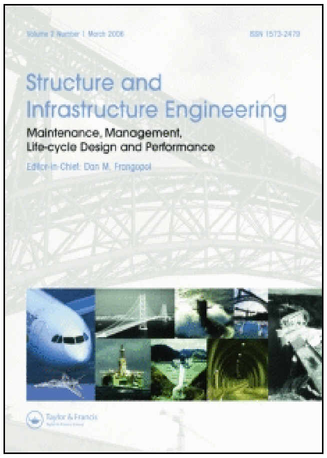

Structure and Infrastructure Engineering
Maintenance, Management, Life-Cycle Design and Performance
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713683556

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First Published on: 28 October 2006
To cite this Article: Bhattacharya, B., Li, D. and Chajes, M. (2006) 'Bridge rating using in-service data in the presence of strength deterioration and correlation in load processes', Structure and Infrastructure Engineering, 4:3, 237 - 249
To link to this article: DOI: 10.1080/15732470600753584
URL: http://dx.doi.org/10.1080/15732470600753584

Structure and Infrastructure Engineering, Vol. 4, No. 3, June 2008, 237 – 249

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Bridge rating using in-service data in the presence of strength deterioration and correlation in load processes

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(*Received 9 June 2005; accepted in revised form 12 April 2006*)

This paper presents a probability-based methodology for load rating bridges that can accommodate detailed site-specific in-service structural deterioration and response data in a load and resistance factor rating (LRFR) format. The use of site-specific structural response allows the elimination of a substantial portion of modelling uncertainty in live load characterization. Inclusion of structural ageing allows the bridge owner the choice to rate for longer intervals than, say, the usual two-year inspection cycle. This methodology allows the live load-effect sequence on bridges to be statistically stationary with a weakened mixing-type dependence that asymptotically decreases to zero with increasing separation in time, instead of making the common assumption of independent and identically distributed sequences of live loads. In addition, uncertainties in field measurement, modelling uncertainties and Bayesian updating of the empirical distribution function are considered to obtain an extreme value distribution of the time-dependent maximum live load. Gross section loss due to corrosion occurring with a random rate governed by an exponentiated Ornstein-Uhlenbeck type stochastic noise is considered. An illustrative example utilizes in-service peak strain data from ambient traffic collected on a high-volume steel girder bridge. In-service load and ageing resistance factor rating (ISLARFR) equations corresponding to plastic collapse of critical girder cross-section over a range of service lives are developed.

Keywords: Bridge rating; Extreme value analysis; Extremal index; Stochastic process; Structural reliability; Corrosion

1. Introduction

As bridge infrastructures age throughout the world, more and more bridges are being classified as 'structurally deficient.' Unfortunately, due to limited financial resources, bridge owners are not able to immediately repair or, if needed, replace all of the structurally deficient bridges in their inventory. As a result, methods for accurately assessing a bridge's true load-carrying capacity are needed so that the limited resources can be spent wisely.

When a bridge is designed, the behaviour of the as-built bridge, as well as the nature of the site-specific traffic, can only be estimated. Many secondary sources of stiffness and strength are either neglected in design or are difficult to compute. The calibrated load and resistance factors in the AASHTO LRFD (load and resistance factor design) Specifications (AASHTO 1994) are thus, by necessity, conservative. Also, the condition of a bridge at any future time is likely to be different from the as-built condition due to aging. Incorporation of aging effects in future bridge ratings is commonly not performed quantitatively. Rather, aging effects are incorporated using primarily qualitative information gathered during visual inspections. Nevertheless, inclusion of accurate time-dependent structural

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Structure and Infrastructure Engineering
ISSN 1573-2479 print/ISSN 1744-8980 online © 2008 Taylor & Francis
http://www.tandf.co.uk/journals
DOI: 10.1080/15732470600753584

aging description in the rating methodology would allow the bridge owner the choice to rate for longer intervals than, say, the usual two-year inspection cycle and, as has recently been suggested by JCSS (2001), to develop more rational and economical maintenance strategies.

When load rating a bridge, the best model is the bridge itself. By monitoring the bridge, one can gather in-service traffic and performance data and conduct in-service evaluations. The Manual for Bridge Rating through Load Testing (NCHRP 1998) was published as an outcome of NCHRP Project 12-28(13)A (NCHRP 1987). This manual provides *deterministic* methods for determining bridge capacities based on field testing and the quantification of site-specific bridge behaviour. Most recently, NCHRP Project 12-46 (NCHRP 1999b) has led to the development of a Load and Resistance Factor Rating (LRFR) Manual that is consistent with the LRFD Specifications. Like the LRFD Specifications, the evaluation procedures developed are probability based, and like LRFD, LRFR specifications are still based on design parameters and non-site-specific data. Nevertheless, they do open the door for using site-specific information to load rate bridges. For example, the manual discusses the use of weigh-in-motion data to calibrate site-specific live-load factors (NCHRP 2001).

It may be relatively time consuming and expensive to inspect and instrument every bridge in a jurisdiction's inventory. If in-service response from a limited number of sites can be deemed representative of a larger suite of bridges, the rating factors can be 'optimized' for the entire suite of bridges (similar to the principle applied in LRFD and LRFR), and bridge owners may determine the safety of bridges in their inventory using such optimized rating equations.

This paper presents a probability-based methodology for load rating bridges using site-specific in-service structural response data in an optimized LRFR format. Possible dependence in the loading process as well as gross section loss due to corrosion are considered.

1.1 *Properties of bridge rating*

As detailed in Bhattacharya *et al.* (2005), bridge rating should ideally use site- or region-specific data and should account for uncertainties in strength (including aging) and loads over the rating interval. Following the LRFR lead and using peak live-load strain data from an instrumented bridge incorporating new sensor technology, a reliability-based rating methodology, referred to as In-Service Load and Aging Resistance Factor Rating (ISLARFR), has been developed to yield a bridge rating that satisfies the above three criteria. The in-service data acquisition procedure requires a minimum of equipment, no load truck, and no traffic restriction. By measuring actual structural response, the method accounts for both site-specific traffic and as-built bridge response.

As in LRFD and LRFR, the scope of this paper is restricted to assessment of structural *components* (as opposed to the *system*), and the focus is on flexural behaviour, although the methodology can be easily extended to other individual limit states such as shear if relevant. Gross section loss due to random corrosion of steel has been included in the methodology. Distribution of the yearly maximum live load-effect is projected from the in-service data using extreme value theory. Dependence in the loading process has also been considered. Furthermore, since this method uses the actual load-effect data instead of vehicle weights, it eliminates a substantial portion of the modelling uncertainty that is commonly associated with live load characterization (e.g. that related to truck weight statistics, dynamic impact and girder distribution factors). Therefore, the resulting bridge ratings are expected to be more accurate than present methods. A bridge that rates above 1.0 using the present method will not require any (new) load restrictions for the entire duration for which the rating equation is valid provided the following are satisfied: (i) traffic observed during in-service measurement reflects the true traffic pattern, (ii) vehicles do not become significantly heavier over the years, and (iii) the target reliability for the limit state under consideration is acceptable. Application to permit vehicles will require additional procedures.

The time-dependent component reliability model described in this paper can subsequently be incorporated in an appropriately formulated systems reliability analysis, but will require additional work. In addition to the components having adequate reliability, the *system* reliability too must meet its target value – a target that is commensurate with the consequences of system failure. System reliability computation should account for load sharing, load path dependence, load redistribution after initial member failures for redundant structures, non-linear behaviour and non-brittle failure of the components, and possible statistical dependence among the basic variables.

1.2 *In-service strain measurement system*

The proposed ISLARFR methodology uses a recently developed in-service strain monitoring system (Shenton III *et al.* 2000). The system, which is analogous to a weigh-in-motion system, is used to measure peak live-load bridge strains due to site-specific traffic over extended periods of time. The prototype system consists of a digital data acquisition system, a full-bridge strain transducer, a battery pack, and an environmental enclosure. The single-channel system was assembled from specially modified instruments, off-the-shelf components, and custom-fabricated parts. The data acquisition system consists of a specially modified Snap Shock Plus^{TM} (SSPM4), manufactured by

Instrumented Sensor Technologies. The SSPM4 is small and weighs only 204 g. It is powered by a single 9 volt battery and has an on-board microprocessor, a 16 kilobyte EEPROM memory, a 12 bit Analogue-to-Digital converter, and a serial communication link. Strains are measured using an Intelliducer^{TM} strain transducer, manufactured by Bridge Diagnostics Inc. This sensor requires a regulated 5 volt excitation and is powered by a 9 volt battery pack. The entire system, including the SSPM4, 5 volt regulator, and 9 volt battery pack, fits in a $150 \times 150 \times 100$ mm environmental enclosure. The system continuously digitizes an analogue signal at 1200 Hz, and when a pre-specified strain threshold is exceeded, the system evaluates the response and records the time at which the event took place, the peak strain during the event, and the area under the strain-time curve. The system can operate unattended for over two weeks and can store up to 1475 data records (events). In this research, only the peak strain during an event and its time stamp are used. We admit that for steel girders and slab bridges it may not always be possible to ascertain from the observed strain data if they are a result of a bridge acting compositely or noncompositely. Compositely-designed bridges are generally assumed to act compositely unless load tests show otherwise. Many noncompositely-designed bridges, however, may act compositely under service loads, but the composite action is likely to be lost near failure load (Bakht and Jaeger 1990). However, we do not account for any loss of composite behaviour at high loads in this paper.

2. Bridge performance function in the presence of aging

It is common knowledge that bridges lose strength as they age. The deterioration may be due to accidents, overweight vehicles or cumulative physical/chemical processes. In this paper, we consider deterioration only in the form of general corrosion, although the methodology will be found general enough to apply to other slow degradation mechanisms such as high-cycle fatigue. Application to pitting corrosion may require additional considerations due to the potentially rapid rate of pit growth and the highly local nature of pit damage.

Atmospheric corrosion of bridge members depends both on the macro-environment, which refers to the general atmosphere at and around the bridge, and on the micro-environment, which refers to localized conditions (such as leaky expansion joints) which might considerably alter the deterioration due to just the macro-environment. Rural environments are not very aggressive towards steels because of the absence of corrosive agents like salt, sulphur oxides, etc. while urban and industrial environments contain all of the above that, along with moisture, promote the corrosion of steel. The losses from corrosion are even higher in marine environments because of salt spray, humidity, winds, and daily temperature fluctuations (NCHRP 1987).

General corrosion loss as a function of time t, $C(t)$, can be modelled most simply as a power law: $C(t) = At^B$ (Komp 1987). The exponent B assumes the value of 0.5 if the process is purely diffusion controlled. In general, A and B are random variables, possibly correlated, and account for noise in the observed data. This model can be generalized by incorporating a random initiation time (T_I) as in Ellingwood *et al.* (1996):

$$C(t) = A(t - T_I)^B, \quad t > T_I, \tag{1}$$

where T_I accounts for the time to activate the corrosion process due to breakdown of protective paint or oxide coatings for example. Since the above models produce perfectly dependent sample functions (meaning that at any two instants t_1 and t_2, the values $C(t_1)$ and $C(t_2)$ are statistically completely dependent, as each is completely determined by the initial values of A, B and T_I), and may appear unrealistic in some situations, they can be generalized by an additive noise, $\varepsilon(t)$, to yield models of the type $C(t) = At^B + \varepsilon(t)$ (as reviewed by Melchers (2003)) such that the future growth of corrosion still has some uncertainty even if the process up to the present instant is known. The noise term is most commonly taken to be an independent, stationary and zero-mean Normal sequence.

Simple additive noises particularly of the Gaussian type, however, have the potentially undesirable consequence of turning the rate or the process negative, which for corrosion loss, is inadmissible. We therefore propose a new model for corrosion rate that incorporates a multiplicative noise term ensuring that the corrosion loss function is non-decreasing in time:

$$\frac{dC}{dt} = \begin{cases} 0, & t \le T_I \\ \beta(t - T_I)^{\gamma} e^{\eta(t)}, & t > T_I \end{cases}, \tag{2}$$

where β and γ are random parameters independent of time. We would like the exponentiated noise, $\eta(t)$, to have the following desirable properties: (i) it should be zero-mean and be symmetric about the mean so that the classical power law form would produce the median rate, (ii) it should be stationary in time so that it reflects the same type of environment, and (iii) it allows dependence in the rate at different times so that the dependence decreases with increasing separation in time. These properties are satisfied if $\eta(t)$ is an Ornstein-Uhlenbeck process following the Langevin equation of the type:

$$\frac{d\eta(t)}{dt} = -k\eta(t) + \sqrt{D}\xi(t), \tag{3}$$

where k and D are constants and $\xi(t)$ is the white noise. The process $\eta(t)$ quickly becomes stationary with mean zero (if the initial state is zero) and variance $D/(2k)$. The stationary autocorrelation function at lag τ is $\exp(-k\,|\,\tau\,|)$ such that the correlation length of the stationary process is $1/k$ (Gardiner 2004). Since corrosion loss directly affects the strength of structural members, the time-dependent strength, $R(t)$, of a critical cross-section can be conveniently expressed as:

$$R(t) = R_0 f[C(t)] = R_0 G(t), \tag{4}$$

where R_0 is the initial strength and $G(t)$ is a non-increasing dimensionless stochastic process describing the degradation in strength with time normalized by the initial strength. Along with the strength of a structural component, the live load-effect, L, on it is also a time-indexed random process. Vehicle loads on a bridge can be approximated as random pulses. Therefore, the time-dependent limit state equation for a bridge component can be expressed as:

$$R(\tau) - D - L(\tau) = 0 \quad \text{for } \tau \in [0,\, t]. \tag{5}$$

We ignore load combinations involving earthquakes, wind, etc. and concentrate only on traffic loading in this paper. The random dead load-effect, D, is generally assumed not to vary with time. The cumulative failure probability, $P_f(t)$, over an interval $[0, t]$, or its complement the time-dependent reliability function, $\mathrm{Rel}(t)$, is given by

$$P_f(t) = 1 - \mathrm{Rel}(t) = P[R(\tau) - D - L(\tau) \le 0 \quad \text{for any } \tau \in [0,\, t]]. \tag{6}$$

Evaluation of the first passage probability in equation (6) is involved but can be simplified by using the property in equation (4) that sample functions of $R(\tau)$ are non-increasing in time. The failure probability in that case can be conservatively estimated as:

$$P_f(t) = 1 - \mathrm{Rel}(t) \le P\left[\bigcup_{i=1}^{n} R_i - D - L_{\max,i} \le 0\right] \quad \text{for } 0 = \tau_0 < \tau_1 < \tau_2 < \cdots < \tau_n = t, \tag{7}$$

where $R_i = R(\tau_i)$ and $L_{\max,i}$ is the maximum live load-effect on the bridge during (τ_{i-1}, τ_i). Please note that for each interval (τ_{i-1}, τ_i), this choice of the 'representative' resistance as the value at the right end point of the interval is conservative. The degree of conservatism depends on the number of intervals, n, and on the rate of degradation over those intervals (τ_{i-1}, τ_i).

Since live load-effects are measured directly as strain, it is convenient to consider the above strength limit state in the strain domain as well. Therefore, the variables R_i, D and $L_{\max,i}$ are expressed in terms of strain throughout this paper. As long as the structural response is elastic, this formulation is completely equivalent to the more common flexural moment based approach, although a correction is needed for the inelastic domain as discussed later. The time-dependent nature of the resistance has been discussed above and in the following section, a statistical description of $L_{\max,i}$ is developed.

3. Distribution of maximum live load-effects

We define a 'loading event' as the passing of one vehicle or the simultaneous passing of more than one vehicle over the bridge. The loading events constitute a marked ordinary point process, $N(t)$, where the marks are the peak strain responses $L_1, L_2, \ldots, L_{N_t}$ in which N_t denotes the number of events during the interval $[0, t]$. It should be noted that the marks are random in nature, and the number of events, N_t, is a random variable as well. We assume that the peak strains are caused by a truck population whose characteristics do not evolve over time, and that traffic pattern, loading and volume have memory (i.e. statistical dependence) in the short term. However, we assume that the dependence falls off with increasing separation in times of occurrence.

The above assertions are formalized as follows. The loading sequence $\{L_n\} = \{L_1, L_2, \ldots\}$ constitutes a strictly stationary but dependent sequence with common marginal distribution F (also called the parent distribution). Let M_n denote the maximum of the sequence $\{L_n\}$. The dependence structure of $\{L_n\}$ is such that the well-known Leadbetter's 'Conditions $D(u_n)$ and $D'(u_n)$' are satisfied (u_n represents a sequence of increasing thresholds) (Leadbetter *et al.* 1983). Condition $D(u_n)$ ensures that groups from the sequence $\{L_n\}$ become asymptotically independent (in the statistical sense) with increasing separation between the groups. The Condition $D'(u_n)$ limits the possibility of clustering of very large values.

It can then be shown that the asymptotic distribution of M_n has only three possible forms that are identical to the three classical extreme value distribution types, H_c (the *classical* case arises from a sequence of statistically independent and identically distributed (i.i.d.) random variables). The rate of convergence, however, is slower than in the i.i.d. case, and can be quantified using the *extremal index*, θ, of the sequence, defined below. Further, the point process constituting the instants when $\{L_n\}$ exceeds the threshold u_n becomes asymptotically Poisson as n increases. Consequently, the maxima in disjoint time intervals become asymptotically independent as well. Full details of the analytical development is provided in Bhattacharya (2005).

3.1 *The extremal index of the loading process*

The extremal index, θ, of a sequence can be interpreted as the reciprocal of the mean limiting cluster size above high thresholds (Leadbetter *et al.* 1983). θ is a number between 0 and 1, and measures the strength of the dependence in the sequence $\{L_n\}$. Heuristically, $\theta = 0$ corresponds to an infinitely long memory sequence, $0 < \theta < 1$ corresponds to a short memory sequence, and $\theta = 1$ corresponds to a memoryless sequence (Hsing 1993).

It is convenient to introduce the associated sequence $\{\hat{L}_n\}$that is i.i.d. and has the same marginal distribution, F, as the original sequence $\{L_n\}$. Let $\hat{M}_n$ be the maximum of the i.i.d. sequence $\{\hat{L}_n\}$. Classical extreme value theory (e.g. Galambos 1987) gives the well-known result that under suitable normalization and regularity conditions that are satisfied by most common parent distributions, F, the distribution of the maximum $\hat{M}_n$, converges to one of the three classical types, $H_c(z) = \exp[-(1+cz)^{-1/c}]$, $1 + cz > 0$. Here $z = (x - \varepsilon)/\delta$ in which ε and $\delta > 0$ are appropriate location and scale parameters of the distribution. H_c represents the generalized extreme value distribution, in which the parameter c determines the type of the distribution. It is of: (i) Type I (the Gumbel type) if $c = 0$, where H_c is interpreted as the limit $\exp(-\exp(-z))$ as $c \to 0$, (ii) Type II (the Frechet type) if $c > 0$, and (iii) Type III (the Weibull type) if $c < 0$.

It can be shown that if the associated i.i.d. sequence possesses a maximum distribution, then under Conditions $D(u_n)$ and $D'(u_n)$, so does the original sequence $\{L_n\}$. Further, the distribution of M_n converges to the type of H_c^θ, where $\theta > 0$ is the extremal index of $\{L_n\}$:

$$P[M_n \le a_n x + b_n] \to H_c^\theta(z) = \exp\left[-\theta(1+cz)^{-1/c}\right], \quad 1 + cz > 0. \tag{8}$$

The converse is also true. Clearly, H_c and $H_c^\theta$are of the same type for any given value of c. The significance of this result is that the distribution of the maximum M_n of a stationary dependent sequence, provided it converges (which can be guaranteed by Conditions $D(u_n)$ and $D'(u_n)$), may be estimated, at least in the right tail, simply with the help of the marginal distribution F and the extremal index θ of the underlying process. Equation (8) is also significant as it highlights the degree of conservatism that may be introduced by the common and rather indiscriminate engineering practice of assuming a sequence to be i.i.d. when estimating the distribution of its maximum (for details see Bhattacharya (2005)).

Defining $M_{p,q} = \max\{L_p, \ldots, L_q\}$, the runs estimator of the extremal index, $\hat{\theta}_R$, is given by Smith and Weissman (1994) and Weissman and Novak (1998):

$$\hat{\theta}_R(x; r, n) = \frac{\sum_{i=1}^n \mathbf{I}_{B,i}(L_i > x \ge M_{i+1,i+r-1})}{\sum_{i=1}^n \mathbf{I}_{A,i}(L_i > x)}, \quad r \ge 2, \tag{9}$$

in which $\mathbf{I}_{A,i}(\cdot)$ and $\mathbf{I}_{B,i}(\cdot)$ are indicator functions verifying the truth of the respective condition in parentheses. The estimate is basically the reciprocal of the average cluster size above high thresholds (x) in which two consecutive exceedances are part of the same cluster if they are less than r observations apart. Note that $\hat{\theta}_R$ also depends on the run length, r, a parameter that must be chosen with care. As explained in Bhattacharya (2005), we use Vanmarcke's scale of fluctuation, τ_c, as an estimate of the run length, r.

3.2 *Maximum of the associated i.i.d. sequence*

In order to find the distribution of the maximum live load-effect, we first look at the maximum, $\hat{L}_{\max,t}$, of the associated i.i.d. peak strain sequence $\hat{L}_1, \hat{L}_2, \ldots, \hat{L}_{N_t}$. The number of occurrences, N_t, is asymptotically Poisson as mentioned above. Hence, the unconditional distribution of $\hat{L}_{\max,t}$ is:

$$F_{\hat{L}_{\max,t}}(x) = P\left[\hat{L}_{\max,t} \le x\right] = \exp[-\lambda t\{1 - F(x)\}], \tag{10}$$

where λ is the rate of the Poisson process. For large λt, $F_{\hat{L}_{\max,t}}(x)$ approaches one of the classical extreme value distributions (equation (8)); the best fit model may be determined and its parameters estimated by one of several standard methods (Castillo 1988). Effects of additional uncertainties may also be incorporated in equation (10) as described below. The maximum of the actual loading process, $L_{\max,t}$, can then be obtained using the extremal index of the process $\{L_n\}$ as given by equation (8). Uncertainties arising from sampling and measurement errors are discussed next.

3.3 *Sampling and measurement-related uncertainties*

Recall that the parent distribution, $F(x)$, of the peak strains in equation (10) can only be *estimated* from the observed data. Thus, for any given x, the true value of the c.d.f., $F(x)$, is unknown, hence we can describe it as a random variable $P(x)$. The unknown $P(x)$ is estimated from the sample as:

$$\hat{p}(x) \equiv \hat{F}(x) = \frac{1}{n+1} \sum_{k=1}^n \mathbf{I}(L_k \le x). \tag{11}$$

Before any data are collected, let the (prior) probability density function of $P(x)$ be $f'_{P(x)}$. Since the L_ks are stationary, $\hat{p}(x)$ is an asymptotically unbiased estimator of $F(x)$ regardless of the fact that the L_ks form a dependent sequence, although its variance is larger than that in the i.i.d. case. Based on the n observations, $\underline{I}$, of the indicator function $\underline{\mathbf{I}}$, we can perform a Bayesian updating of the probability law of P and obtain its posterior (updated) density function $f''_{P(x)}(p) = f_{P(x)|\underline{\mathbf{I}}=\underline{I}=}(p)$ as:

$$f''_{P(x)}(p) = \frac{1}{C} \mathsf{L}(p; \underline{I}) f'_{P(x)}(p), \tag{12}$$

where C is the normalizing constant, $\mathsf{L}(p;\underline{I}) = P[\underline{\mathbf{I}} = \underline{I}| P(x) = p]$ is the likelihood function, and $f'_{P(x)}(p)$ is the prior probability density function of $P(x)$. $\mathsf{L}(p;\underline{I})$ can be interpreted as the probability of observing *exactly* $k = [(n+1)\hat{p}]$ samples less than or equal to x out of n samples (where $x = F^{-1}(p)$) if the unknown parameter $P(x)$ was indeed equal to p. It can be shown that (Bhattacharya 2005), under Conditions $D(u_n)$ and $D'(u_n)$ and for values of p close to 1, the posterior density of P is of the Beta type, given by:

$$f''_{P(x)}(z;\alpha_1,\alpha_2) = \begin{cases} \frac{1}{\mathrm{B}(\alpha_1,\alpha_2)} z^{\alpha_1-1}(1-z)^{\alpha_2-1}, & 0 \le x \le 1 \\ 0, & \text{elsewhere.} \end{cases} \tag{13}$$

The two parameters α_1 and α_2 are dependent on given values of x and are given by $\alpha_1 = ([(n+1)\hat{p}(x)] + 1)\theta + 1$, $\alpha_2 = (n - [(n+1)\hat{p}(x)])\theta + 1$ where n is the number of observations, and the estimate $\hat{p}(x)$ is given by equation (11). The mean and variance of $P(x)$ can therefore be given by $\alpha_1/(\alpha_1+\alpha_2)$ and $\alpha_1\alpha_2/\{(\alpha_1+\alpha_2)^2(\alpha_1+\alpha_2+1)\}$ respectively. Clearly, the updated mean of $P(x)$ is very close to the estimate $\hat{p}(x)$ regardless of the value of θ; its variance, however, is inversely proportional to the extremal index. In a more sophisticated load analysis (Bhattacharya 2005) the occurrence rate, Λ, may be taken to be a stochastic process resulting in a Cox process model for the load process. Here we find it sufficient to approximate Λ as simply a Normal random variable, as has been demonstrated in Bhattacharya *et al.* (2005).

In light of the above uncertainties, equation (10) can now be restated as the conditional distribution of the maximum of the associated i.i.d. sequence during an interval of length t given fixed values of the parent distribution, rate of occurrence and location error: $F_{\hat{L}\max,t}(x \mid P = p, \Lambda = \lambda) = \exp(-\lambda t(1-p(x))$. The unconditional distribution of the associated i.i.d. sequence, $\hat{L}_{\max,t}$, may be obtained as,

$$F_{\hat{L}\max,t}(x) = \int_b \int_p \int_\lambda \exp(-\lambda t(1-p(x)) \times f_\Lambda(\lambda) f''_{P(x)}(p)\ d\lambda\ dp, \tag{14}$$

which may be estimated numerically using Monte-Carlo simulations.

4. Development of rating equations for a suite of bridges

In terms of LRFR methodology (NCHRP 1998), the rating factor (RF) for an existing bridge is

$$\mathrm{RF} = \frac{\phi R_n - \gamma_D D_n}{\gamma_L Q_n}, \tag{15}$$

where R_n is the nominal resistance, D_n and Q_n are the nominal (or characteristic) values of dead and live load-effects respectively, ϕ is the resistance factor, and γ_D and γ_L are the load factors for rating. Elastic buckling is generally not encountered in bridge flexural members, hence, for the first yield limit state the nominal strength, R_n, is equal to the nominal yield strength, Y_n. For the plastic collapse limit state, the nominal resistance is $R_n = f_p Y_n$, where f_p is an amplification factor accounting for post-yield reserve strength. Note that if a bridge is not instrumented its nominal live load, Q_n, needs to be estimated indirectly. Note also that because it is a load-effect, Q_n already includes dynamic impact effects.

A reliability-based bridge rating factor could be defined in a variety of ways, such as the ratio β/β_T, where $\beta = \Phi^{-1}$ (Rel) is the reliability index and β_T is its target value (defined in the next section) that would satisfy the desirable features mentioned at the beginning of this paper, as well as equation (15). Nevertheless, the format in equation (15) conforms to current professional practices and was adopted in this paper.

4.1 *Target reliability index for bridge rating*

The target or minimum acceptable reliability, β_T, for a given failure mode is intended to ensure that the structural component under consideration has an adequate level of safety up to the end of a reference period. The target reliability, β_T, used implicitly in LRFD of new bridge components in flexure is 3.5 with a typical design life of 75 years (NCHRP 1999a, 1999b). This value is based on calibration with a representative sample of existing bridges. One should note that when target reliability is *calibrated* to existing service-proven design standards, the results depend upon the method of reliability analysis, the assumptions regarding random variables, the mechanistic model, etc.

For evaluating existing bridges, a value of $\beta_T = 2.5$ corresponding to typical inspection intervals of 5 years has been suggested (NCHRP 1998, Ghosn 2000) mainly from economic considerations. It was argued that the marginal cost of increasing bridge reliability *before* construction (i.e. at the design stage) is small compared to that for an *existing* bridge (through repair/rehabilitation). Since the total expected cost over the *remaining* life of the bridge has to be minimized in this case, the revised optimal target reliability would be clearly lower than that in a new design in this approach.

In-service bridge rating at two different levels has been proposed for bridge structural components in Bhattacharya *et al.* (2005) such that bridge owners may choose either one or both to rate their bridges. The first level corresponds to a *first yield* limit state for a reference period not exceeding 2 years with $\beta_T = 2.5$, and the second level corresponds to *plastic collapse* (i.e. *ultimate* limit state) over any duration up to the end of service life with $\beta_T = 3.5$. Since we are concerned with failure of aging bridges here, the relevant limit state in this paper is the *ultimate* one with a target reliability index of 3.5.

4.2 *Optimum load and resistance rating factors*

As in LRFD where a design equation is optimized for a suite of bridges, the rating equation should preferably be valid for at least a sizeable fraction of a given bridge inventory. The series of limit state equations (7) can be normalized by the rating equation (15) to yield the cumulative failure probability as:

$$P_f(t) = 1 - \mathrm{Re\,l}(t) = \Phi[-\beta(t)] = P\left[\bigcup_{i=1}^{n}\left\{\frac{X_{1,i}}{\phi} - \frac{X_2 + \left(\frac{Q_n}{D_n}\right)X_{3,i}}{\gamma_D + \left(\frac{Q_n}{D_n}\right)(\mathrm{RF})\gamma_L} \le 0\right\}\right], \qquad (16)$$

where $\beta(t)$ is the equivalent time-dependent reliability index. As stated before, this series decomposition of a time-continuum problem is conservative. However, the degree of conservatism can be controlled by choosing the number, n, and size, $\tau_i - \tau_{i-1}$, of those intervals for the given process of strength degradation. The terms in equation (16) are defined as follows: $X_{1,i}$ is the normalized resistance at time i. For plastic collapse limit state, the initial resistance, $R_0 = F_p Y$, where F_p is the random plastic strength factor and f_p is its nominal value. The normalized resistance at any time i then equals $X_{1,i} = (F_p/f_p)(Y/Y_n)G(t_i)$. The term $X_2 = D/D_n$ is the normalized dead load. Although the *nominal* dead load D_n is usually estimated indirectly, we assume that the estimation-related error is negligible. The normalized maximum live load in the i^{th} interval is given by $X_{3,i} = L_{\max,i}/Q_n$.

Figure 1 shows the scheme for obtaining optimized load and resistance factors (LRFs) for rating a suite of bridges that have statistically similar loading and strength degradation properties. The acceptance criteria used in the optimization procedure are:

$$\begin{aligned} &\min\ \Delta(\phi, \gamma_D, \gamma_L) = \sum_{j=1}^{k} (\beta_j - \beta_T)^2 w_j \\ &\text{subject to:} \\ &\quad RF = 1 \\ &\quad \phi \le 1, \\ &\quad \gamma_L \ge \gamma_D \ge 1, \end{aligned} \qquad (17)$$

where k is the total number of nominal load ratios (Q_n/D_n) in the suite of bridges, and w_j denotes the relative frequency (weight) of the j^{th} nominal load ratio with $\sum_{j=1}^{k} w_j = 1$. The reliability index for each load ratio is a function of $\beta_j = f(RF, \phi, \gamma_D, \gamma_L; (Q_n/D_n)_j)$ as given by equation (16). The constraints on the decision variables, i.e. the LRFs ϕ, γ_D and γ_L, are intended to conform to accepted engineering practices. It should be noted that the optimal LRFs thus obtained are unique to an arbitrary factor in the sense that they could each be multiplied by any arbitrary constant and still yield the same minimum weighted error. The equality constraint $\mathrm{RF} = 1$ (instead of an inequality constraint such as $\mathrm{RF} \ge 1$) ensures that bridges that rate at 1.0 *just satisfy* the target reliability (on the average) such that rating factors above 1.0 indicate reliabilities above β_T and vice versa. The local response surface fit for the objective function, Δ, as depicted in figure 1, is optional but may be found desirable from the numerical efficiency point of view for: (i) smoothing the noise generated by the finite size of the Monte-Carlo sampling, and (ii) cheaply computing the gradient of the objective function.

5. A numerical example of rating an aging bridge using in-service data

The proposed rating procedure is now demonstrated with a brief example involving highway bridges. For this purpose, all highway bridges in the State of Delaware were assumed to constitute the bridge inventory for which the optimal rating equation will be developed. The bridge selected for instrumentation and data acquisition was Bridge 1-791, which is a 3-span continuous, slab-on-steel girder structure carrying two lanes of Interstate-95 over Darley Road in Delaware. In-service strain data were recorded at the midspan of the critical girder of the approach span (beneath the right travel lane) during an approximate 11 day period in August 1998 (figure 2). A trigger level was set at 85 $\mu\varepsilon$ so that only the larger truck events would be recorded. The effect of raising the threshold (in steps up to 160 $\mu\varepsilon$) on the statistical dependence in the loading sequence and the properties of the extreme loads have been studied in Bhattacharya *et al.* (2005) and Bhattacharya (2005).

A histogram of the observed raw data is shown in figure 3, which represents 533 loading events. The data were analyzed to project the probability distribution of daily and yearly maximum load-effects (also shown in figure 3). Gross section loss due to corrosion in an urban atmosphere leading to deterioration in girder sectional modulus was incorporated. Load and resistance factors (LRFs) for rating were derived for the suite of bridges for periods ranging up to 25 years. Needless to say, it is for the purpose of illustration alone that we are relying on only one bridge and only 11 days of data. Developing optimized LRFs for a suite of bridges requires a careful selection of representative bridges and in-service observation windows for deriving live load statistics.

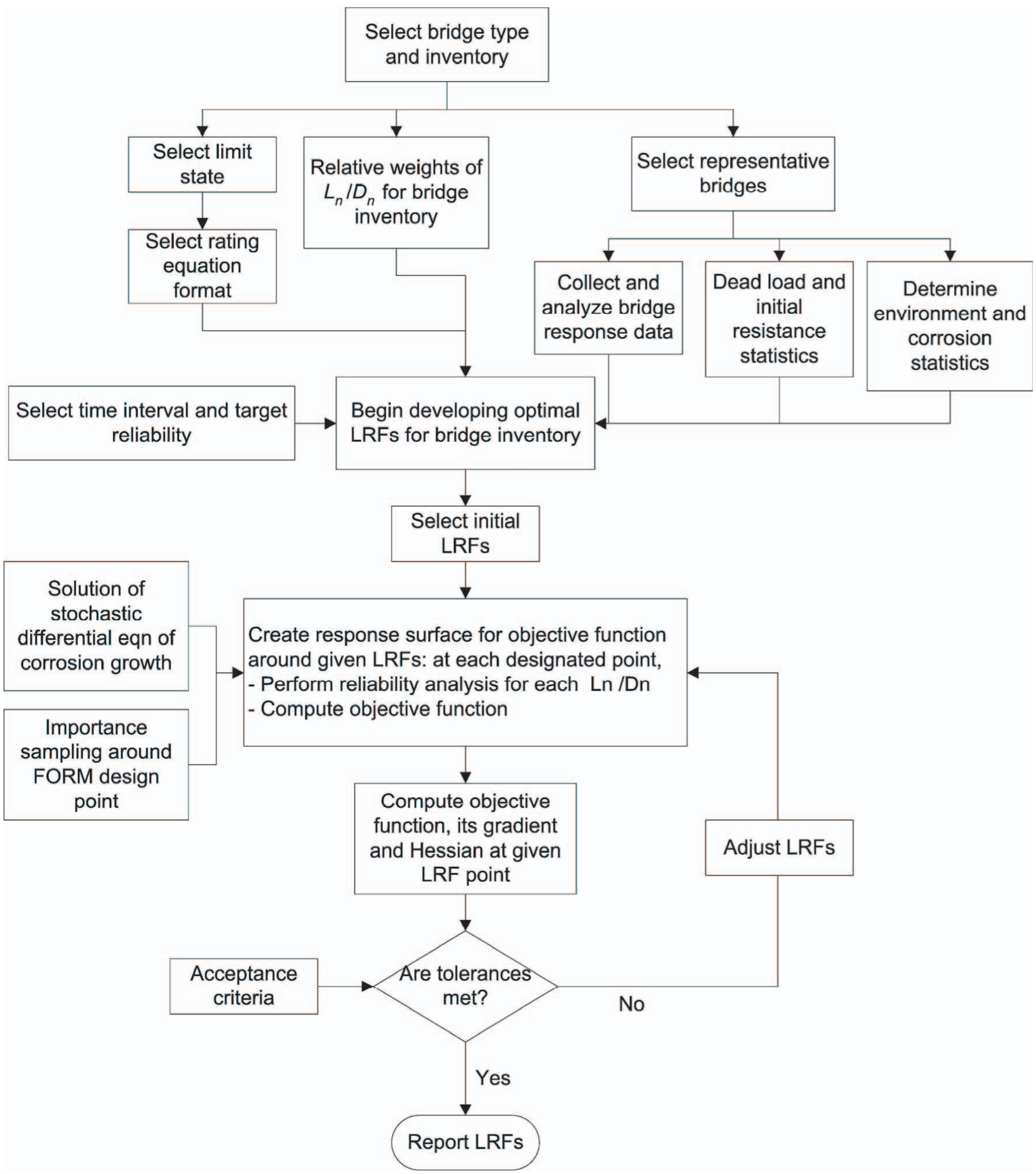

Figure 1. Flowchart for determining optimal load and resistance factors.

5.1 *Random degradation of girder strength*

The corrosion statistics are adopted from the existing literature and not from any in-service inspection. We obtained the properties of the random curve fitting parameters β and γ in equation (2) as follows. Using $\beta = AB$ and $\gamma = B - 1$ (where A and B are as in equation (1)), we adopted the statistics of A and B from Komp (1987). For urban environments, A is normally distributed with mean 80.2 microns and a c.o.v. of 42%, while B is normally distributed with mean 0.593 and a c.o.v. of 40%. The correlation coefficient between A and B is 0.68. We choose a moderate value of 0.05 for the stationary variance of the dimensionless noise in equation (2), the correlation length is taken to be 0.25 years to account for seasonal dependence in the rate of corrosion. The corrosion initiation time T_I is taken to be Lognormally distributed with mean 5 years and a c.o.v. of 30%.

The measure of strength degradation due to the corrosion process described above is taken as the normalized reduction in the plastic section modulus of the critical girder section. The uncorroded plastic section modulus of the steel girder in consideration is 307.1 in^3. Figure 4 shows about 15 sample paths of the stochastic degradation function, $G(t)$.

5.2 *Statistics of maximum live load-effect*

We first estimate the distribution of the maximum load, $\hat{L}_{\max,t}$, during the interval $(0, t]$ of the associated i.i.d.

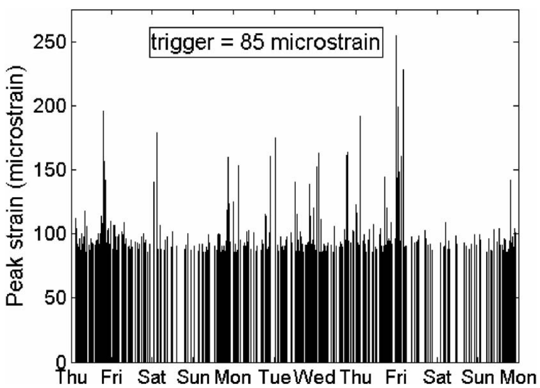

Figure 2. Time-line of loading events spanning 11 days in August 1998 on Bridge 1-791 on I-95.

sequence. Point estimates of the c.d.f., $\hat{p}$, of the load sequence $\{L_n\}$ at nine different strain values (l) are listed in table 1. As is desirable, only the right tail of the parent distribution is used in estimating the distribution of the maximum. A Bayesian updating of the c.d.f. is performed (using equation (13)), and the mean and the c.o.v. of the updated distribution are listed in the table at various values of l. The c.o.v. of P is found to be very small (as a result of the reasonably large sample size and high extremal index), especially at the upper tail, and was considered to be deterministic, i.e. $P \equiv \hat{p}(l)$ for each l. Eleven point estimates of the random arrival rate Λ were available producing a mean of 48.5 events/day and a c.o.v. of 59.0% (Bhattacharya *et al.* 2005). Since the arrival rate is by definition non-negative, a left-truncated Gaussian distribution was used for Λ in the simulations (the truncation point was $\lambda = 0$ corresponding to an original c.d.f. of about 5%). We select the time interval $t = 1$ day. To estimate equation (14) for each value of l, 10000 Monte Carlo simulations were used.

As discussed above, the maximum from an i.i.d. sequence approaches one of the three classical extreme value distributions for largest values for most parent distributions. Of these, the Gumbel (i.e. Type I maximum) and the Frechet (i.e. Type II maximum) distributions were tried for $\hat{L}_{\max,1d}$. The third, Weibull distribution for maxima, was

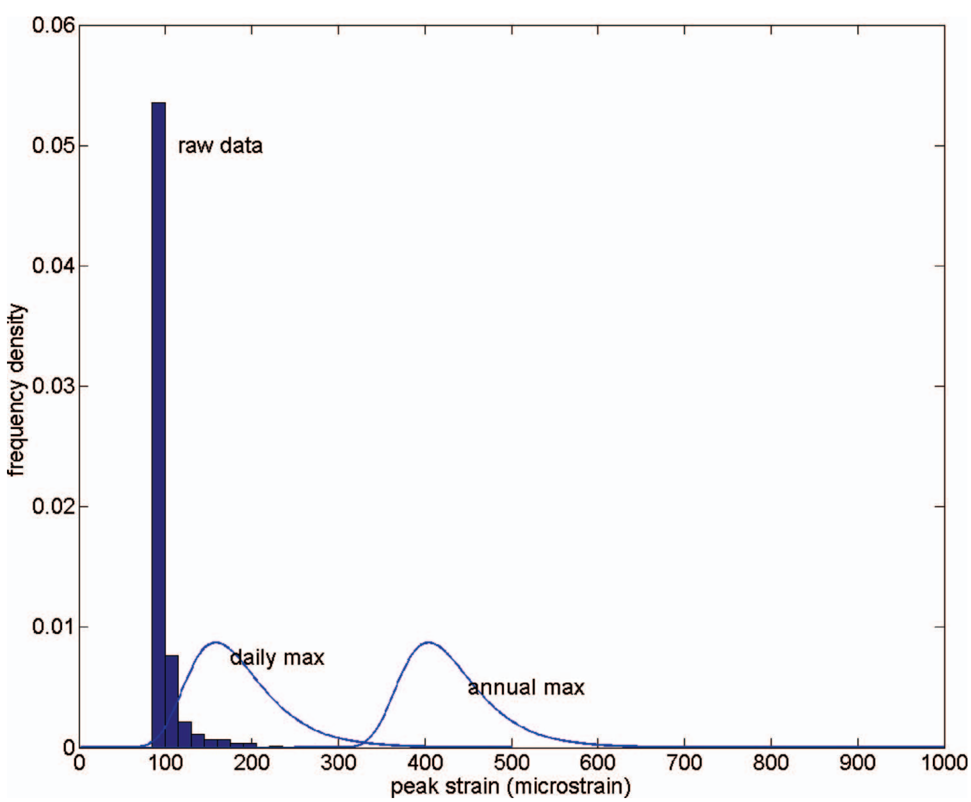

Figure 3. Distribution of observed raw data compared with projected daily maximum live load strain (from the associated i.i.d. sequence) and the projected annual maximum live load strain (from the actual sequence).

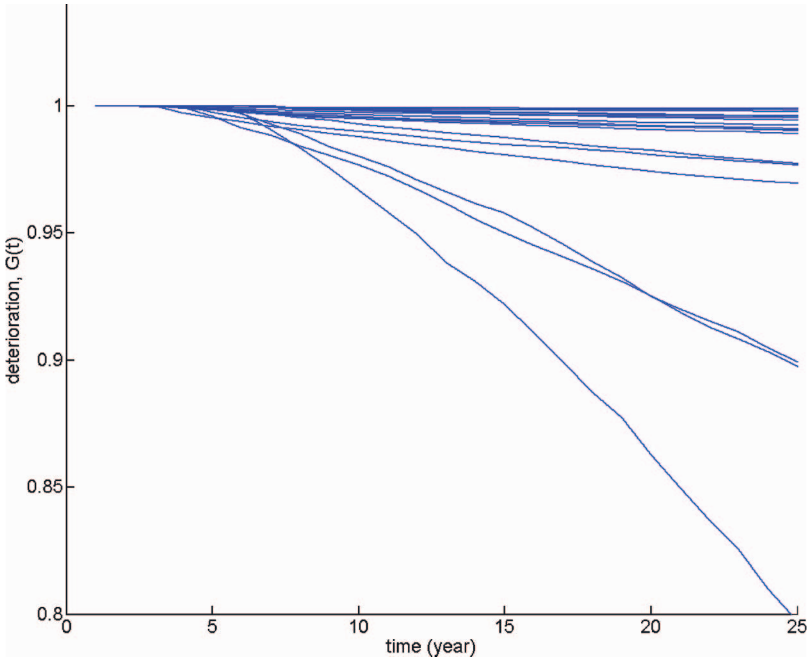

Figure 4. Sample paths of the normalized deterioration function.

Table 1. Estimates of daily maximum peak strain.

Interval ($\mu\epsilon$)	Right endpoint x ($\mu\epsilon$)	Counts (k)	c.d.f. of load-effect: Point estimate $\hat{p}(x) = \Sigma k/(n+1)$	c.d.f. of load-effect: Updated Beta distribution parameters for P: mean	c.d.f. of load-effect: Updated Beta distribution parameters for P: c.o.v.	Predicted max load-effect c.d.f. $F_{L\max,1day}(x)$
<85	85	0	0	–	–	–
85–100	100	428	0.8015	0.8019	2.15%	0.0252
100–115	115	61	0.9157	0.9159	1.31%	0.0776
115–130	130	17	0.9476	0.9477	1.02%	0.1550
130–145	145	9	0.9644	0.9645	0.83%	0.2461
145–160	160	5	0.9738	0.9738	0.71%	0.3354
160–175	175	5	0.9831	0.9832	0.56%	0.4782
175–190	190	3	0.9888	0.9888	0.46%	0.6021
190–205	205	3	0.9944	0.9944	0.32%	0.7674
205–255	255	2	0.9981	0.9981	0.19%	0.9146

not tried here since it is limited on the right, although this property can be attractive in situations where geometric, load posting or other constraints put a clear upper limit on loads that can be placed on the bridge. The Gumbel fit was found to be clearly better in the present case, and was adopted for $\hat{L}_{\max,1d}$ in this paper:

$$F_{\hat{L}_{\max,1d}}(x) = \exp[-\exp(-\hat{\alpha}_{1d}(x - \hat{u}_{1d}))], \quad (18)$$

where $\hat{\alpha}$ and $\hat{u}$ are the scale and mode, respectively, of the maximum of the associated i.i.d. sequence and the subscript denotes the model corresponds to a duration of 1 day. The parameters are estimated as $\hat{\alpha}_{1d} = 0.0237$ and $\hat{u}_{1d} = 158.3$ microstrain.

The extremal index of the loading sequence, $\{L_n\}$, is estimated using equation (9). For a given run length, r, the estimate is found to depend on the threshold, u, according to the nonlinear relation:

$$\hat{\theta}(u) = \beta_0 + \beta_1 q(u)^{\beta_2}, \quad q \to 0, \quad (19)$$

where the exceedance probability $q(u) \equiv 1 - p(u)$ is estimated from equation (11). We found that the estimate $\hat{\theta}$

shows a decreasing trend with increasing run length, r, for any particular value of the threshold, u. This is consistent since the extremal index is the reciprocal of the average number of exceedances per cluster, and with increasing run length the number of clusters goes down. This points to the need for correctly identifying the run length. The run length is estimated as 2 which involves a slight degree of conservatism (Bhattacharya 2005). The minimum squared error fit to the data according to equation (19) is shown in figure 5, yielding a value of the extremal index as $\theta = 0.93$. This high value of θ indicates that the load sequence is almost independent, a likely consequence of the rather high trigger of 85 $\mu\varepsilon$ set for the in-service recording device.

Since the distribution of the maximum of the associated i.i.d. sequence and the actual dependent stationary sequence are of the same type (compare to equation (8)), differing only in terms of the factor θ, for the Gumbel family, this leads to an unchanged α (hence an unchanged variance) and a mode (and mean) shifted to the left by an amount $(1/\alpha)\ln(1/\theta)$, $0 < \theta \leq 1$. Since the Gumbel family is closed under maximization, $\hat{L}_{\max,rd}$ for any other interval $t = r$ days (in integral multiple of days) is also Gumbel distributed with parameters:

$$\begin{aligned} \alpha_{rd} &= \hat{\alpha}_{1d} \equiv \alpha \\ u_{rd} &= \hat{u}_{1d} - \frac{1}{\alpha}\ln\left(\frac{1}{\theta}\right) + \frac{1}{\alpha}\ln(r). \end{aligned} \tag{20}$$

The mean and c.o.v. of the annual maximum live load-effect are thus 428.2 $\mu\varepsilon$ and 12.6%, respectively.

5.3 *Time-dependent LRFs optimized for a suite of bridges*

According to Delaware Department of Transportation, the state has 333 single-span bridges and 317 multi-span bridges (only aqueducts, culverts and bridges shorter than 5 m are excluded). The estimated nominal live to nominal dead load-effect ratio, Q_n/D_n, calculated with BRASS (1992) (with Q_n corresponding to HL93 in the AASHTO LRFD Specifications (AASHTO 1994)), varied from 1.0 to 4.0 for the above mentioned inventory. The relative frequency, w_i, of the Q_n/D_n ratios 1.0, 1.5, 2.0, 2.5, 3.0 and 4.0 were 4%, 9%, 13%, 18%, 23% and 33% respectively (Hastings 2001). This skew in favour of higher values ($Q_n/D_n \geq 3$) is presumably due to the inclusion of very short bridges in the database (about half of which were in the 5–15 m range).

This study did not involve any experimental analysis of dead load or initial resistance; the statistics of these quantities are adopted from those published and widely used by the professional community. The dead load statistics, taken from NCHRP (1999b), were that the normalized dead load, X_2, is normally distributed with mean 1.04 and c.o.v. 9%. Pending more sophisticated analysis, the nominal plastic strength factor, f_p, is simply taken as the ratio of the girder's ultimate to yield moment capacities, assuming a bilinear moment curvature relationship and, in this example, $f_p = 1.16$. The corresponding random factor $F_p = f_p PF$ where P is the random professional error factor and F is the random fabrication error factor (Ellingwood *et al.* 1980). F_p is thus Lognormally distributed with mean 1.03 f_p and c.o.v. of 7.1%. The

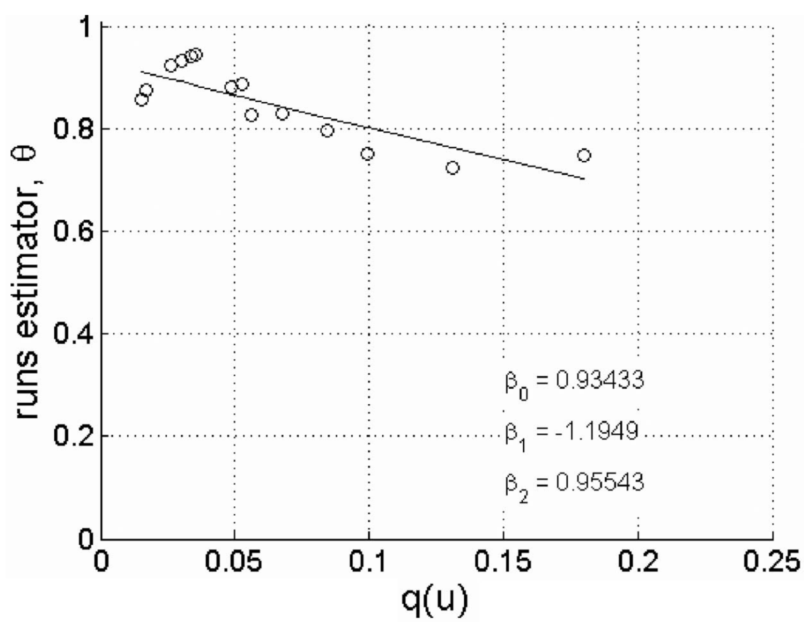

Figure 5. Estimation of the extremal index.

normalized yield strain is taken to be Lognormally distributed with mean 1.05 and c.o.v. 11.7%. The normalized initial resistance is thus Lognormal with mean 1.09 and c.o.v. 13.7%. As stated below equation (16), all normalization mentioned in this paragraph is with respect to the nominal or characteristic value of each random variable. The nominal dead load-effect on Bridge 1-791, computed by BRASS (1992), is 96 $\mu\varepsilon$. The girder is constructed of A36 grade steel whose nominal yield resistance is taken to be 1241 $\mu\varepsilon$. The nominal live load is taken to be the annual median live load effect, i.e. the load level with a 2 year return period coinciding with the typical inspection period, and equals 419.6 $\mu\varepsilon$. This value may be compared to the nominal live load-effects produced by two design trucks on the same bridge: (i) 322.7 $\mu\varepsilon$ by HS20, and (ii) 409.8 $\mu\varepsilon$ by HL93. If future in-service measurements are performed, the nominal live load may be updated following the same procedure. The random strength deterioration due to corrosion is as described above and is considered independent of the initial strength and the random loading process. For the purpose of this example, we assume the normalized strength deterioration to be statistically the same for all bridges under consideration. However, in practice, this may be true only for a subgroup of the entire suite of bridges.

The optimal rating equation LRFs for different time intervals with and without aging are shown in table 2. As stated previously, the target reliability, β_T, equals 3.5 for each reference period (t) listed in the first column. For each numerical evaluation of the objective function, Δ (equation (17)), and its gradients at a given set of values of the decision variables ϕ, γ_D and γ_L, a linear response surface was fitted locally for Δ on a 3-D grid with n^3 points. The n points for ϕ were chosen according to: $\phi + (k - (n-1)/2)\Delta\phi, k = 0, \ldots, n-1$, and similarly for γ_D and γ_L. We found $n = 4$ and $\Delta\phi = \Delta\gamma_D = \Delta\gamma_L = 0.05$ to be acceptable for this exercise. The non-linear optimization is performed using a sequential quadratic programming method in Matlab (TM).

For each set of values for ϕ, γ_D and γ_L and for the load ratio Q_n/D_n, the limit state probability (equation (16)) was computed with the help of importance sampling (IS). For each estimate of β, 100 000 IS trials were found to be sufficient. Benchmark analyses established that the optimal IS distribution for the series reliability analysis of equation (16) required shifting the means of only $X_{1,0}$ and X_2 while keeping the c.o.v.s the same. For each given set of ϕ, γ_D, γ_L, Q_n/D_n and t, the two means were shifted to the respective design point values obtained by a first order reliability method (FORM) analysis of the limit state equation $X_{1,t'}/\phi - (X_2 + X_{3,t'})/(\gamma_D + (Q_n/D_n)\gamma_L) = 0$ where $t' = \max(E[T_I] + (t - E[T_I])/2, 1)$. The FORM analysis involved the Rackwitz and Fiessler (1978) algorithm for mapping the basic variables to the uncorrelated standard normal space.

The left half of table 2 presents the optimal load and resistance factors for various reference periods, t, up to 25 years when aging effects are not considered. The corresponding rating factors for Bridge 1-791, obtained using equation (15) in each case, are also listed. If aging is not considered, the bridge rates more than adequately for the foreseeable future. As expected, the rating factor drops with increasing t, although the decrease is fairly moderate and tapers off with time. The sole reason for this decrease is the shifting of the live load distribution to the right with time.

The right half of table 2 presents the picture when aging effects are included. It is clear that the effects of aging on the LRFs and the RF are rather insignificant for up to about 10 years. This is due first to the existence of the corrosion initiation period (which has a mean of 5 years) and subsequently to the rather gentle deterioration process as evidenced by figure 4. Beyond 15 years or so, the cumulative effect of aging becomes clear and the bridge rating falls below 1.0 at around 17 years. Thus, in this example, if the bridge owners are confident about the aging model and the in-service loading data, they may decide to schedule a comprehensive maintenance operation at the end of 16 years and perform only limited or no inspection up to that time. For the purpose of comparison, rating factors for Bridge 1-791 using existing methods (LFD (load factor design) and LRFR) that do not account for aging or correlation in the load process may be found in Bhattacharya *et al.* (2005).

Table 2. Illustrative rating equation LRFs and resultant rating factors under ambient traffic for highway girder bridges in Delaware with and without aging effects.

	Aging not considered				With stochastic aging process			
Reference time, t (yr.)	ϕ	γ_D	γ_L	RF	ϕ	γ_D	γ_L	RF
5	0.85	1.20	1.80	1.47	0.85	1.20	1.80	1.47
10	0.85	1.20	1.89	1.40	0.85	1.20	1.89	1.40
15	0.85	1.20	1.93	1.37	0.85	1.20	2.32	1.14
20	0.85	1.20	1.94	1.36	0.80	1.50	3.11	0.77
25	0.84	1.20	1.94	1.34	0.80	1.50	3.88	0.62

6. Conclusions

The recent LRFR method uses a probabilistic approach to ensure that existing bridges can be rated and compared against a common target reliability level. Nevertheless, it does not accommodate the use of site-specific information, nor does it explicitly account for time-dependent aging effects. This paper presented a methodology that allows the use of in-service peak strain data to evaluate the safety of existing bridges in a fully probabilistic manner. A significant part of the effort has involved statistical characterization of the live load-effect based on extreme value theory including the consideration of statistical dependence in the loading data. Furthermore, a random aging mechanism leading to loss of plastic section modulus due to general corrosion occurring with a random initiation time and a stochastic rate with temporal dependence was also considered. The proposed in-service load and aging resistance factor rating (ISLARFR) methodology is consistent with both the LRFD and LRFR procedures, and because it can incorporate actual bridge response and health condition, it can lead to more accurate condition assessments.

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