

Estimation of High-Cycle Fatigue Life by using Re-analysis

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ABSTRACT

In design of real-life systems, such as the suspension of a car, an offshore platform or a wind turbine, there are significant uncertainties in the model of the inputs. For example, scarcity of data leads to inaccuracies in the power spectral density function of the waves and the probability distribution of the wind speed. Therefore, it is necessary to evaluate the performance and safety of a system for different probability distributions. This is computationally expensive or even impractical. This paper presents a methodology to assess efficiently the fatigue life of structures for different power spectra of the applied loads. We accomplish that by reweighting the incremental damage calculated in one simulation. We demonstrate the accuracy and efficiency of the proposed method on an example which involves a nonlinear quarter car under a random dynamic load. The fatigue life of the suspension spring under loads generated by a sampling spectrum is calculated. Then, the fatigue life for different spectra is estimated by using re-analysis. We compare the results with those from simulation to validate the method.

CITATION: Norouzi, M. and Nikolaidis, E., "Estimation of High-Cycle Fatigue Life by using Re-analysis," *SAE Int. J. Mater. Manf.* 5(1):2012, doi:10.4271/2012-01-0066.

INTRODUCTION

In real-life applications, 50 to 90 percent of service failures in machines are due to fatigue [1]. Therefore, the evaluation of the performance of a design under fatigue failure is crucial in the design process. There are always uncertainties involved in the excitations, the material properties and the geometries of the real-life systems. A designer wants to study the sensitivity of the design to changes in design loads. In order to perform such analyses usually Monte Carlo Simulation (MCS) in the time domain is employed to measure the reliability of a system under stochastic loads. For most real-life problems performing MCS is impractical.

MCS is a robust tool but its computational cost is a major drawback. Many researchers are trying to improve the performance of MCS, and develop new methods without performing MCS. Farizal and Nikolaidis [2] introduced a Probabilistic Reanalysis (PRRA) approach for estimating lower and upper bounds of the probability of failure of a system when the parameters of the probability distributions of the random input variables are known. They demonstrated the performance of the approach on a single degree of freedom system with a dynamic vibration absorber with uncertain natural frequencies. They showed that PRRA can estimate bounds for the probability of failure at one fiftieth of the cost

of MCS. Li and Nikolaidis [3] evaluated and optimized discrete event systems using PRRA.

Most reliability assessment studies focus on time-invariant problems. These involve random variables. However, the applied loads on real-life systems vary in time. A car driven on a rough road, a ship sailing in a rough sea and a wind turbine under wind loads are subjected to dynamic excitations. Characterization of the inputs to these systems and assessment of their reliability requires use of random processes. The objective of this paper is to propose a method that extends application of PRRA from static to dynamic problems. Specifically, the paper presents a method to predict the high-cycle fatigue damage inflicted on a dynamic system for multiple power spectral densities (PSD) of the stochastic load. In order to apply PRRA to random vibration problems, we use Shinozuka's method [4] to generate load time histories. Next section explains this method then the performance of PRRA is demonstrated through one example.

METHODOLOGY

Using PRRA to Estimate High-Cycle Fatigue Damage

In this paper, our focus is on estimation of high-cycle fatigue damage on systems subjected to loads represented by stochastic processes. Random frequencies will be drawn from the input spectrum to generate time histories of the input

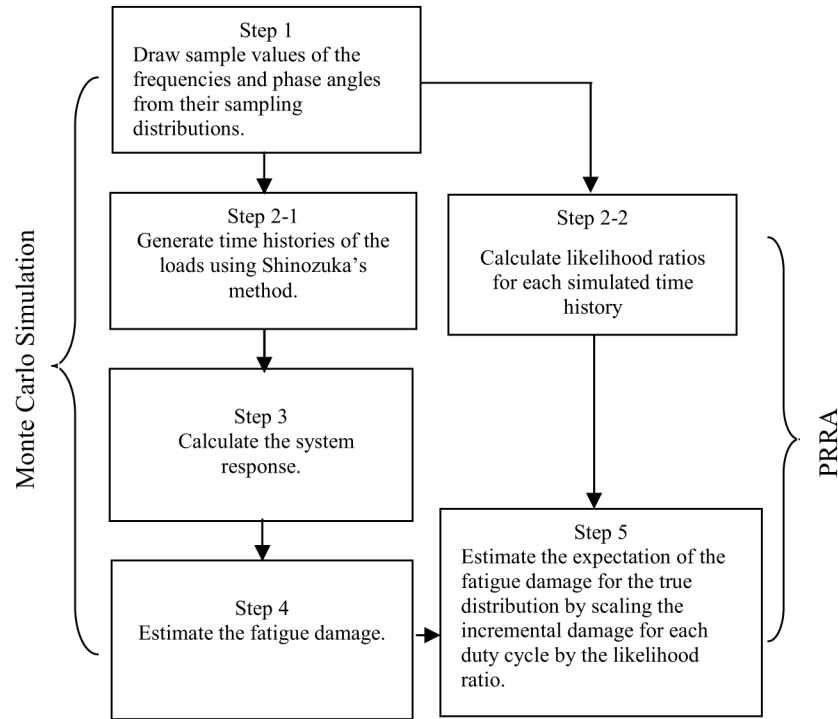


Figure 1. PRRA for fatigue reliability assessment

loads. The response of the system is also a stochastic process that can be calculated by using a computational tool such as commercial FEM software. Fig. 1 demonstrates the method for calculating fatigue damage in a system under stochastic loads by using both MCS and PRRA.

In the first step of the above procedure, the frequencies are drawn from a probability density function, which is equal to the PSD of the load normalized by the area under the PSD. The 3rd step is the most expensive part of the fatigue reliability assessment. PRRA enables the analyst to bypass this step thereby dramatically reducing the computation cost.

The likelihood ratio is calculated by Eq. (1). The numerator and the denominator are the PDF of the true and the sampling spectra, respectively.

$$w_k = \prod_{i=1}^N \frac{f^T(\omega_i)}{f^S(\omega_i)} \quad (1)$$

In the above equations ω_i are the frequencies in Shinozuka's equation [4] for simulating stochastic processes.

Load realizations are generated by Shinozuka's method [4], and the corresponding stress time histories at a critical point in the structure are calculated. The next step is to estimate the fatigue damage for every replication. We assume that the stresses are in the elastic region, and Basquin's equation is suitable for estimation of the fatigue damage. In order to determine the effective stress cycles, a cycle counting method, such as the rain flow algorithm [5], should

be employed. We calculate the cumulative damage by using Palmgren-Miner rule [6, 7].

For a structure under random loads, we generate multiple realizations of the loads and calculate the resulting system response. Then the total damage for every stress time history is calculated, and the expected damage is estimated by Eq. (2),

$$\hat{E}(D) = \frac{1}{K} \sum_{k=1}^K D_k \quad (2)$$

where D_k is the damage that the k^{th} load history inflicts, and K is the total number of simulated load histories. The standard deviation of the mean damage is estimated as follows,

$$S_{\hat{E}(D)} = \frac{1}{\sqrt{K(K-1)}} \sqrt{\sum_{k=1}^K [D_k]^2 - K \hat{E}^2(D)} \quad (3)$$

We stop the simulation when we achieve a required level of accuracy. Usually, accuracy is quantified by the coefficient of variation, which is the standard deviation of the damage normalized by its expectation.

Consider that a MCS is run for a sampling PDF, and the total damage is estimated for every realization. Then total