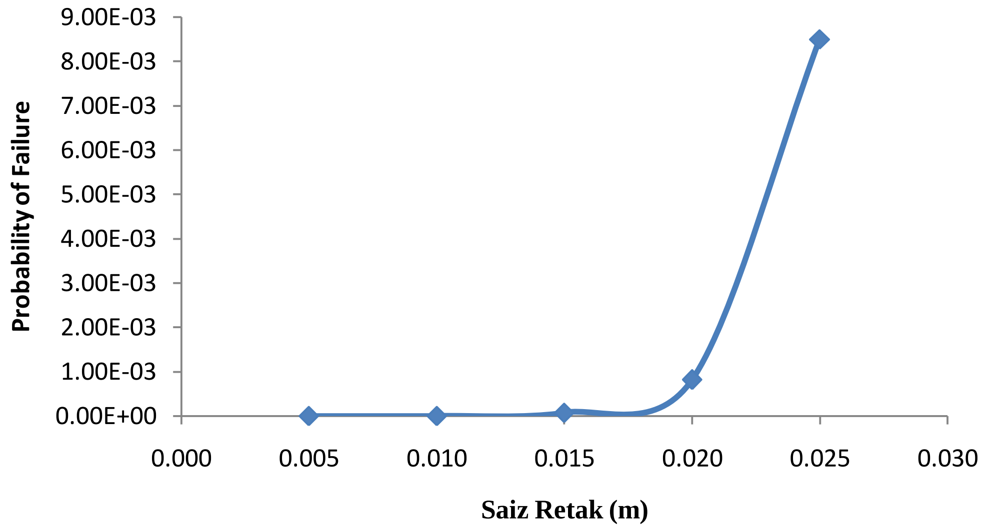


Figure 4.15 Crack Size Effect on Probability of Failure

#### 4.4.4.3 Varian constants

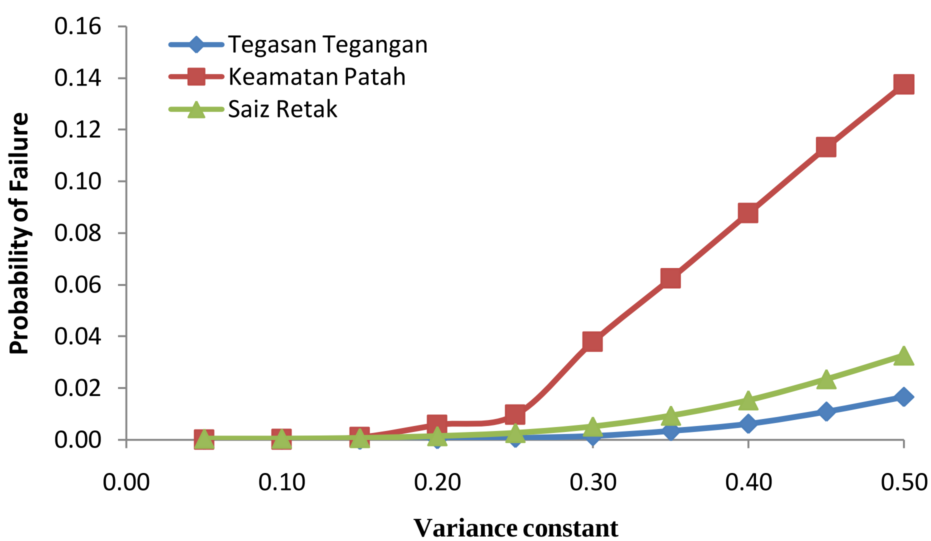


Figure 4.16 Effects of Random Variables on Probability of Failure

## 4.7 ENGINEERING APPLICATIONS

### 4.7.1 Bridge Girder

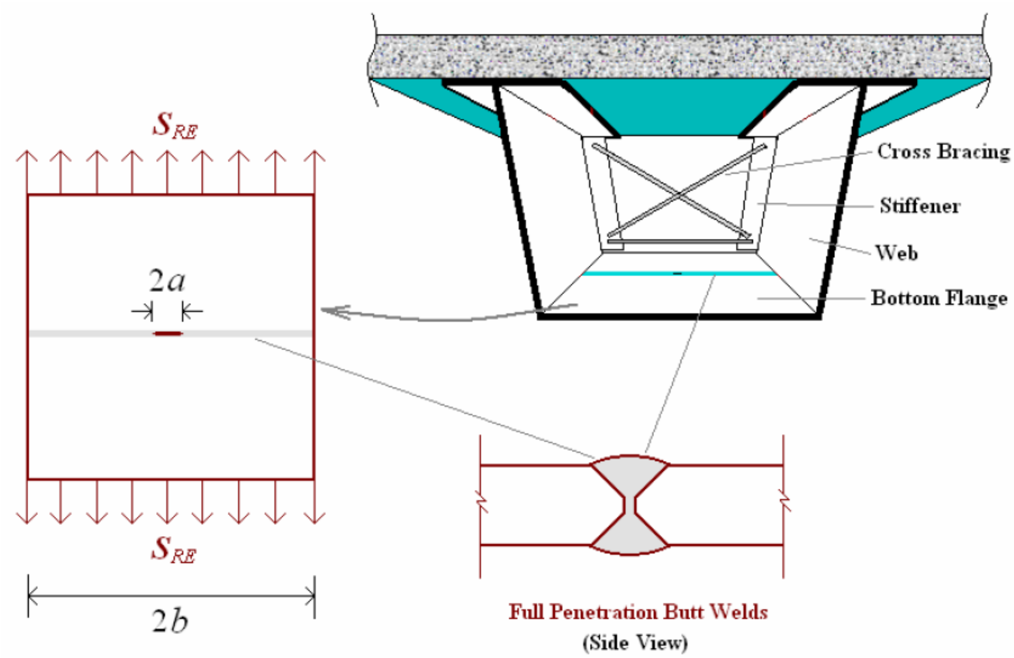


Figure 4.25 Crack problem at the Bridge

$$g(X) = \int_{a_0}^{a_c} \frac{da}{\left[f(a/w)\sqrt{\pi \cdot a}\right]^m} - C \cdot S_{RE}^m \cdot \left(365 \cdot ADTT \cdot C_s \cdot Y\right) \tag{4.5}$$

where $C_s$ is the number of stress cycles per truck passage, and $ADTT$ is the average daily truck traffic.

$$f(a/w) = \frac{1 - 0.5(a/w) + 0.370(a/w)^2 - 0.044(a/w)^3}{\sqrt{1-(a/w)}} \tag{4.6}$$

Jadual 4.7 Variables Related to Stress fractures of the Bridge

| Variable | Type Distribution | Average | COV |
|---|---|---|---|
| $a_0$ | Lognormal | 0.020 in | 0.500 |
| $a_c$ | constant | 2.000 in | 0.000 |
| $C$ | Lognormal | $2.05\text{x}10^{-10}$ | 0.630 |
| $m$ | Normal | 3.000 | 0.100 |
| $S_{RE}$ | Normal | 9.85 ksi | 0.300 |
| $C_s$ | constant | 1.000 | 0.000 |
| $ADTT$ | constant | 300.000 | 0.000 |
| $W$ | constant | 42.000 in | 0.000 |

### 4.7.2 Fatigue Reliability Index

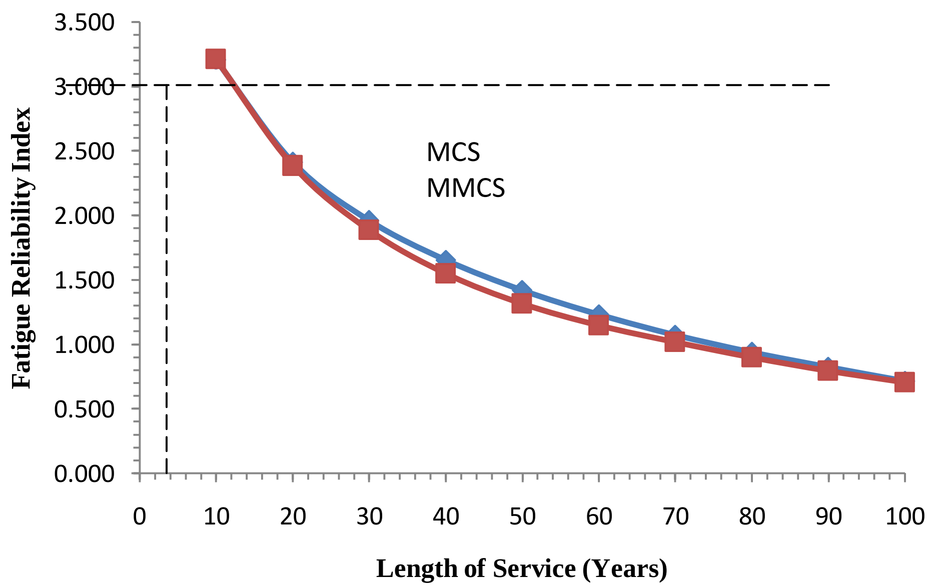


Figure 4.26 Fatigue Reliability Index in 100 years

### 4.7.3 Comparison of Monte Carlo simulation and Midified Monte Carlo Simulation

Jadual 4.8 The comparison of time of simulation and the percentage reduction in the MCS and MMCS

| Method | time of simulation (sec) | time of simulation (hour) | reduction (%) |
|---|---|---|---|
| MCS | 122436.359 | 34.01 | - |
| MMCS | 72493.484 | 20.14 | 40.79 |

# LAMPIRAN C

Initial Crack Size Distribution from Multiple Sources

| Detail | Initial Crack Size $a_0$ | | | Reference |
|---|---|---|---|---|
| | Distribution | Mean (in) | COV | |
| Weld Toe Undercut in Butt Weld | Exponential | 4.331E-3 | 1.00 | Bokalrud and Karlsen (1982) |
| Fillet Welded Joint | Lognormal | 4.900E-3 | 0.34 | Engesvik and Moan (1983) |
| HSLA Rolled Beam | Lognormal | 1.276E-3 | 0.45 | Yazdani (1984) |
| HSLA Welded Beam | Lognormal | 3.472E-2 | 0.36 | |
| HSLA Transverse Stiffener | Lognormal | 1.741E-2 | 0.71 | |
| HSLA Cover Plate | Lognormal | 1.084E-2 | 0.80 | |
| HSLA Thick Cover Plate | Lognormal | 1.843E-2 | 0.28 | |
| QT Rolled Beam | Lognormal | 5.100E-5 | 1.78 | |
| QT Welded Beam | Lognormal | 9.159E-3 | 0.47 | |
| QT Transverse Stiffener | Lognormal | 5.280E-3 | 0.57 | |
| QT Cover Plate | Lognormal | 1.700E-4 | 0.19 | |
| Tubular Joint | Exponential | 4.331E-3 | 1.00 | Kirkemo (1988) |
| TLP Joint | Lognormal | 2.874E-2 | 1.07 | Kountouris and Baker (1989) |
| Tubular Joint | Lognormal | 2.874E-2 | 1.07 | Shetty and Baker. (1990) |
| Tubular Joint | Exponential | 4.331E-3 | 1.00 | Pedersen et al. (1992) |
| Butt Weld | Lognormal | 2.000E-2 | 0.50 | Zhao et al. (1994a) |
| Cover Plate | Lognormal | 2.000E-2 | 0.50 | Zhao and Haldar (1996) |
| Stiffener to Bottom Flange | Lognormal | 2.362E-2 | 0.10 | Cremona (1996) |
| 30 North Sea Jackets | Exponential | 3.701E-2 | 1.00 | Moan et al. (1997) |
| Stiffener to Bottom Flange | Lognormal | 4.921E-3 | 0.36 | Lukic and Cremona (2001) |
| Butt Weld | Lognormal | 7.874E-3 | 0.50 | Zhang and Mahadevan (2001) |
| Butt Weld | Lognormal | 7.874E-3 | 0.20 | Righiniotis and Chryssanthopoulos (2003) |
| Cover Plate | Lognormal | 2.362E-2 | 0.40 | Righiniotis and Chryssanthopoulos (2003) |
| Gusset Plate | Lognormal | 3.937E-3 | 0.20 | Righiniotis and Chryssanthopoulos (2003) |
| Butt Weld at a Hole | Lognormal | 3.937E-3 | 0.20 | Righiniotis and Chryssanthopoulos (2003) |

Sumber: Chung 2004

# LAMPIRAN D

## Critical Stress Intensity Factor for A36, A588 dan A514 Steel

| Steel Type | Mean (ksi $\sqrt{\text{in}}$ ) | COV |
|---|---|---|
| A36 | 40.0 | 0.18 |
| A588 | 45.1 | 0.19 |
| A514 | 70.1 | 0.24 |

# LAMPIRAN E

Fatigue Crack statistical parameters from various sources

| Steel Type | Environment | *C* | | *m* | Reference |
|---|---|---|---|---|---|
| | | mean | COV | | |
| A36 (*n*=89) | Air | 9.476E-11 | 0.221 | 3.183 | Klingerman and Fisher (1973) |
| A36, A588 (*n*=260) | Air | 7.831E-11 | 0.076 | 3.523 | Barsom and Novak (1977) |
| Martensitic | Air | 4.650E-09 | – | 2.250 | Barsom and Rolfe (1999) |
| Ferrite-Pearlite | Air | *3.600E-10 | – | 3.000 | Barsom and Rolfe (1999) |
| Austenitic | Air | *3.000E-10 | – | 3.250 | Barsom and Rolfe (1999) |
| X52 (*n*=321) | Air | 5.183E-10 | 0.140 | 3.725 | Mayfield and Maxey (1982) |
| A36, A588 (*n*=724) | Air | 9.344E-11 | 0.200 | 3.202 | Roberts et al. (1986) |
| HSLA steel (*n*=1394) | Air | 8.291E-11 | 0.226 | 3.344 | Yazdani and Albrecht (1989) |
| A36, A588 (*n*=505) | Aqueous | 2.231E-10 | 0.150 | 3.279 | Yazdani and Albrecht (1989) |
| A514 (*n*=372) | Air | 2.794E-11 | 0.088 | 3.026 | Barsom and Novak (1977) |
| A514 (*n*=499) | Air | 1.324E-11 | 0.187 | 2.456 | Roberts et al. (1986) |
| QT (*n*=871) | Air | 1.174E-09 | 0.167 | 2.534 | Yazdani and Albrecht (1989) |
| QT (*n*=484) | Aqueous | 2.975E-09 | 0.156 | 2.420 | Yazdani and Albrecht (1989) |
| 1020 (HR) | Air | 2.960E-10 | – | 3.070 | Hertzberg (1995) |
| 4130 (QT) | Air | 3.730E-10 | – | 2.590 | Hertzberg (1995) |

*n*: number of test data
*: upper bound
The units of *C* assume units of inches for crack size and ksi $\sqrt{\text{in}}$ for $\Delta$K
HSLA: high strength low alloy steel
QT: quenched and tempered steel
HR: hot rolled steel
Aqueous Environment: 3% solution sodium chloride in distilled water

# LAMPIRAN F

Statistical parameters for fatigue crack propagation Waterways From Various Sources

| Environment | *C* mean | *C* COV | *m* | Reference |
|---|---|---|---|---|
| Air | 2.587E-10 | 0.55 | 3.10 | DNV Classification Notes No. 30.2 (1984) |
| Air | 3.319E-10 | 0.77 | 3.50 | |
| Air | 7.031E-10 | 0.55 | 3.10 | DNV-RP-404 (1988) |
| Air | 3.319E-10 | 0.77 | 3.50 | |
| Air | 1.360E-09 | 0.10 | 3.30 | Bokalrud and Karlsen (1982) |
| Air | 2.271E-10 | 0.1 | 3.10 | Cortie and Garrett (1988) |
| Air | 2.418E-10 | 0.3 | 3.30 | Aaghaakouchak et al. (1989) |
| Air | 3.343E-10 | 0.25 | 3.00 | Shetty and Baker (1990) |
| Air, R~0.1 | 2.478E-10 | 0.35 | 3.00 | BSI PD 6493 (1991) |
| Air, R>0.5 | 4.130E-10 | 0.37 | 3.00 | |
| Air, R~0.1 Stage 1 | 1.786E-15 | 1.31 | 8.16 | |
| Air, R~0.1 Stage 2 | 4.295E-10 | 0.35 | 2.88 | |
| Air, R>0.5 Stage 1 | 1.365E-11 | 1.69 | 5.10 | |
| Air, R>0.5 Stage 2 | 6.324E-10 | 0.60 | 2.88 | |
| Seawater, R~0.1 Stage 1 | 2.199E-10 | 0.93 | 3.42 | |
| Seawater, R~0.1 Stage 2 | 5.037E-07 | 0.26 | 1.30 | |
| Seawater, R>0.5 Stage 1 | 3.937E-10 | 1.10 | 3.42 | |
| Seawater, R>0.5 Stage 2 | 1.146E-06 | 0.16 | 1.11 | |
| Air | 4.130E-10 | 0.54 | 3.00 | BS 7910 (1997) |
| The units of *C* assume units of inches for crack size and ksi $\sqrt{in}$ for $\Delta K$ | | | | |