Performance Evaluation of Existing Bridges under Vehicle Dynamic Effects

C.S. Cai\textsuperscript{1, a}, Wei Zhang\textsuperscript{2, b}, Lu Deng\textsuperscript{3, c} and Miao Xia\textsuperscript{4, d}

\textsuperscript{1-4} Dept. of Civil and Environmental Engineering, Louisiana State University, Baton Rouge, USA
\textsuperscript{a} ccai@lsu.edu (corresponding author),
\textsuperscript{b} wzhlsu@gmail.com, \textsuperscript{c} ludeng9@gmail.com, \textsuperscript{d} mxia@lsu.edu

Keywords: Vehicle effects, existing bridges, calibrations, reliability, performance evaluation, extreme values, DAFS

Abstract. This paper summarizes the recent work by the first author’s research group related to the performance evaluation of existing bridges under vehicle dynamic effects. Based on the data from short-term monitoring of existing bridges, a framework to estimate the extreme structure responses from the live load in a mean recurrence interval is developed in the first part. The Gumbel distribution of the extreme values was derived from an extreme value theory and Monte Carlo Simulation. In the second part, a framework of fatigue damage and reliability assessment for existing bridges is presented to include the effects of the progressively deteriorated road conditions and random dynamic vehicle loads in bridge’s life cycle. The random effects of vehicle speed and type, road profiles, and stress ranges are included. Studies have shown that the vehicle-induced dynamic allowance IM value prescribed by the AASHTO LRFD code may be underestimated under poor road surface conditions (RSCs) of some existing bridges. In addition, multiple dynamic stress ranges induced by vehicles cannot be included in the maximum displacement-based dynamic allowance IM values. In the third part of this paper, the reliability indices of a selected group of prestressed concrete girder bridges are calculated by modeling the IM explicitly as a random variable for different RSCs. Nevertheless, a reliability based dynamic amplification factor on stress ranges (DAFS) for fatigue design is proposed to include the fatigue damages from multiple stress range cycles due to each vehicle passage at varied vehicle speeds under various road conditions in the bridge’s life cycle.

Introduction

In a bridge’s life cycle, vehicle dynamic loads can endanger bridge safety either in the strength capacity or structural integrity. The performance evaluations of existing bridges should be based on both the maximum dynamic responses and the dynamic stress range histories that can be obtained either from structural health monitoring (SHM) systems or via numerical simulations of the vehicle-bridge dynamic system.

Structural health monitoring (SHM) systems of bridges can provide useful information for bridge performance assessment and prediction. Instead of measuring the weight of every vehicle passing through bridges, SHM techniques can conveniently record structural response such as strains under routine service traffic loads. The procedure of reliability assessment using monitoring data includes collecting data, identifying the distribution type of live load effects, and estimating its distribution parameters by curve fitting techniques. The extreme load effects are derived from the response of a bridge directly including each possible combination of the number of loaded lanes multiplied by a corresponding multiple presence factor to account for the probability of simultaneous lane occupation [1]. For reliability calculations, with the help of the monitored data, one can minimize the uncertainties and apply fewer assumptions in structural analysis, thus make the reliability calculation more rational. One of the aims of this study is to develop a methodology that can
establish the maximum live load effect distribution for a mean recurrence interval with extreme
value theories based on short-term monitoring data of structural response.

In order to ensure the structural integrity, the maximum dynamic response is not enough for
fatigue damage assessment. The dynamic stress range histories are needed. In order to consider
multiple scenarios of vehicle types, vehicle speeds, and road surface conditions, numerical
simulations are more versatile. In a fatigue design, the load-induced fatigue effect should be less
than the nominal fatigue resistance. Naturally, the fatigue requirement can also be stated as the
fatigue life consumed by the load being less than the available fatigue life of the bridge detail.
However, the vehicle speed and road roughness conditions are not considered in a typical fatigue
analysis such as in the American Association of State Highway and Transportation Officials
(AASHTO) specifications [2]. It has been proven that these two factors have significant effects on
the dynamic responses of short span bridges [3, 4]. In the present study, the deterioration of the road
surface due to environmental corrosions and passages of truckloads is considered. In addition, the
road may be resurfaced when the road surface becomes unacceptable. Therefore, the road roughness
coefficient is considered to change periodically with time. A limit state function is defined in the
present study to calculate the fatigue reliability. Besides the random vehicle speeds and road
profiles, the traffic increase rate is taken into account in the present study to compare their effects
on the fatigue reliability index and fatigue life.

Studies have shown that the vehicle-induced dynamic allowance IM value prescribed by the
AASHTO LRFD code may be underestimated under poor road surface conditions (RSCs) of some
existing bridges. In addition, multiple dynamic stress ranges induced by vehicles cannot be included
in the maximum displacement-based dynamic allowance IM values. In the third part of this paper,
the reliability indices of a selected group of prestressed concrete girder bridges are calculated by
modeling the IM explicitly as a random variable for different RSCs. Nevertheless, a reliability
based dynamic amplification factor on stress ranges (DAFS) for fatigue design is proposed to
include the fatigue damages from multiple stress range cycles due to each vehicle passage at varied
vehicle speeds under various road conditions in the bridge’s life cycle.

**Estimation of Extreme Structural Response**

With the structural health monitoring system, dynamic responses from vehicles can be obtained
in order to evaluate the performances of existing bridges. In the early version of AASHTO LRFD
Bridge Design Specifications (1994), the live load models were derived from the statistical data of
9250 selected truck surveys and weigh-in-motion measurements[5]. The reliability index of
structures is related to the maximum load distributions in a structure’s life cycle. When a normal
distribution of individual truck loads is assumed, the maximum live load moments or shear for
various time periods can be obtained.

**Extreme Value Prediction**

Let the live load effects following a certain distribution $\Omega$, and the number of trucks in the
surveying interval $T_{sur}$ is $N_{sur}$. Then, the total number of trucks $N_{exp}$ passing through the bridge in an
expected service life $T_{exp}$, will be

$$N_{exp} = N_{sur} T_{exp} / T_{sur} \tag{1}$$

The maximum live load effects $Q_{l, max}$ corresponding to any expected bridge service life is

$$Q_{l, max} = \Phi^{-1}(1-1/N_{exp}) \tag{2}$$

where $\Phi^{-1}$ is the inverse of the standard distribution function. According to AASHTO
specifications, the expected service life for a new bridge $T_{exp}$ is 75 years.
According to Orcesi and Frangopol [1], the extreme value distribution of SHM data is assumed to approach a *Gumbel* probability distribution [6].

$$F(x; \mu, \sigma) = \exp(-\exp(-\frac{x - \mu}{\sigma})) \quad -\infty < x < \infty$$  \hspace{1cm} (3)

where $F(x)$ is the cumulative distribution function of the *Gumbel* probability distribution, both $\mu$ and $\sigma$ are constants to be determined from the measured data. Thus, the extreme values of the SHM data in a mean recurrence interval, $T$, ($T$ is longer than the monitoring period), can be predicted as

$$x(T) = \mu - \sigma \cdot \ln[-\ln(1 - \frac{1}{N_{\text{exp}}})]$$  \hspace{1cm} (4)

when the methods for extreme vehicle load estimation are used, the number of vehicles passing through the bridges are necessary. However, the number of vehicles is hard to obtain since it is not easy to identify each truck passage with only the recorded strain data. In addition, the maximum structural response in some cases is due to the presence of multiple vehicles running side by side or one by another, which are still excluded in the reliability calculation. The aim of this part is to develop a methodology that can establish the maximum live load effects distribution for a mean recurrence interval with extreme value theories based on short-term monitoring data of structural response.

Since only the maximum structure response is concerned, it is reasonable to use extreme theories to estimate the long-term maximum response from the short-term records of structure response monitoring. In this study, the *Gumbel* distribution is used to model the extreme values of long (finite) sequences of independent, identically distributed random variables. *Gumbel* distributions also known as *Type I* extreme value distribution within the extreme value theory. Let the variable $X$ be the maximum of $n$ independent random variables $Y_1$, $Y_2$, $Y_3$. Since the inequality $X \leq x$ implies $Y_i \leq x$ for all $i = 1, 2, \ldots, n$, it follows that

$$F(X \leq x) = \text{Prob}(Y_1 \leq x, Y_2 \leq x, \ldots, Y_n \leq x) = F_{Y_1}(x)F_{Y_2}(x)\cdots F_{Y_n}(x)$$  \hspace{1cm} (5)

The probabilities $F_{Y_i}(x)$ are referred to as the initial distributions of the variables $Y_i$. In the particular case in which all the variables $Y_i$ have the same probability distribution $F_{Y_i}(x)$, the probability distribution of $X$ becomes

$$F_X(x) = [F_{Y_i}(x)]^n$$  \hspace{1cm} (6)

If the number $n$ becomes large enough, the cumulative distribution $F_X(x)$ of the largest values approach limits known as *Type I* or *Type II* extreme value distributions if the initial distributions are of the exponential or of the Cauchy type, respectively [7].

**Probabilistic Modeling of Maximum Live Load Effects for a Mean Recurrence Interval**

The yearly maximum live load effects are used for demonstration. The yearly maximum live load effect is the extreme value of live load effects the structure is subjected in a year. A year can be divided into $n$ time segments; the maximum live load effects in each time segment, $Q_{\text{seg}_i}$, is a variable and can be obtained with bridge health monitoring system. The extreme values are assumed to be independent with each other and have the same distribution with a cumulative distribution function $F_{\text{seg}}(Q)$. The probabilities, $F_{\text{seg}}(Q)$, is referred to as the initial distribution. The distribution of yearly maximum live load effect can be derived according to Eqs. (5) and (6) as:

$$F_y(Q) = [F_{\text{seg}}(Q)]^n$$  \hspace{1cm} (7)

The accuracy of the estimation of the yearly maximum live load effects probability distribution depends on the accuracy of the distribution of the initial population and the number of the intervals. For different number of time segments $n_1$ and $n_2$ (or different length of time segments, $\text{seg}_1$ and $\text{seg}_2$), initial distribution $F_{\text{seg}_1}(Q)$ and $F_{\text{seg}_2}(Q)$ can be obtained. The distribution of the extreme
live load effects in a mean recurrence interval can be derived in terms of $F_{\text{seg}_1}(Q)$ and $F_{\text{seg}_2}(Q)$ as follow:

$$F_y(Q) = [F_{\text{seg}_1}(Q)]^n = [F_{\text{seg}_2}(Q)]^n$$  \hspace{1cm} (8)

For example, the yearly extreme structure response distribution can be derived from initial distributions based on time segments of an hour or a minute as:

$$F_y(Q) = [F_{\text{hr}}(Q)]^{365 \times 24} = [F_{\text{min}}(Q)]^{365 \times 24 \times 60}$$  \hspace{1cm} (9)

where $F_{\text{hr}}(Q)$ and $F_{\text{min}}(Q)$ are initial distributions and they represent the maximum structure response cumulative distribution function for 1 hour and 1 minute, respectively. The initial distribution can be derived by distribution fitting of the monitored data. It shows in Eq. (8) and Eq. (9) that the yearly maximum live load distribution is unique; the initial distributions corresponding to different lengths of time segments are not unique. The following two principles need to be satisfied to estimate a reasonable number of intervals or to determine the length of the time segment [8]: The time segment is long enough so that the maximum live load in every interval satisfies independence requirement; The length of the time segment is reasonable so that the maximum live loads in every interval follow the same distribution.

These two conditions require the length of the time segments is long enough so that the structural response record in every time segment is a stationary and ergodic process. The property of stationarity of a stochastic process always refers to the process being unchanged when shifting along the time axis [9]. For an ergodic process, its statistical properties (such as its mean and variance) can be deduced from a single, sufficiently long sample (realization) of the process. In other words, statistical properties obtained from a single time-series will approach definite limits independent of the particular series as the length of the series increases. Once the initial distribution of the parent population is determined, the maximum distribution in any mean recurrent intervals can be derived from Eq. (8) and Eq. (9).

**Case Study**

Time history records of strains at the mid-span of a steel girder in the CORIBM Bridge were recorded, which is located on route LA 70 in District 61, Assumption Parish of Louisiana. Since only three hours monitoring data is available, it is not advisable to estimate extreme strain distribution for a very long mean recurrence interval. The extreme strain distribution (Gumbel distribution) for mean recurrence intervals of 1 day, 10 days, 30 days, 180 days and one year were estimated using the maximum likelihood estimation method as shown in Fig. 1.
The yearly extreme strain distribution can be derived from the initial distributions with time segments of 90s or 300s as

\[ F_y(Q) = \frac{F_{90s}(Q)}{365 \times 24 \times 3600} = \frac{F_{300s}(Q)}{365 \times 24 \times 3600/300} \]

where the initial distributions \( F_{90s}(Q) \) and \( F_{300s}(Q) \) have been obtained from distribution fitting previously. It is difficult to prove directly that Eq. (10) is tenable and it is difficult to derive the parameters of yearly extreme response distribution through an analytical method. In the present study, an alternative method is used to generate samples that follows the distributions on the right side of Eq. (10) using Monte Carlo simulations. And the samples are fitted with the selected distribution function, Gumbel distribution (maximum cases). The factors derived from distribution fitting were shown in Fig. 2. Both the location factor \( \mu \) and the scale factor \( \sigma \) suggest that the converging property increases with the increase of the length of time segments. For different mean recurrence intervals, \( \mu \) converges to different values, but \( \sigma \) converges to a fixed value. The location factor \( \mu \) determines the mode value of the distribution while the shape factor \( \sigma \) determines the variance or the standard deviation of the distribution. Its location shifts to the right direction as the mean recurrence interval increases. The distributions have different mode values but the same variance for different mean recurrence intervals. The PDF of extreme strain distribution for mean recurrence intervals of 1 day, 10 days, 30 days and one year are shown in Fig. 3.

![Figure 1 Initial distribution fitting using Gumbel distribution: time segment of](image)

(a) 8s; (b) 50s; (c) 90s; (d) 300s

![Figure 2 Extreme strain distributions parameter, \( \mu, \sigma \), derived from different initial distributions](image)
Vehicle-Induced Fatigue Reliability Assessment of Existing Bridges

In addition to the method of acquiring dynamic effects from the structural health monitoring system, numerical simulation of vehicle-bridge dynamic system provide a more versatile way to obtain dynamic vehicle effects on various vehicle and road surface conditions.

Prediction of Vehicle Induced Bridge Vibration

To predict vehicle-induced vibrations for fatigue assessment, the vehicle is modeled as a combination of several rigid bodies connected by several axle mass blocks, springs and damping devices [10]. The tires and suspension systems are idealized as linear elastic spring elements and dashpots. The equations of motions for the vehicle and bridge can be built and they are coupled through the contact condition, i.e., the wheel-bridge contact forces acting on bridges and vehicles. After transforming the contact forces to equivalent nodal forces and substituting them into the mass and stiffness matrices, the final equations of motion for the coupled system are as follows [4]:

$$ \begin{bmatrix} M_b & C_{bb} + C_{bv} & C_{vr} \\ C_{vb} & M_v & C_{vr} \\ C_{vr} & C_{vr} & M_v \end{bmatrix} \begin{bmatrix} \frac{d_b}{d_y} \\ \frac{d_b}{d_y} \\ \frac{d_y}{d_y} \end{bmatrix} + \begin{bmatrix} K_{bb} + K_{bb} & K_{bb} & K_{bb} \\ K_{bb} & K_{bb} & K_{bb} \\ K_{bb} & K_{bb} & K_{bb} \end{bmatrix} \begin{bmatrix} \frac{d_b}{d_y} \\ \frac{d_b}{d_y} \\ \frac{d_y}{d_y} \end{bmatrix} = \begin{bmatrix} F_{br} \\ F_{vr} + F_{r}^G \end{bmatrix} $$

(11)

The terms $C_{bb}, C_{bb}, C_{vb}, K_{bb}, K_{bb}, K_{bb}, F_{br}$ and $F_{vr}$ in Eq. (11) are the expansion terms for the damping, stiffness matrices and force vectors due to the contact force. When the vehicle is moving along the bridge, the bridge-vehicle contact points change with the vehicle position and the road roughness at the contact point. The time independent terms in mass, stiffness and force matrices or vectors are built via finite element method. The time dependent terms are generated and updated in each time step after the new position of each vehicle is identified. Then the equations of motions are solved in time history using Runga-Kutta method. At the each time step, the contact force is calculated, as well. When it turns into tension force, it suggests that the vehicle tire leaves the riding surface and the force is set to zero. The corresponding time dependent terms in the equations of motions are updated simultaneously.

After obtaining the bridge dynamic response $\{d_b\}$, the stress vector can be obtained by [11]:

$$ [S] = [E] [B] [d_b] $$

(12)

where $[E]$ is the stress-strain relationship matrix and is assumed to be constant over the element, and $[B]$ is the strain-displacement relationship matrix assembled with $x$, $y$ and $z$ derivatives of the element shape functions.
In the current AASHTO LRFD specifications [2], the dynamic effects due to moving vehicles are attributed to two sources, namely, the hammering effect due to the vehicle riding surface discontinuities, such as deck joints, cracks, potholes and delaminations, and dynamic response due to long undulations in the roadway pavement. The long undulations in the roadway pavement can be assumed as a zero-mean stationary Gaussian random process, and it can be generated through an inverse Fourier transformation [12]. In order to include the progressive pavement damages due to traffic loads and environmental corrosions, a progressive road roughness deterioration model for the bridge deck surface is used [13]:

$$\phi(n_t) = 6.1972 \times 10^{-9} \times \exp \left[8.39 \times 10^{-6} \phi_0 e^{\eta t} + 263(1 + SNC)^{-\delta}(CESAL)\right] / 0.42808 + 2 \times 10^{-6}$$ (13)

where $\phi_i$ is the road roughness coefficient at time $t$; $\phi_0$ is the initial road roughness coefficient directly after completing the construction and before opening to traffic; $t$ is the time in years; $\eta$ is the environmental coefficient varying from 0.01 to 0.7 depending upon the dry or wet, freezing or non-freezing conditions; $SNC$ is the structural number modified by sub grade strength; and $(CESAL)_i$ is the estimated number of traffic in terms of AASHTO 18-kip cumulative equivalent single axle load at time $i$ in millions.

To demonstrate the methodology, a 12m long and 13 m wide slab-on-girder bridge is analyzed, which is designed in accordance with AASHTO LRFD bridge design specifications [2]. In the present study, after conducting a sensitivity studying by changing the meshing, 27543 solid elements and 43422 nodes are used to build the finite element model of the bridge. The damping ratio is assumed to be 0.02. The present study focuses on the fatigue analysis at the longitudinal welds located at the conjunction of the web and the bottom flange at the mid-span. Since the design live load for the prototype of the bridge is HS20-44 truck, this three-axle truck is chosen as the prototype of the vehicle in the present study. In addition, only one vehicle in one lane is considered to travel along the bridge for fatigue analysis due to its short span length.

**Fatigue Assessment**

For variable amplitude stress cycles, the Palmgren-Miner damage law, which is also called the linear fatigue damage rule (LDR), is often used [14, 15]:

$$D(t) = \sum_i \frac{n_i}{N_i} = \frac{n_{tc}}{N}$$ (14)

where $n_i$ is number of observations in the predefined stress-range bin $S_{ri}$, $N_i$ is the number of cycles to failure corresponding to the predefined stress-range bin; $n_{tc}$ is the total number of stress cycles and $N = A \times S_{re}^{-m}$ is the number of cycles to failure under an equivalent constant amplitude loading [16], $S_{re}$ is the equivalent stress range and $A$ is the detail constant taken from Table 6.6.1.2.5-1 in AASHTO LRFD bridge design specifications [2]. Either using the Miner’s rule or Linear Elastic Fracture Mechanics (LEFM) approach, the equivalent stress range for the whole design life is obtained through the following equation [17]:

$$S_{re} = \left(\sum_{i=1}^{n} \alpha_i \cdot S_{ri}^m\right)^{1/m}$$ (15)

where $\alpha_i$ is the occurrence frequency of the stress-range bin, $n$ is the total numbers of the stress-range bin and $m$ is the material constant that could be assumed as 3.0 for all fatigue categories [18].

The analytical and experimental results on several bridges indicated clearly that more than one or two stress ranges could be induced by each truck passage. On a basis of equivalent fatigue damage, a revised equivalent stress range, $S_{re}$, is used to combine the two correlated parameters for simplifications, i.e. the equivalent stress range and the number of stress cycles per truck passage. Namely, the fatigue damage of multiple stress cycles due to each truck passage is considered as the
same as that of a single stress cycle of $S_w$ [13]. For truck passage $j$, the revised equivalent stress range is:

$$S_w^j = \left( N_j \right)^{1/m} S_{re}^j$$  \hspace{1cm} (16)

where $N_j$ is the number of stress cycles due to the $j^{th}$ truck passage, and $S_{re}^j$ is the equivalent stress range of the stress cycles by the $j^{th}$ truck.

After counting the number of stress cycles at different stress range levels using the rainflow counting method, fatigue damage increment $\Delta D_i = \sum n_j / N_j$ in the blocks of stress cycles can be obtained. When the fatigue damage variable $D$ increases to 1, a fatigue failure is expected. In the probabilistic approach, a limit state function (LSF) needs to be defined first in order to ensure target fatigue reliability [19]:

$$g(X) = D_f - D_i$$  \hspace{1cm} (17)

where $D_f$ is the damage to cause failure and is treated as a random variable with a mean value of 1; and $g$ is a failure function such that $g<0$ implies a fatigue failure. The accumulated damage at the end of stress block $i$ is

$$D_i = D_{i-1} + \Delta D_i$$  \hspace{1cm} (18)

and $\Delta D_i$ is the fatigue damage increment at stress block $i$. In the present study, the target reliability index $\beta$ is chosen as 1.65, which corresponds to a 5% failure probability or a 95% survival probability [16].

For fatigue assessment, all the random variables in the LSF for predicting fatigue reliabilities are assumed to follow certain distributions. $D_f$, the accumulated damage at failure, is considered as a random variable. Its mean and COV value is assumed as 1.0 and 0.15, respectively. The COV value are chosen to ensure that 95% of variable amplitude loading tests have a life within 70-130% (±2 Standard deviation) of the Miner’s rule prediction [19]. The present study is concerned with the fatigue cracks that may develop at the longitudinal welds located at the conjunction of the web and the bottom flange at the mid-span, which falls into fatigue detail Category B [2]. When the fatigue detail coefficient $A$ is assumed to follow a lognormal distribution, the mean and COV are calculated based on the test results of welded bridge details. Based on the tests performed by Keating and Fisher [18], the mean and COV are calculated as $7.83\times10^{10}$ and 0.34. $S_w$, the revised equivalent stress range, is calculated for given combinations of vehicle speed and road roughness condition. In the present study, the chi-square goodness-of-fit test is used to check the distribution type of the parameter $S_w$ for each combination of vehicle speed and road roughness condition. Both normal and lognormal are acceptable for revised equivalent stress range $S_w$ based on the Chi-Square test.

Based on the assumption that all the variables (i.e. $A$, $D_f$ and $S_w$) follow a certain distribution, the fatigue reliability index is obtained using the method in the literature (Estes and Frangopol 1998). Based on such a method, an arbitrary initial design point can be chosen and the solving process for the complex equation of $g()=0$ can be avoided. After several iterations, convergence can be achieved without forcing every design points to fall on the original failure surface.

Fatigue reliability indices are listed in Fig. 4 (b). Generally, the fatigue reliability indices are found to decrease with the increase of vehicle speed and road roughness coefficient. If a 5% failure probability, i.e., a 95% survival probability is assumed, the corresponding reliability index is 1.65 [16]. The reliability index in all the thirty cases is larger than the target index of 1.65. Accordingly, the survival probability of all the thirty cases is larger than 95%. It clearly indicates the effects of the vehicle speed and the road surface condition on the fatigue lives. In general, the higher vehicle speed, the smaller reliability index and the higher probability of failure the structure will have in most cases. The road condition makes significant changes to the reliability index and results in a
change from zero to more than 10. The change in the reliability index due to the vehicle speed was found to be less but still cannot be neglected.

![Figure 4 Results for short span bridges](image)

Calibration of Impact Factor for Existing Bridges

Displacement-based dynamic load allowance (IM)

Impact factors of existing bridges may be significantly different from code specified values. Therefore, in the present study the impact factor of existing bridges is calibrated through a reliability approach. The following design equation, recommended by the current LRFD code [2] for considering situations with only dead loads and vehicle live loads, was used in the calibration process.

\[
\phi R \geq 1.25 DC + 1.50 DW + 1.75 L_L + 1.75(1 + IM)L_L
\]

(19)

where \( R \) = nominal value for the resistance, \( DC \) = effects due to design dead loads excluding the weight of wearing surface, \( DW \) = effects due to wearing surface weight, \( L_L \) = effects due to design lane load, \( IM \) = effects due to the most demanding between truck and tandem load, and \( \phi = resistance factor \). For prestressed-concrete bridges, the current AASHTO LRFD code suggests a resistance factor of 1.0 and 0.85 for moment and shear, respectively, based on the study by Nowak [20].

In order to calibrate the impact factors for existing bridges, a group of seven prestressed concrete girder bridges were selected as benchmark bridges in this study. The detailed configurations and properties of the seven prestressed concrete girder bridges are described by Deng and Cai [3]. By assuming certain statistical properties of the impact factors under different road surface conditions (RSCs) and explicitly modeling the \( IM \) as an individual random variable, calibrations can be performed with respect to different RSCs [21].

The proposed \( IM \)s have been chosen with the aim of balancing three different needs, i.e., (1) obtaining reliability indices consistent with the target reliability index of 3.5 for all bridges under any RSC, (2) ensuring as much as possible consistency with the AASHTO LRFD code [2], and (3) minimizing the modifications to the \( IM \) values suggested by the AASHTO LRFR manual (2003).

Table 2 provides, for all the RSCs considered, (1) the minimum values of \( IM \) required to reach the target reliability index of 3.5 for both moment and shear strength limit states for all the bridges considered here, (2) the proposed values of \( IM \) for rating of existing bridges, and (3) the values of \( IM \) proposed by Deng and Cai in a previous study [3]. From Table 1, it is observed that the \( IM \)s proposed in the present study are close to those proposed in Deng and Cai [3], except for the case of very poor RSC.
Table 1. Comparison between the proposed dynamic load allowance IMs in the present study and those by Deng and Cai [3]

<table>
<thead>
<tr>
<th>Road Surface Condition</th>
<th>Deng and Cai [3]</th>
<th>Present study</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Proposed IMs</td>
<td>Theoretical Minimum IMs</td>
</tr>
<tr>
<td>Very Poor</td>
<td>1.99</td>
<td>2.50</td>
</tr>
<tr>
<td>Poor</td>
<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>Average</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>Good</td>
<td>0.33</td>
<td>0.15</td>
</tr>
<tr>
<td>Very Good</td>
<td>0.23</td>
<td>0.05</td>
</tr>
</tbody>
</table>

To verify whether the proposed IM can lead to a consistent reliability index of 3.5 for all RSCs, the reliability indices are recalculated for the seven bridges designed following Eq. (19) while employing the proposed IM values. These results confirm that using the proposed IM values produce more consistent reliability indices that are very close to the target reliability index of 3.5, regardless of what the actual RSC is.

It is noteworthy that, when the RSC is below average, the proposed IM values are greater than the value of 0.33 suggested by the current LRFD code. In particular, the IM value proposed for very poor RCS is significantly larger than 0.33 (i.e., more than seven times larger). Since a significant portion (i.e., more than 17%) of all bridge decks in the United States belong to fair or worse RSCs, it is concluded that the use of different IMs, which account for the different RSCs, is necessary for accurate performance evaluation of existing bridges.

Stress-based dynamic amplification factor (DAFS)

Due to varied dynamic amplification effects in different regions, the calculated live load stress ranges might not be correct if the IM is used for the fatigue design. Based on an example presented by Billing[22], the difference of the fatigue life estimation could be as large as 29% if the maximum displacement based dynamic amplification factor is used to predict fatigue life of existing bridges. In this part, the dynamic amplification factor on stress ranges (DAFS) is defined and a parametric study of the DAFS in the life cycle is carried out.

Since each truck passage might induce multiple stress cycles, two correlated parameters are essential to calculate the fatigue damages done by each truck passage, i.e. the equivalent stress range and the number of stress cycles per truck passage. On a basis of equivalent fatigue damage, a revised equivalent stress range, $S_{wn}$, is used to combine the two parameters for simplifications; namely, the fatigue damage of multiple stress cycles due to each truck passage is considered as the same as that of a single stress cycle of $S_w$ [13]. The live load stress range is a random variable. For the convenience of fatigue analysis, a nominal live load stress range, $S_{wn}$, is defined corresponding to a reliability index $\beta$ of 3.5, typically used in AASHTO LRFD [2]. In other words, the probability of $S_{wn}$ not being exceeded by the real live load stress ranges corresponds to the reliability index of 3.5. The nominal live load stress range is predicted based on 20 randomly generated road profiles for the given vehicle speed and road roughness coefficient. If the cumulative distribution functions of the live load stress range are defined as $F$, the nominal live load stress range, $S_{wn}$, can be calculated as:

$$S_{wn} = F^{-1}\left[\Phi(\beta)\right]$$

where $\Phi(\cdot\cdot\cdot)$ denotes the standard normal cumulative distribution function.

The reliability based dynamic amplification factor on revised equivalent stress ranges (DAFS) can be defined and obtained as:
DAFS = \frac{S_{\text{cin}}}{S_{\text{st}}} \tag{21}

where $S_{\text{st}}$ is the maximum static stress range due to the passage of the live loads without considering the dynamic effects.

In order to appreciate the difference of the proposed DAFS and traditional DAF, the calculated fatigue lives from six different approaches are compared with each other for the same target reliability index $\beta=3.5$. The DT-DAF corresponds to the AASHTO LRFD [2] deterministic fatigue analysis methodology. The DT-DAFS is the same as DT-DAF except using the proposed DAFS to replace the DAF. In the PB-DAFS and PB-DAF approaches, a probabilistic fatigue analysis is conducted based on a limit state function, using the deterministic DAFS and DAF, respectively. For the purpose of comparison, in the PB-SWE and PB-SWM approaches, instead of using the developed deterministic DAFS and DAF, the equivalent stress ranges are treated as random variables in the limit state function. The PB-SWE approach includes all the stress ranges in one vehicle-passing-bridge analysis, while only the maximum stress range is included in the PB-SWM approach.

While DAF only reflects the largest stress amplitude during one vehicle passing on the bridge, DAFS includes the fatigue damages from multiple stress range cycles due to each vehicle passage. The DAF is less than the DAFS and leads to an overestimation of fatigue life. Correspondingly, the fatigue lives using the DAF are overestimated to a scale of 3 to 4 compared with that using the DAFS. Based on the PB-SWE approach, the fatigue life of all the 84 cases with varied faulting days, speed limits, COV of vehicle speeds, and truck distributions are calculated and shown in Fig. 5. Correspondingly, the fatigue lives obtained through the approaches of PB-DAFS and DT-DAFS are plotted in the figure, as well. The fatigue lives decrease with the increase of the DAFS for the approaches of PB-DAFS and DT-DAFS. All the data sets obtained from PB-SWE approach are in-between the results from the PB-DAFS and DT-DAFS approaches. The large differences between the two methods (DT-DAFS and PB-DAFS) originate from the load factor $\gamma$. In AASHTO LRFD [2], the load factor $\gamma$ is to reflect the load level found to be representative of the truck population with respect to a large number of return cycles of stresses and to their cumulative effects. Since the truck distribution and varied stress cycles for different trucks have been considered in the present study, the load factor $\gamma = 0.75$ is not necessary in the DT-DAFS approach. The recalculated results for $\gamma = 1.0$ are labeled as DT-DAFS-COF in the figure and they are much closer to those of PB-DAFS.

![Figure 5 Fatigue life versus DAFS](image)
Summary

This paper summarizes the recent work by the first author’s research group related to the performance evaluation of existing bridges under vehicle dynamic effects. Based on the data from short-term monitoring of existing bridges, a framework to estimate the extreme structure responses from the live load in a mean recurrence interval is developed in the first part. The Gumbel distribution of the extreme values was derived from an extreme value theory and Monte Carlo Simulation. In the second part, a framework of fatigue damage and reliability assessment for existing bridges is presented to include the effects of the progressively deteriorated road conditions and random dynamic vehicle loads in a bridge’s life cycle. The random effects of vehicle speed and type, road profiles, and stress ranges are included. Studies have shown that the vehicle-induced dynamic allowance IM value prescribed by the AASHTO LRFD code may be underestimated under poor road surface conditions (RSCs) of some existing bridges. In addition, multiple dynamic stress ranges induced by vehicles cannot be included in the maximum displacement-based dynamic allowance IM values. In the third part of this paper, the reliability indices of a selected group of prestressed concrete girder bridges are calculated by modeling the IM explicitly as a random variable for different RSCs. Nevertheless, a reliability based dynamic amplification factor on stress ranges (DAFS) for fatigue design is proposed to include the fatigue damages from multiple stress range cycles due to each vehicle passage at varied vehicle speeds under various road conditions in the bridge’s life cycle.

References


