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Bridge fatigue reliability assessment using probability density functions of equivalent stress range based on field monitoring data

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A B S T R A C T

This paper focuses on fatigue reliability assessment of steel bridges by using probability density functions of equivalent stress range based on field monitoring data. To date, existing steel bridges have experienced fatigue cracks initiated and propagated. As a result, bridge structural integrity may not be preserved safely up to its anticipated service life. For this reason, it is necessary to assess and predict bridge fatigue reliability. The AASHTO Specifications can be used to estimate capacity of structural details in the fatigue reliability assessment, whereas long-term monitoring data can be used to provide efficient information for fatigue in terms of equivalent stress range and cumulative number of stress cycles. Under uncertainties, an approach using probabilistic distributions associated with stress ranges is proposed to effectively predict equivalent stress ranges for bridge fatigue reliability assessment. The fatigue detail coefficient, *A*, and the equivalent stress range, S_{re}, are both treated as random variables in the proposed fatigue reliability approach. This approach is illustrated on two existing bridges which are expected to experience finite or infinite fatigue life.

1. Introduction

Over the past decades, the initiated fatigue cracks in steel bridges have propagated due to the increase of service years under uncertainties associated with environmental and mechanical stressors, errors in design, fabrication and/or construction, and unexpected traffic increase. Therefore, steel bridge performance, which may be seriously affected due to fatigue, should be steadily assessed and predicted. For this purpose, fatigue reliability approach can be used.

Structural reliability analysis has been well developed and widely applied in many fields. Reliability theory is concerned with determining the probabilistic measure of safe performance. For estimating fatigue reliability, both resistance (capacity) and load effect (demand) have to be evaluated. Typically, bridge fatigue resistance and load demand are evaluated by using the S–N curves provided in the AASHTO Specifications [1] and field monitoring data, respectively. In general, if the AASHTO Category of the structural detail is correctly classified, the necessary information on fatigue resistance of structural members can be easily obtained from the AASHTO Specifications [1]. However, finding the loading history is impossible without field monitoring data.

Modern concepts for bridge maintenance and monitoring programs under uncertainty have been developed [15,17,16]. Several researchers have studied the effective design of monitoring systems to produce more reliable results. The measured data associated with monitoring systems can be used for fatigue reliability assessment [18]. In this context, the application of several probability density functions (PDFs) based on field monitoring data can be effectively considered in prediction models.

In 1982, the ASCE Committee on Fatigue and Fracture Reliability [3] discussed possible use of probabilistic distributions for fatigue analysis. The application of several PDFs for estimating equivalent stress range was reported by Chung [5]. Weibull, Beta, and Lognormal distributions for loading were used to estimate equivalent stress range. Pourzeynali and Datta [23] applied Weibull and Lognormal distributions to perform fatigue reliability analysis of suspension bridges. Thus, various PDFs of load effects can be applied in fatigue reliability assessment. However, fatigue reliability may be significantly affected by the type of PDF of stress range. For this reason, goodness-of-fit tests have to be conducted to find the best fit.

In fatigue reliability assessment based on monitoring data, there are two important parameters to consider: (i) fatigue detail coefficient, *A*, in terms of resistance; and (ii) equivalent stress range, S_{re}, in terms of loading. Fatigue detail coefficient, *A*, is provided as deterministic based on the AASHTO Specifications [1]. Equivalent stress range, S_{re}, is considered also as deterministic. However, these two parameters may need to be taken into account

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as random variables for more reliable fatigue performance assessment under uncertainty. A and S_{re} are herein treated as random variables.

It is extremely important to define the threshold that directly affects calculation of equivalent stress range. Indeed, fatigue life can be overestimated or underestimated by the computed equivalent stress range according to the predefined cut-off stress range. According to Connor and Fisher [7], the applicable cut-off stress ranges are predefined and used to estimate the mean value and standard deviation of equivalent stress range, S_{re}.

Based on all necessary information from the AASHTO Specifications [1] and the monitoring data, fatigue reliability analysis of structural members is conducted by using the reliability softwares CalREL [21] and RELSYS [11]. As illustrations, structural details of two existing bridges, the Neville Island Bridge and the Birmingham Bridge, which are both located in Pittsburgh, Pennsylvania, are investigated for fatigue reliability assessment. The Neville Island Bridge is representative for finite fatigue life, whereas the Birmingham Bridge is representative for infinite fatigue life. The field monitoring data for both bridges are provided by the National Engineering Research Center, ATLSS, at Lehigh University [8,9].

2. Fatigue reliability assessment

Many of the existing aging steel bridges have experienced structural deterioration due to fatigue. As indicated previously, bridge fatigue life can be predicted more reliably if fatigue assessment is conducted based on both the AASHTO S–N curve for bridge capacity and the monitoring data for loading considering uncertainties.

2.1. Monitoring data

In fatigue life assessment of a bridge, field monitoring data provide essential information on load effects caused by traffic. The long-term monitoring system will automatically record and store data obtained in installed strain gages whenever heavy vehicles cross. The system may need to be fully automatic, to require little operator intervention, and to be remotely accessible via modem or other wireless communication links [4]. Monitoring program is mainly performed at potential critical regions. Stress-range bin histograms are produced by using the rain-flow cycle counting method [10]. This is widely accepted and used for fatigue assessment.

In general, there are two types of tests to investigate live load effects: controlled and uncontrolled tests. The effects of vehicle speed and position on the bridge deck are captured in the controlled live load tests. On the other hand, the overall influence of real traffic is investigated from the uncontrolled live load testing. Stress range histogram data are usually collected during the uncontrolled monitoring. Equivalent stress range and average daily truck traffic are computed based on the created stress-range bin histogram from long-term monitoring program. Actual monitoring data are in this study used not only to compute equivalent stress range and average daily number of cycles according to predefined stress range cut-off level but also to compare the results obtained by the proposed fatigue reliability assessment method with the remaining fatigue life calculated by using the AASHTO fatigue equations. If monitoring data is not available, fatigue truck analysis based on the AASHTO fatigue truck model can be adopted by using influence line analysis to estimate approximately lifetime load effects (i.e., PDF of equivalent stress range) for bridges. The computed moment ranges can be used to approximately calculate equivalent stress range.

2.2. Probability density functions (PDFs)

In fatigue reliability analysis, it is important to use the appropriate PDFs regarding loading, S, and resistance, R. As already mentioned, monitoring for fatigue reliability assessment and prediction can provide efficient information for fatigue loading, especially for the estimation of equivalent stress range and the number of stress cycles accumulated by traffic. Due to loading uncertainties, a probabilistic approach considering various PDFs for load effects can be used to predict stress ranges during fatigue lifetime. Similarly, PDFs can be effectively used in terms of fatigue resistance. Thus, various PDFs of both S and R are used to perform fatigue reliability evaluation.

The AASHTO [1] approach to fatigue reliability assessment is based on the S–N curves and the Miner's rule [22]. Typically, the S–N (i.e., stress-life) relationship is established based on the scatter from numerous test data. Assuming that scatter is measured by the standard deviation in fatigue life, there is an observed increase in it as stress amplitude is decreased. The AASHTO S–N relationship of a detail corresponds to its mean life shifted horizontally to the left by two standard deviations [13]. In addition, it should be kept in mind that the mean value of applied stress associated with a single stress cycle can have a significant influence on the S–N curve. However, in this study which is limited to welded details studied extensively by Fisher et al. [12], the conclusions of the NCHRP Report 102 [12] were adopted; (a) stress range was the dominant stress variable for all welded details and beams tested, and (b) other stress variables such as minimum stress, mean stress, and maximum stress (although sometimes statistically significant) were not significant for design purposes. Nevertheless, the effect of the random mean stress on the stress-life relationship has to be further investigated.

The AASHTO basic equation for the resistance is $\Delta F = (A/N)^{1/m}$, where A is the fatigue detail coefficient for each category, m is material constant, N is number of stress range cycles, and ΔF is nominal fatigue resistance. From a fracture mechanics approach, fatigue life can be expressed in terms of cycles to failure, $N_t = A \cdot S_{re}^{-m}$, or, alternatively, as $\log N_t = \log(A) - m \log(S_{re})$. According to Fisher et al. [13], given that ΔF is simply the stress range at its permissible value for the given number of cycles, ΔF and N_t are equivalent. The AASHTO Specifications [1] for each fatigue detail category provide the fatigue detail constant, A, and a material constant representing the slope of the S–N curves, m, which can be assumed as $m = 3.0$ for all fatigue categories.

Based on extensive test results of welded steel bridge details performed by Keating and Fisher [20], the mean value and standard deviation of the fatigue detail coefficient, A, on a log basis, are calculated for the Neville Island and Birmingham bridges and used when A is treated as random in fatigue reliability evaluation (see Table 1). The Miner's critical damage accumulation index, Δ, is assumed as Lognormal [24]. The PDF associated with the stress range, S, is assumed as: (a) Lognormal; (b) Weibull; or (c) Gamma. In this study, three-parameter PDFs including cut-off threshold, s_c, as well as two-parameter PDFs with $s_c = 0$ are considered. The PDFs of these distributions are:

(a) Lognormal distribution

$$f_S(s) = \frac{1}{(s - s_c)\cdot\zeta\cdot\sqrt{2\cdot\pi}}\cdot\exp\left[-\frac{1}{2}\cdot\left(\frac{\ln(s - s_c) - \lambda}{\zeta}\right)^2\right] \quad \text{for} \quad s > s_c \tag{1}$$

where λ is the location parameter, ζ is the scale parameter, and s_c is the cut-off threshold

$$E(S) = \exp(\lambda + 0.5\cdot\varsigma^2) + s_c, \quad \text{and}$$
$$\mathrm{Var}(S) = [E(S) - s_c]^2\cdot[\exp(\varsigma^2) - 1] \tag{2}$$