Load and Resistance Factor Rating Using Site-Specific Data

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Traditional techniques for bridge evaluation are founded on design-based deterministic equations that use limited site-specific data; they do not necessarily conform to a quantifiable standard of safety and often are quite conservative. The newly emerging method of load and resistance factor rating (LRFR) addresses some of these shortcomings and allows bridge rating in a manner consistent with load and resistance factor design but is not based on site-specific information. A probability-based method for load rating of bridges using site-specific in-service structural response data in an LRFR format is presented. The use of site-specific structural response data eliminates a substantial portion of modeling uncertainty in live load characterization (involving dynamic impact and girder distribution) and yields more accurate bridge ratings. Rating at two limit states—yield and plastic collapse—is proposed for specified service lives and target reliabilities. This method considers a conditional Poisson occurrence of independent and identically distributed loads as well as uncertainties in field measurement and modeling and Bayesian updating of the empirical distribution function to obtain an extreme value distribution of the time-dependent maximum live load. An illustrative example uses in-service peak strain data from ambient traffic collected on a high-volume bridge and develops in-service LRFR equations to rate the instrumented bridge. Results from the proposed method are compared with ratings derived from more traditional methods.

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

When a bridge is designed, behavior of the as-built bridge and the nature of site-specific traffic can only be estimated. The calibrated load and resistance factors in the AASHTO load and resistance factor design (LRFD) specifications (*1*) are conservative by necessity, and many secondary sources of stiffness and strength are either neglected in design or are too difficult to compute. When a bridge is being load rated, however, 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. Bridge diagnostic and proof load tests are routinely conducted to evaluate in situ bridge capacity (*2–6*), and not surprisingly, bridge field tests typically find that calculated load-carrying capacities underestimate safe load-carrying capacities (*7–10*). The *Manual for Bridge Rating Through Load Testing* (*9*), published as an outcome of NCHRP Project 12-28(13)A, provides deterministic methods for determining bridge capacities on the basis of field testing and the quantification of site-specific bridge behavior.

Most recently, NCHRP Project 12-46 led to the development of *Manual for Condition Evaluation and Load and Resistance Factor Rating of Highway Bridges,* which is consistent with LRFD specifications (*11*). Like the LRFD specifications, the evaluation procedures developed are probability based, and the process is referred to as load and resistance factor rating (LRFR). Like LRFD, LRFR specifications are based on design parameters and non-site-specific data. Nevertheless, they open the door for the use of site-specific information to calculate bridge load ratings. For example, the manual discusses the use of weigh-in-motion data to calibrate site-specific live load factors (*12*).

METHOD: BRIDGE RATING UNDER AMBIENT TRAFFIC

Ratings for bridge evaluations should ideally possess the following characteristics:

- The rating should be based on a measurable, clearly defined concept of safety and should clearly distinguish safe bridges from unsafe ones under given service conditions and inspection intervals;
- A higher rating should signify a correspondingly higher margin of safety (and vice versa for lower ratings) so that limited bridge management resources may be allocated optimally; and
- The rating method should use site- or region-specific information about traffic loading and should account for uncertainties in strength and future loads.

Following the LRFR lead and using peak live load strain data from an instrumented bridge incorporating new sensor technology, a reliability-based method that yields a bridge rating that satisfies the above three criteria has been developed: in-service load and resistance factor rating (ISLRFR).

As in LRFD and LRFR, the scope of ISLRFR is restricted to the assessment of structural components (as opposed to the system), and the focus is on flexural behavior, although the method can be easily extended to other limit states, such as shear, if relevant. Distribution of the maximum live load effect for various reference periods is projected from the in-service data by using extreme value theory. The 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

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bridge response. In addition, by using the data from actual load effects instead of vehicle weights, the user can eliminate a substantial portion of the modeling uncertainty that is commonly associated with live load characterization (e.g., that related to dynamic impact and girder distribution factors). The resulting bridge ratings therefore are expected to be more accurate than present methods.

Furthermore, because the present method uses maximum loads over a specified time interval under ambient traffic, the resulting in-service rating factor would provide a rating that is at least as stringent as the so-called inventory rating for unposted bridges. For posted bridges, the rating factor using the proposed method will give a measure of adequacy of the imposed load restrictions. Hence, 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 that three criteria are met:

- Traffic observed during in-service measurement reflects the true traffic pattern;
- Vehicles do not become significantly heavier over the years; and
- Target reliability for the limit state under consideration is acceptable.

Application to permit vehicles will require additional procedures.

Finally, it may be relatively time-consuming and expensive to conduct load tests on every bridge in a jurisdiction's bridge inventory. If in-service response from a limited number of sites can be deemed representative of a larger suite of bridges, then 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 by using such optimized rating equations.

In-Service Strain-Measurement System

The proposed ISLRFR method uses a recently developed in-service system of strain monitoring (*13*). Analogous to a weigh-in-motion system, the system measures peak live load strains on the bridge due to site-specific traffic over extended periods. 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 primary component of the system is the data-acquisition system, which consists of a specially modified Snap Shock Plus (SSPM4) manufactured by Instrumented Sensor Technology (Okemos, Mich.). The SSPM4 is small and weighs only 204 g (7 oz.). It is powered by a single 9-volt battery and has an on-board microprocessor, a 16-kilobyte electrically erasable programmable read-only memory (EEPROM), a 12-bit analog-to-digital converter, and a serial communication link. Strains are measured with an Intelliducer strain transducer manufactured by Bridge Diagnostics, Inc. (Boulder, Colo.). 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- × 150- × 100-mm environmental enclosure (Figure 1).

As designed, the rapidly deployable stress-in-motion system is perfectly suited for use in routine bridge inspection and field evaluation. The system continuously digitizes an analog signal at 1,200 Hz and waits for a prespecified strain threshold to be exceeded. When this 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 more than 2 weeks and can store up to 1,475 data records (events). In this research, only the peak strain during an event and its time stamp were used.

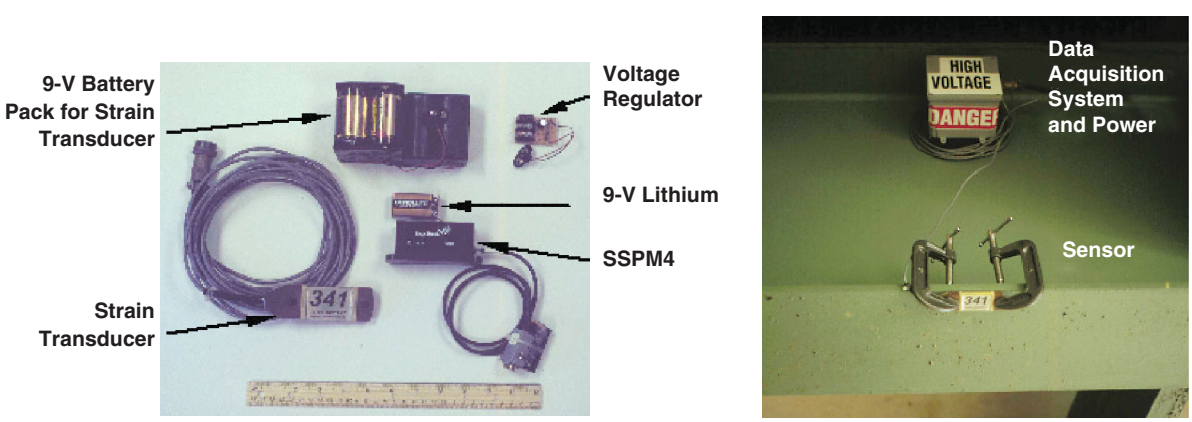
Distribution of Maximum Peak Strains

Here load combinations involving earthquake, wind, and so on are ignored; and the focus is only on traffic loading. The limit state equation thus simplifies to

$$R_e - D - L_{\max,t} = 0 \tag{1}$$

where

R_e = time-invariant random resistance at the time that inspection is performed,
D = time-invariant dead load, and
$L_{\max,t}$ = maximum live load effect on the bridge during $[0, t]$.



(a) (b)

FIGURE 1 Components of (*a*) data-acquisition system and (*b*) typical field setup.

The time-dependent reliability function is the probability

$$\mathrm{Rel}(t) = 1 - P\left(R_e - D - L_{\max,t} \le 0\right) \tag{2}$$

As mentioned before, significant uncertainties exist in the live load characterization on a bridge, and an important objective of this paper is to determine a realistic statistical description of $L_{\max,t}$. It, in turn, will be used to derive accurate bridge-assessment methodologies.

The maximum live load effect may be caused by one single heavy truck on the bridge or by the simultaneous presence of two (or more) trucks on the bridge. In the proposed method, in-service live load strain data are used directly to derive statistical information on $L_{\max,t}$; hence, it is not necessary to first estimate various loading scenarios individually, as would be required if the analysis started with truck weights and location on the bridge deck and went on to find the structural response.

Because live load effects are measured directly as strain, it is convenient to consider the above strength limit state in the strain domain as well; hence, the variables R_e, D, and $L_{\max,t}$ are expressed in terms of strain throughout this paper. As long as the structural response is elastic, then this formulation is completely equivalent to the more common flexural moment–based approach; a correction is needed for the inelastic domain, as discussed later.

Let L_i represent the peak strain caused by the ith loading event, where a loading event is the passing of one vehicle or the simultaneous passing of more than one vehicle over the bridge, as discussed above. The peak strains are random in nature, and the number of events, N_t, during the interval $[0, t]$ is a random variable as well.

It may be important to emphasize here that the peak strain measured by the in-service monitoring system, L'_i, is generally different from (and lower than) the true maximum peak strain L_i, discussed earlier. It is because the location of the sensor (which is where the maximum peak strain is expected to occur) may not coincide with that of the maximum response (e.g., due to unsymmetrical bending, uncertain support conditions, or longitudinal variations in the structure) for every vehicle event. Let this location-related error be expressed by the random variable $B_{\mathrm{loc}} = L_i/L'_i$ for all i. $L_{\max,t}$ over the duration t is then a random variable given by

$$L_{\max,t} = B_{\mathrm{loc}} \max\{L'_1, L'_2, \ldots, L'_n\} \tag{3}$$

If there is no error associated with the placement of sensors, then the term B_{loc} is identically equal to 1.

The following assumptions are now made:

- The loading events occur according to a point process $N(t)$ with a continuous, nonnegative, time-dependent rate $\Lambda(t)$. Because of the high trigger value of the data-acquisition system, an observed Λ is usually a fraction of average daily truck traffic. In this paper we treat Λ as a random variable. Consequently, $N(t)$ does not have independent increments (traffic pattern and volume do have memory, at least in the short term). However, we assume that conditional on a fixed value of Λ (i.e., for uniformly flowing traffic with a constant rate), the process $N(t)$ is memoryless, that is, has independent increments. In other words, $N(t)$ is a conditional or mixed Poisson process.
- The peak strains are identically distributed and statistically independent (iid) of each other. That is, L'_i and L'_j are independent for $i \neq j$, and all L'_i values are distributed according to the cumulative distribution function (cdf), P. The existence of a threshold strain level that triggers the recording device helps ensure independence of the marks.

The extent to which the data support these assumptions needs to be investigated in each application [as performed by Bhattacharya et al. (*14*)], and a more sophisticated model may be required if there is strong evidence of dependence and nonstationarity in the loading process.

Based on the above assumptions, the cdf of the maximum live load effect during time t can be given by

$$F_{L\max,t}(x) = \int_b \int_p \int_\lambda \exp\{-\lambda t[1 - p(x/b)]\} f_p(p) f_\lambda(\lambda) f_{B_{\mathrm{loc}}}(b) d\lambda\, dp\, db \tag{4}$$

where

$p(l) = \dfrac{1}{n+1}\sum_{k=1}^{n} I\left(L'_k \le l\right)$ is the estimate of P from the sample, where I is the indicator function;

f_P = probability density function (pdf) of P that accounts for sampling uncertainties through Bayesian updating and is of the Beta(q, r) type between the limits 0 and 1 with parameters $q = np + 1$, $r = n(1 - p) + 1$;

f_Λ = pdf of the random occurrence rate Λ and is of the normal type; and

$f_{B_{\mathrm{loc}}}$ = pdf of B_{loc}.

Details of the derivation may be obtained from Bhattacharya et al. (*14*).

With increasing t and under a set of general conditions, F_L max, t approaches one of the three classical extreme value distributions for largest values. The generalized form of the extreme value distribution for maxima is

$$H_c(z) = \exp\left[-(1 + cz)^{-1/c}\right], 1 + cz > 0 \tag{5}$$

The parameter c determines the nature of the distribution: It is of the Gumbel type if $c = 0$, the Frechet type if $c > 0$, the Weibull type if $c < 0$ (*15*). Determination of the type and estimation of the parameters of the extreme value distribution from observed data must be performed with caution.

For steel girder and slab bridges, it may not always be possible to ascertain whether observed strain data are a result of a bridge acting compositely or noncompositely. Bridges designed to act compositely are assumed to act compositely unless load tests show otherwise. Many bridges designed to act noncompositely, however, may act compositely under service loads, but the composite action will likely be lost as the load approaches the failure load (*7*). Although some guidelines are available about the threshold shear stress at which this transition occurs [e.g., NCHRP's *Manual for Bridge Rating Through Load Testing* (*9*)], they do not appear to have been based on substantial testing programs, and in any case, no consensus seems to exist in the professional community on the threshold shear stress. Furthermore, it is reasonable to assume that structural response characteristics of a bridge that has been in service for several years will likely continue to be in that state until the next scheduled inspection. Thus although in a more sophisticated analysis the projected distribution of $L_{\max,t}$ for noncomposite bridges could be transformed appropriately to account for the loss of composite behavior at high loads, that approach is not taken in this paper.

Development of Rating Equation for Instrumented Bridge

In terms of the LRFR method (*9*), the rating factor (RF) for an existing bridge is

$$\mathrm{RF}=\frac{\phi R_n - \gamma_D D_n}{\gamma_L L_n} \tag{6}$$

where

R_n = nominal resistance;
D_n and L_n = nominal (or characteristic) values of dead- and live load effects, respectively;
ϕ = resistance factor; and
γ_D and γ_L = dead and live load factors for rating, respectively.

Elastic buckling is generally not encountered in bridge flexural members; hence, for first yield limit state, nominal resistance R_n is equal to nominal yield strength y_n. For plastic collapse limit state, nominal resistance is $R_n = f_p\ Y_n$, where f_p is an amplification factor accounting for postyield reserve strength. The live load effect statistics, including the nominal value, are estimated from the data. However, if a bridge is not instrumented, then its nominal live load L_n needs to be estimated indirectly. Because it is a load effect, L_n already includes dynamic impact effects.

The rating equation must conform to a desired target reliability. The reliability of the bridge (or a structural component of the bridge) is a nonincreasing function of time and, for a given *t,* is often expressed in terms of the reliability index β, which is related to the reliability as $\beta = \Phi^{-1}$ (Rel), where Φ is the normal distribution function. β is a popular measure of reliability and usually ranges from 2 to 5 for most structural components. To be meaningful, a value of β should be accompanied with the relevant time period, failure mode, load combination, and types of uncertainty considered in the analysis.

The target reliability, β_T (used implicitly in LRFD for new bridge components in flexure), is 3.5 (*11, 16, 17*). For evaluating existing bridges, a value of $\beta_T = 2.5$ has been suggested (*9, 18*), mainly from economic considerations. Although cost-based optimization of target reliability of structural systems is a rational method, it was not adopted in this paper for two reasons. First, as stated in NCHRP's *Calibration of Load Factors for LRFR Bridge Evaluation* (*12*), some of the key cost data involved in this approach are difficult to obtain and were not available for this project; second, the cost-based optimal reliability formulation always has a lower bound on the reliability that often governs and is set by sociopolitical considerations (e.g., value of human life, perceived risks of engineering activities, and acceptable fatal accident rate) that do not have a well-defined cost metric. Through a risk-based approach to setting target reliability [as detailed by Bhattacharya et al. (*14*)], a target reliability index of 3.5 is adopted for bridge components against collapse.

Nevertheless, rating a bridge with reference to only one failure mode and hence only one set of target reliability and reference periods may not be adequate for all purposes (*19*). Setting safety targets at two or more levels is consistent with the performance-based trend that has evolved in structural engineering over the past 3 decades (*20*). For example, Wen proposes a bilevel reliability requirement for structures against natural hazards corresponding to "incipient damage" and "incipient collapse" limit states (*21*). Collins et al. propose a dual-level, reliability-based seismic design criteria: a serviceability-type limit state to ensure (nearly) elastic response during small to moderate earthquakes, and an ultimate limit state to control the nonlinear inelastic behavior due to severe earthquakes (*22*). Nowak et al. recommend a (lifetime) target component reliability index of 3.5 in the ultimate limit states for bridge structures; for serviceability limit states, they recommend a target component (i.e., girder) reliability index of 1.0 in tension and 3.0 in compression (*23*). Ghosn and Moses list four limit states for a highway bridge: first member failure (m), system ultimate (u), system functionality (f), and damaged condition (d) (*24*). They propose the following relations among the three target reliability indices: $\beta_u - \beta_m \geq 0.85$, $\beta_f - \beta_m \geq 0.25$, and $\beta_d - \beta_m \geq -2.7$.

In view of the above discussion, the following two-level rating of bridge components is proposed with the use of in-service live load data. It is up to the bridge owner to define the adequacy of the bridge in terms of successful rating in either one or both of the following criteria:

- $\beta_T = 2.5$ for first yield limit state in flexure under the action of maximum live load effect over a duration not exceeding 2 years and
- $\beta_T = 3.5$ for plastic collapse (i.e., ultimate) limit state in flexure under the action of maximum live load effect over the reference period.

The assumption here is that exceeding the yield limit state of a girder requires limited rehabilitation work, whereas exceeding the collapse limit state requires major rebuilding or even replacement. The cost associated with the former is further assumed to be roughly an order of magnitude less than that associated with collapse [hence, $\Phi(-2.5)/\Phi(-3.5) \approx 10$], as is borne out by cost examples worked out in *NCHRP Report 483* (*25*).

As stated above, the rating equation can be optimized for a suite of bridges of a given type having similar traffic characteristics (*14*). A reliability-based bridge rating factor could be defined in various ways, such as the ratio β/β_T, which would satisfy the desirable features mentioned at the beginning of this paper at least as well as Equation 6. Nevertheless, the format in Equation 6 conforms best to current professional practices and was adopted in this paper.

EXAMPLE: BRIDGE RATING USING IN-SERVICE DATA

The proposed rating procedure is demonstrated with a brief example involving a highway bridge in Delaware. The bridge selected for instrumentation, data acquisition, and rating was Bridge 1-791, a three-span continuous slab-on-steel girder structure that carries two lanes of Interstate 95 over Darley Road. In-service strain data were recorded at midspan of the critical girder of the approach span (beneath the right travel lane) during 11 days in August 1998 (Figure 2). A trigger level was set at 85 $\mu\epsilon$ so that only the larger loading events would be recorded. The probability distribution of maximum load effects for intervals of 1 year (annual inspection), 2 years (normal inspection cycle), and 10 years (potential repair cycle) was estimated from the data, as described in the following sections.

Statistics of Maximum Live Load Effect

Point estimates of the cdf of the peak strains caused by the loading events are listed in Table 1. Based on these observations, a Bayesian updating of the cdf is performed; the mean and the coefficient of variation (cov) of *P* are listed in Table 1 at various values of *l.* Because the data spanned 11 days, 11 point estimates of the random occurrence rate Λ were available. The normal probability fit of Λ is illustrated in Figure 3*a*. The probability paper fit yielded the following parameters for Λ: mean = 48.5 events/day and cov = 59.0%. Because of lack of suitable data, location-dependent randomness was ignored

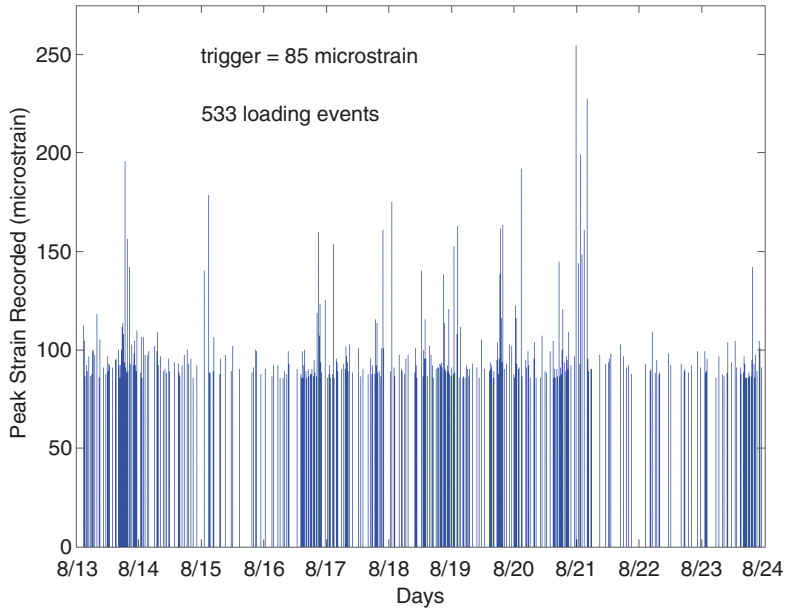


FIGURE 2 Timeline of loading events spanning 11 days in August 1998 on Bridge 1-791.

in Equation 4 (i.e., B_{loc} was taken to be deterministic and equal to 1). The cdf of $L_{max,1d}$ at each value of l (Equation 4) is listed in the last column of Table 1; 10,000 Monte Carlo simulations were used in estimating Equation 4 in each case.

Recall that as the time interval increases, the probability distribution of the maximum load approaches one of the classical extreme value distributions (Equation 5). Of the three classical extreme value distributions for largest values, the Gumbel (i.e., Type I maximum) and the Frechet (i.e., Type II maximum) distributions were tried for $L_{max,1d}$ (Figure 3). The third, Weibull, distribution for maxima, was not tried here, because it is limited on the right; however, this property of the Weibull distribution can be attractive in situations in which geometric, posting, or other constraints put a well-defined upper limit to the vehicular load that can be placed on the bridge. The Gumbel fit was clearly better in the present case and was adopted for $L_{max,1d}$ in this paper:

$$F_{L_{max,1d}}(x) = \exp\{-\exp[-\alpha_{1d}(x - u_{1d})]\} \tag{7}$$

where α and u are the shape and scale parameters, respectively. The mean and cov of this distribution were $\mu_{1d} = 181.2$ microstrains and $V_{1d} = 32.8\%$, respectively. This Gumbel model can also be verified using the peaks-over-threshold (POT) method—an elegant tool for predicting the asymptotic distribution of the largest values from an i.i.d. sample, as detailed by Bhattacharya et al. (*14*). The Gumbel distribution is quite often adopted for extreme loads in civil engineering applications—for example, for bridge live loads (*26*); structural live loads (*27*); maximum value of a variable action on a structure within a chosen reference time (*28, 29*); and annual maximum wind speed, wave height, and current in the case of marine and other structures (*30*).

Because the loads are assumed to be iid, it is consistent to assert that the daily maxima are independent and identically distributed as

TABLE 1 Estimates of Daily Maximum Peak Strain

Interval	Right Endpoint L	Counts (k)	c.d.f. of Load Effect: Point Estimate $p(l) = \Sigma k/(n+1)$	Updated Beta Distribution Parameters for P: Mean	c.o.v.	Predicted Max Load Effect $F_{Lmax,1day}(l)$ [Eq. 4]
<85	85	0	0	-	-	-
85-100	100	428	.8015	.8019	2.15%	.0252
100-115	115	61	.9157	.9159	1.31%	.0776
115-130	130	17	.9476	.9477	1.02%	.1550
130-145	145	9	.9644	.9645	0.83%	.2461
145-160	160	5	.9738	.9738	0.71%	.3354
160-175	175	5	.9831	.9832	0.56%	.4782
175-190	190	3	.9888	.9888	0.46%	.6021
190-205	205	3	.9944	.9944	0.32%	.7674
205-255	255	2	.9981	.9981	0.19%	.9146

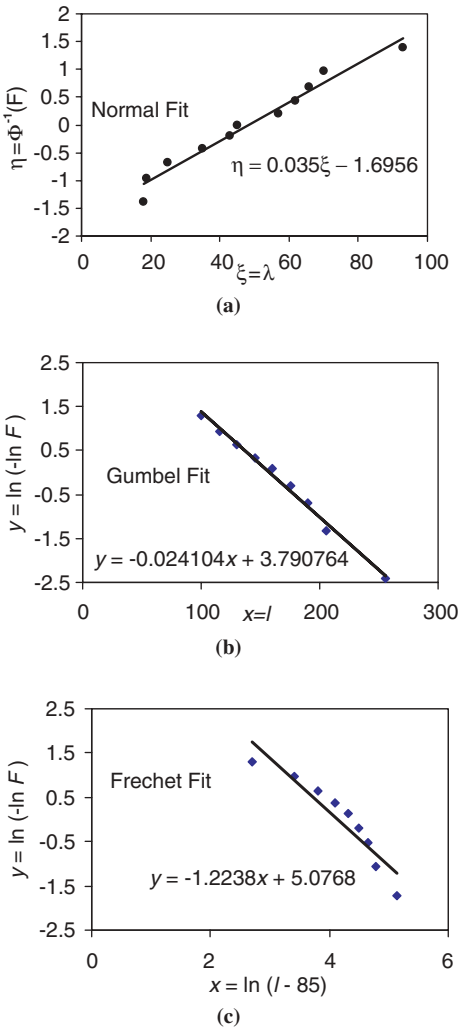


FIGURE 3 Three probability distributions: (*a*) normal fit for random occurrence rate, (*b*) Gumbel fit of daily maximum live load strain, and (*c*) Frechet fit for daily maximum live load strain.

well. Consequently, the maximum strain for any other interval $t = r$ days (in an integral multiple of days) is also Gumbel distributed. The shape parameter α remains unchanged for this new distribution, and the location parameter u moves to the right:

$$u_t = u_{1d} + \frac{1}{\alpha_{1d}} \ln(r) \tag{8}$$

The nominal live load used in rating equations (for all reference periods and limit states) can be set arbitrarily as long as it is internally consistent with the statistical analysis of maximum live load effect. Therefore, we adopt the load effect with a predicted 2-year return period, L^*_{2yr}, as the nominal live load effect, L_n. By definition L^*_{2yr} is exceeded on average once every 2 years (the usual inspection interval) and is equal to the median annual maximum. This way, the same statistics for the normalized live load effect, $X_{3,t}$, may be used for bridges that have similar traffic patterns in the inventory. In the current example, this quantity is $L^*_{2yr} = 417.2$ με for Bridge 1-791. The robustness of the proposed method in predicting maximum live load statistics to changes in the in-service monitoring system (if, for example, the trigger were set at 100 με instead of 85 με) has been discussed by Bhattacharya et al. (*14*).

The mean and cov of the maximum live load effect and also of the normalized $X_{3,t}$ for various time periods are listed in Table 2. With increasing t, the maximum live load effect distribution shifts to the right and becomes narrower. The latter property has sometimes been cited against the use of extreme value distributions in modeling maximum loads, though incorrectly. If samples are taken repeatedly from a stationary truck population and if the record of only the heaviest truck up to the current instant is retained, then there is less certainty at the beginning that a very heavy truck has entered the sample when it is, say, a few weeks old. But as the sample size becomes larger (say, several years old), it becomes increasingly more certain that a heavy truck has indeed appeared in the sample and thus erased all record of less heavy trucks.

The statistics in Table 2 may now be compared with those used in the LRFR manual (*11*). The maximum live load in LRFR is assumed to be lognormally distributed with a bias of 1.0 (the nominal being the effect of AASHTO 3S2) and a cov of 18% (regardless of reference period). The proposed method thus predicts the maximum live load in this example with significantly less uncertainty than that assumed in calibrating the LRFR manual (cov of around 10% to 13% instead of 18%). Part of this reduction can be ascribed to (*a*) circumvention of modeling uncertainty in structural analysis (e.g., those related to girder distribution and impact factors, because load effect is measured and used directly in the proposed method) and (*b*) use of site- or region-specific in-service data, as suggested in NCHRP's *Calibration of Load Factors for LRFR Bridge Evaluation* (*12*). This illustrative example used data from only one bridge gathered over only 11 days; when data from several sites and seasons are gathered for use in a practical application, the composite distribution for a given t quite possibly may be wider than that listed in Table 2.

This study did not involve any experimental analysis of dead load or resistance; the statistics of these quantities are adopted from those published and widely used by the professional community. No aging effect is considered. The dead load statistics [taken from

TABLE 2 Maximum Live Load Statistics for Different Time Intervals

	Maximum Live Load Effect, $L_{max,t}$				Normalized $X_{3,t} = L_{max,t}/L_n$	
Time, t	Location Parameter, u	Shape Parameter, α	Mean	c.o.v.	Mean	c.o.v. (%)
1 year	402.0	0.0241	426.0	12.5%	1.02	12.5%
2 years	430.8	0.0241	454.7	11.7%	1.09	11.7%
10 years	497.6	0.0241	521.5	10.2%	1.25	10.2%

NOTE: L_n = two-year return period value.

TABLE 3 Statistics of Strength Parameters

Limit state	R_e	R_n	Yield strain, Y	Plastic factor, F_p	Normalized resistance, X_1	Remarks
First yield	Y	Y_n	LN ($1.05Y_n$, 11.7%)	NA	$X_1 = Y/Y_n$, X_1~LN(1.05,11.7%)	$Y = S/E$, where S~LN($1.05S_n$, 10%), E~LN($1.00E_n$,6%)
Plastic collapse	$F_p\,Y$	$f_p\,Y_n$	same as above	LN(1.03 f_p, 7.1%)	$X_1 = (Y/Y_n)(F_p/f_p)$ X_1~LN(1.09,13.7%)	Assumed $F_p/f_p = PF$, P~LN(1.03,5%), F~LN(1.00,5%),

NOTE: LN(μ,V) implies lognormal random variable with mean = μ and c.o.v. = V; subscript n implies nominal value; NA = not applicable; S = yield stress; E = elastic modulus; P = modeling (professional) error; F = fabrication error; statistics of S, E, P and F are from Ellingwood et al. (*33*). No aging effect is considered.

NCHRP's *Calibration of LRFD Bridge Design Code* (*17*)] were normalized dead load, $X_2 = D/D_n$, normally distributed with mean 1.04 and cov 9%. Strength statistics, including nominal values, are listed in Table 3.

The load and resistance factors for rating equation are listed in Table 4 for different time intervals and the two limit states. In each case, the limit state probability was computed with the help of the first-order reliability method (FORM), in which the Rackwitz–Fiessler algorithm (*31*) was used for mapping the basic variables to the uncorrelated standard normal space. For comparison with the current LRFR manual (*11*), proposed load and resistance factors corresponding to a target reliability index of 2.5 against collapse have also been listed.

Comparison with Traditional Bridge Rating

Table 5 lists rating factors using the proposed ISLRFR method for Bridge 1-791 that correspond to three criteria: yield limit state for a 2-year reference period, plastic collapse limit state for 2-year reference periods, and plastic collapse limit state for 10-year reference periods (relevant LRFs are taken from Table 4). For the purpose of comparison with the current LRFR manual, proposed RFs corresponding to a target reliability index of 2.5 against collapse also have been listed. The dead load effect on Bridge 1-791 is 96 με as computed by BRASS (*32*). The bridge is constructed of A36 grade steel, and its nominal yield resistance is taken to be 1,241 με. Pending more sophisticated analysis, the plastic strength factor f_p (Table 3) is simply taken as the ratio of the girder's ultimate to yield moment capacities, assuming a bilinear moment curvature relationship, which in this example is $f_p = 1.16$. Bridge 1-791 clearly rates satisfactorily in all three limit states under ambient site-specific traffic. The governing limit state in this case is 10-year ultimate (RF = 1.44). However, it is up to the bridge owner to decide on a suitable acceptance criterion based on the three rating factors.

TABLE 4 Proposed Rating Equation Load and Resistance Factors Under Ambient Traffic for Bridge 1-791

Limit state	β_T	Time (yr.)	ϕ	γ_D	γ_L
First yield	2.5	1	0.95	1.35	1.40
		2	0.95	1.45	1.45
Plastic collapse	2.5	1	0.90	1.15	1.35
		2	0.90	1.25	1.40
		10	0.90	1.35	1.55
Plastic collapse	3.5	1	0.85	1.00	1.65
		2	0.85	1.10	1.70
		10	0.85	1.20	1.85

The proposed ISLRFR rating factors may be compared with the rating factors given in the LRFR manual (*11*) and BRASS (*32*) using load factor design for a set of design trucks. Neither of these methods has the ability to rate a bridge using in-service data or for various projected time intervals. For any given design truck, the spread among the three proposed ratings factors is much less than that found in BRASS ratings.

CONCLUSIONS AND FUTURE WORK

The recent LRFR method uses a probabilistic approach to ensure that existing bridges can be rated and compared against a common target reliability level. Although neither the LRFD nor the LRFR procedure is based on site-specific information (even though the LRFR manual discusses some applications of site-specific data), both procedures set the stage for using field data to rate bridges more accurately.

This paper has presented a method that allows the use of in-service peak strain data to evaluate the safety of existing bridges in a fully probabilistic manner. A considerable part of the effort has involved statistical characterization of live load effects based on extreme value theory. The maximum live load effect distribution was projected for reference periods ranging from 1 to 10 years; Gumbel distribution appeared to describe the data best.

The proposed method is consistent with both the LRFD and LRFR procedures; because it is based on actual bridge response, it eliminates a substantial part of live load modeling uncertainties such as those related to dynamic impact and girder distribution factors and can lead to more accurate condition assessments. The method can be used to rate the specific bridge that has been instrumented; it also can be used to rate a group of bridges that have similar traffic characteristics by instrumenting a small but representative subset of the group. Unlike more traditional methods, the proposed method can be applied to various projected time intervals and allows safety checks at two limit states: yield and ultimate. The example presented shows how ratings obtained according to the proposed procedure relate favorably to ratings derived from more traditional methods, although this result cannot nearly be claimed as general without exhaustive comparisons.

TABLE 5 Rating Factors for Bridge 1-791 Using Three Methods Under Different Loading Conditions

Method	Limit state	Rating Factors under Different Loading Conditions					
		In-service site-specific (417.2με)[a]	HL93 (409.8 με)[b]	HS20 (322.7 με)[b]	Type 3 (246.5 με)[b]	Type 3S2 (217.7 με)[b]	Type 3-3 (196.8 με)[b]
Proposed ISLRFR	2 yr yield L.S. $\beta_T = 2.5$	1.72	NA	NA	NA	NA	NA
	2 yr. ultimate L.S. $\beta_T = 2.5$	2.01	NA	NA	NA	NA	NA
	10 yr ultimate L.S. $\beta_T = 2.5$	1.80	NA	NA	NA	NA	NA
	2 yr. ultimate L.S. $\beta_T = 3.5$	1.58	NA	NA	NA	NA	NA
	10 yr ultimate L.S. $\beta_T = 3.5$	1.44	NA	NA	NA	NA	NA
LRFR Manual	5 yr ultimate, $\beta_T = 2.5$	NA	1.84, 2.39[c]	2.27	2.98	3.37	3.73
BRASS	Operating	NA	NA	2.84	3.84	4.22	4.67
	Inventory	NA	NA	1.70	2.30	2.53	2.79

[a] Nominal live-load effect equal to 2-yr return period value based on in-service site-specific measurement.
[b] Nominal live-load effect computed using BRASS with an impact factor of 10% and a distribution factor of 1.34.
[c] 1.84 is the inventory rating, and 2.39 is the operating rating.
NA = not applicable.

Modeling uncertainty B_{loc}, associated with strain gauge locations, was identified in this paper but ignored in the numerical example for lack of supporting data. The postyield amplification factor was simply taken to be the ratio of ultimate to yield moment capacities; nevertheless, a more sophisticated analysis may be desirable. The departure from composite behavior in noncompositely designed bridges at sufficiently high stresses was acknowledged but was not probed further. The proposed method was illustrated with in-service data that spanned only 11 days. This period is clearly inadequate for practical implementation of the method; bridge traffic may have seasonal variations and a general upward trend over time. These aspects should be addressed in future work.

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