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Steel Bridge Service Life Prediction Using Bootstrap Method

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Abstract Steel bridges play an important role in the transportation system of many countries. To ensure that bridges are structurally sound, engineers monitor their performance, which is known as structural health monitoring. Historical evidence indicates that bridge damage is pervasive and that the service life of bridges is decreasing. To manage safety and costs, engineers must be able to accurately predict the service life of bridges. A statistical method to predict service life for steel bridges is presented, which can assist bridge engineers, bridge owners, and state officials in the objective assessment of deteriorated bridges for retrofit or replacement. Timely repair and retrofit of bridges increase their safety levels and decrease costs. A nonparametric statistical approach based on the bootstrap method for stress analysis for fatigue life prediction of steel bridge components is proposed. The bootstrap provides a simple approach for the reproduction of the extremely complex probability distribution of measured strain data. It is completely automated numerical method which requires no theoretical calculations and it is not based on the asymptotic results. The service life index is introduced which quantifies the fatigue life of steel bridges under daily traffic loads. A regression model is developed for the prediction of remaining service life of steel bridges using a service life function. The predicted remaining service life derived from the function can contribute to effective management of steel bridges.

Keywords Steel bridges · Service life · Bootstrap · Service life index · Regression · Simulated strains and stresses

1 Introduction

Bridges play a significant role in the expansion of public transportation network infrastructure in the world. The development of bridges establishes new network connections, which can enhance the economic progress of a country. What is very clear is that damage appears in many of the bridge's components with the passage of time. Therefore, damage detection of bridges is a key issue for managing cost-effective decisions regarding bridge management systems (BMS). Since structural health monitoring (SHM) is becoming increasingly useful and applied in BMS, it is now vital for managing bridges throughout construction, operation and maintenance. One of the significant areas of bridge SHM is service life prediction or bridge prognosis. Changes in properties of structure components during their service life relate to damage of structures that are monitored in SHM. Extensive research has been conducted on service life evaluation of steel bridges using damage detection and fatigue assessment methods. However, as our literature review below reveals, few studies have developed a bridge service life index which considered the damage and fatigue which results from variations in actual daily traffic patterns, which is the primary goal of this research.

There has been a considerable interest worldwide in the field of bridge engineering and much research has been carried out on bridge topics. Wang et al. [1] studied finite element based fatigue assessment of corrugated steel web beams in highway bridges. Their paper presented a finite element analysis and its related experimental test of

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corrugated steel web beams subjected to fatigue loading. Results showed that it is possible to expect the fatigue crack failure arising at the weld root or weld toe corresponding to sections with reference angle using the effective notch stress analysis [1]. Grandic et al. [2] presented evaluation of torsional stiffness in beam and slab bridge decks based on load testing. The results of load testing conducted on series of bridges in Croatia are compared with results obtained on different numerical grillage models in which torsional stiffness of main structural elements was varied. According to conducted analyses, a design value of the coefficient of torsional stiffness reduction for the verification of serviceability limit state of main structural elements of beam and slab bridge deck is proposed [2]. Tarighat [3] focused on model based damage detection of concrete bridge deck using an adaptive neuro-fuzzy inference system. In this paper, an adaptive neuro-fuzzy inference system (ANFIS) is used to detect the possible damage location in a concrete bridge deck modeled by finite element method. Results showed that this method can decrease the time and cost of visual inspections and be used as real-time damage detection caution system in practice [3]. Service life prediction of bridges has been developed and evaluated in many fields. One of the fields is fatigue evaluation for service life prediction. Miner and Calif [4] proposed the “damage cumulative” rule. It was proposed as a simple and conservative life prediction based on the concept of cumulative fatigue damage. Using this concept, they tested different types of aluminum alloy specimens with different stress ratios and different combinations of loading cycles. A percentage of failure at a specified stress level was defined by a number of loading cycles. According to this concept, total damage occurs when the number of cycles reaches 100 percent leading to fatigue failure of the specimen [4]. Soliman et al. [5] studied fatigue assessment and service life prediction of existing steel bridges by integrating SHM into a probabilistic bilinear S–N approach. Soliman et al. (2013) demonstrated that the present methods for fatigue remaining life prediction of steel bridges can be conservative. In their study, a bilinear S–N approach was proposed. They investigated how different slopes above and below the constant amplitude fatigue threshold (CAFT) related to S–N curves for better prediction of fatigue life [5].

In service life prediction of bridges based on monitoring data, measured strain is an important indicator of bridge fatigue behavior. Zhou [6] presented a method for assessment of bridge remaining fatigue life evaluation through field strain measurements. Zhou [6] reported that a large number of bridges appear to have an infinite fatigue life [6]. Also, Ye et al. [7] conducted a statistical analysis of stress spectra for fatigue life assessment of steel bridges with structural health monitoring data. They developed a

method for fatigue life assessment of steel bridges using long-term measured dynamic strain data [7]. Alampalli and Lund [8] proposed a method for estimating fatigue life of bridge components using measured strains. Alampalli and Lund [8] show that most of the critical components had an infinite fatigue life and others had a substantial fatigue life [8]. Likewise, Sanayei et al. [9] performed instrumentation, nondestructive testing, and finite element model updating for bridge evaluation using strain measurements. Therefore, a baseline finite element model was developed and calibrated with nondestructive test data that could be used in fatigue studies [9].

Others have introduced approaches for fatigue reliability assessment of steel bridges in service life prediction. For example, Ni et al. (2013) proposed a monitoring-based fatigue reliability assessment of steel bridges. In the proposed method, they developed a fatigue reliability model of steel bridges using long-term monitoring data. The reliability index and failure probabilities which are related to fatigue life were then determined from the joint probability density function of the hot spot stresses [10]. Wang et al. [11] studied fatigue reliability to update fatigue life evaluation of existing steel bridges. There, a probabilistic fracture mechanics method based on the Bayes theorem was used to update relevant parameters of crack growth models using information from nondestructive inspection. A procedure was proposed for assessing and updating fatigue reliability of existing steel bridge components [11]. Sahrapeyma et al. [12] performed a study on life-cycle prediction of steel bridges using reliability-based fatigue deterioration profile. The effects of repair, rehabilitation, and maintenance on the deterioration profile were specified by a numerical approach. In addition, a reliability index was recommended with a plan for maintenance of an existing bridge [12].

Another field of research used to predict service life of bridges is deterioration due to chloride effects. Oh et al. [13] presented a realistic assessment for safety and service life of reinforced concrete deck slabs with steel girder bridges. A deterioration model due to chloride ingress was established. For structural evaluation, the service life prediction of deck slabs due to loading and environmental effects were presented based on materials used [13]. Also, Cheung et al. [14] studied service life prediction of reinforced concrete deck bridge structures exposed to chlorides. In this research, variations in reinforced concrete deck surfaces were studied considering local climate conditions [14].

Our literature review reveals that previous studies did not consider actual changes in the average daily traffic. At best, they define average daily traffic using a constant annual rate [8, 15]. This research proposes a quantitative service life index which can be computed from actual

strain measurements associated with average daily traffic. This service life index can be used for the estimation of the ultimate fatigue life of existing steel bridges and to consider traffic-induced stress variations. The approach is to obtain the nominal stresses at a specific location (or critical location) using measured strains under daily traffic. Then, a set of new measured strain samples is derived by a statistical approach, termed the bootstrap method. The bootstrap produces new samples of measured strains, which reproduce extremely complex statistical properties of the available strain observations. The bootstrap is used to predict future strain ranges considering the relevant number of cycles that define the service life of a steel bridge. In addition, a life index is defined for ultimate service life prediction of existing steel bridges. Since service life prediction of bridges is a key issue for managing effective decisions by BMS, a regression model is developed using stresses and the associated number of cycles for service life prediction by examining changes in the service life index. These changes lead to a service life function that is defined as the number of cycles experienced by a steel bridge under actual changes of daily traffic using only measured strains. The proposed regression model can be used to evaluate the ultimate fatigue life and remaining fatigue life at critical locations on the existing steel bridges. Here, service life and fatigue life are assumed to have the same meaning.

2 Fatigue Theory

Fatigue damage is a cumulative process related to the number of loading cycles experienced by each specimen through the load carrying system of a structure. The number of loading cycles experienced by each specimen is expressed as a percentage of the failure life at a given stress level, which is proportional to the expected remaining life. All fatigue cycles are converted to the same stress level and the cumulative effects are determined. Miner and Calif (1945) suggest that, “when the total damage, as defined by this concept, reaches 100 percent of the fatigue life, then the structural element would fail” [4]. Bridges are subjected to a high number of heavy trucks loading cycles during their service life. As a result, bridge steel components are directly subjected to this cyclic loading, which can lead to fatigue damage, in particular, at steel connections.

The damage (D) is a function of the number of loading cycles applied to the failure at a specific stress level. It can be shown as, $D_i = f(n_i/N_i)$, where, n_i is the number of cycles applied at a specific stress level (σ_i) and N_i is the number of cycles applied at the same stress level to fatigue failure. The relationship between stresses and the number

of cycles is linear based on Miner’s rule. Miner assumed when the summation of increments of damage, n_i/N_i , for different stress levels is equal to unity then fatigue failure occurs [16]. This protocol for the estimation of fatigue life in steel structures is computed as,

$$\sum D_i = \sum \frac{n_i}{N_i} = 1 \quad (1)$$

There is a constant amplitude fatigue threshold (CAFT) for each S–N curve. CAFT is also called endurance limit, fatigue limit, and fatigue strength. It is a threshold value of stress range, below which the specimen will not develop fatigue cracks during the expected life of the bridge. When the stress is below this limit, the material may endure an infinite number of cycles without failure, “therefore, a requirement on higher-traffic-volume bridges that the maximum stress range experienced by a detail be less than the constant amplitude fatigue threshold provides a theoretically infinite fatigue life, leading to heavier and more expensive steel structures. Instead, the maximum stress range experienced by a detail which is more than the CFAT estimates a theoretically finite fatigue life” [17].

In this paper, it is assumed that critical components are free of cracks. However, if such components suffer from cracks, the cycles below the CAFT should be considered for service life prediction using results of other researchers [5]. The provided S–N curve protocol estimates the fatigue damage when the maximum stress range experienced by a bridge component exceeds the CAFT. Fatigue endurance strain is related to fatigue endurance stress through Hooke’s law for uniaxial linear elasticity. This is a necessary ingredient for comparison of analytical strains with measured strains of steel specimens.

3 Assessment of Bridge Failure

Failure is a general term that refers to two conditions: collapse and distress (unserviceability). It is defined as the inability of a constructed facility; in this case a bridge or its components, to perform as specified in the construction and by design documents [18]. Bridge collapse refers to the failure of all or a substantial part of a bridge that then requires full or partial replacement [19]. Collapse is the loss of integrity and it occurs when the entire or a substantial part of a structure comes down, in which the structure loses the ability to perform its function in carrying a designed load. Collapse can be further classified into two categories: catastrophic collapse and partial collapse. Catastrophic collapse implies that several primary structural members of a span have fallen down, such that no travel lane is passable. Partial collapse suggests a condition where some of the primary structural members of a span

have fallen down, where such a condition endangers the lives of those traveling on or under the structure. Distress is the unserviceability of a structure or its components. Distress may or may not result in a collapse. In this situation, the structure undergoes some deformation without losing whole structural integrity. Loss of serviceability refers to a condition where there are no signs of structural distress or collapse; however, large deformations can lead to a loss of function and the bridge may be closed. In summary, bridge collapse and distress (unserviceability) are subsets of failure.

Bridges are fabricated and constructed with many structural components and there are numerous welded and bolted connections. These connections are mostly the critical locations for fatigue damage and failure; therefore, special attention must be given to structural connections. Values of fatigue damage in the vicinity of welded and bolted connections are compared for detection of possible fatigue failure locations [20]. The fatigue behavior is investigated at critical locations of steel bridges. Since failure of connections in fracture critical steel components can result in bridge failures, then service life of the steel bridge and predicted life of the critical components can be the same. A fracture critical bridge is defined by the FHWA as a steel member in tension, or with a tension element, whose failure would probably cause a portion of or the entire bridge to collapse. In this paper, a methodology for service life prediction of steel bridges is presented by an evaluation of steel connection fatigue failure as critical locations under high-cycle fatigue analysis using a proposed service life function.

4 Service Life Function

A primary goal in this paper is to develop a service life function, $f(\mu)$, to predict service life of existing steel bridges, which accounts for the daily variation in bridge loads. Each S–N curve contains many points and failure of each steel component can occur at one of these points, which are unknown for each component. It is possible to predict service life of a steel component if that point on S–N curve can be found. This is called the equivalent point, which is determined by the service life function. Steel components endure many variable stress cycles in their service life. The stress cycles are determined at each critical location on a steel component and are converted into an equivalent point on corresponding S–N curve using Miner's rule. Then the service life of steel component can be evaluated by the service life function of that point on the S–N curve. The service life function is a decreasing function of the life index. It would be possible to assess service life of steel bridges if measured responses were

available for their entire service life. Although not all variable stresses of steel components, which are related to their service life, can be determined, some of the stresses can be calculated by measured strains. Here, all other stresses are calculated from actual stress measurements using the bootstrap. Then, the bootstrap method is employed to generate all variable stresses of steel components. As a result, the service life of existing steel bridges is predicted based on the service life function. This function is not a damage index to depict safe or unsafe condition of bridges rather the service life function illustrates the relationship between our experiences of the percentage of elapsed service life against ultimate service life of steel bridges. It is used for the calculation of the remaining service life of steel bridges.

5 Bridge Survival Distribution Function With Heavy Truck Events Using Bootstrap Method

Our proposed method requires monitoring of steel bridges with strain gages. When trucks are moving over bridges instrumented with strain gages mounted on steel components close to structural connections, the data acquisition system gathers strain measurements. These measured strains are represented by a single random variable ε_i . The behavior of the magnitude and frequency of this random variable is completely and uniquely determined by its probability density function (PDF), $f(\varepsilon)$, which denotes the probability of occurrence of the random variable ε . The cumulative distribution function (CDF), $F(\varepsilon)$, describes the non-exceedance probability that the random variable ε_i is less than or equal to some value x . The CDF is used to define its complement, known as the survival distribution function (SDF). The survival distribution function of x describes the exceedance probability associated with x such that,

$$S(\varepsilon) = 1 - F(\varepsilon) = P(\varepsilon \geq x) = \int_x^{\infty} f(\varepsilon) d\varepsilon \quad (2)$$

where, ε = measured strain, $f(\varepsilon)$ = probability density function (PDF), $F(\varepsilon)$ = cumulative distribution function (CDF), $S(\varepsilon)$ = survival distribution function (SDF)

The SDF is also known as the survival function. Lifetimes of various processes are described using the SDF [21–23], which is simply the complement of the CDF. Knowledge of the SDF for the measured strains is needed to predict the service life of steel bridges. There are two main categories of statistical approaches for the estimation of the SDF, parametric and nonparametric. A parametric method assumes a theoretical distribution function that requires selection of a suitable form for the SDF and

estimation of the SDF's model parameters. Researchers have shown that the SDF of bridge strain data exhibits very complex shapes, which are challenging to model using traditional analytic SDF models [24]. Instead, a nonparametric statistical approach, the bootstrap method, is used to estimate the SDFs from lifetime data, which, in this case, are the strain measurements.

The bootstrap method is a computational approach that replaces complex analytical statistical theory with computer intensive resampling of the available data. It can be used to solve nearly any traditional statistical problem. Bootstrapping is implemented by resampling observations from an independent and identically distributed set of observed data, with replacement to create additional data sets. The bootstrap samples will have the same properties as the original measurements as long as the resampled observations are independent and identically distributed. The bootstrap samples can then be used in further statistical analysis. The bootstrap can be used to reliably distinguish changes in SDFs associated with bridge strain measurements during its service life as was shown by Follen et al. [25]. An SDF and its sampling properties are readily determined using the bootstrap resampling method. In the field of structural engineering, Bigerelle and Iost [26] and Bigerelle et al. [27] employed bootstrap analysis for fatigue life prediction. Their research showed that the bootstrap is a powerful tool for modeling probability density function of fatigue life time prediction [26, 27]. The theory of the bootstrap has shown that, for independent and identically distributed random variables, such resampling with replacement preserves all the statistical properties of an independent data set, including its SDF and CDF [28].

Here, the estimation of the service life function is described using the bootstrap method. It provides a simple approach for the reproduction of the extremely complex probability distribution of measured strain data. It is completely automated numerical method which requires no theoretical calculations and it is not based on the asymptotic results. The estimation is accomplished by randomly drawing a large number of samples of size m from the original sample (measured strain data), with replacement. Here, the variable of interest is the strain associated steel components during their service life. Each bootstrap sample could include some of the original data points more than once, and possibly some observations may not be resampled. Therefore, each of these bootstrap samples will randomly depart from the original sample, yet theoretically, will exhibit the same probabilistic structure as the original sample [28]. Consider a random sample of size m , which is observed from an unknown probability distribution F ,

$$X_i = \varepsilon_i, X_i \sim F \quad i = 1 \text{ to } m \quad (3)$$

where, X_i is identically and independently distributed according to some unknown probability distribution. F and ε_i are observed random sample of size m from measured strain data.

The use of the bootstrap method for generating new samples of length m from the measured data is as follows:

(1) Create the sample probability distribution \hat{F} , putting numerical mass $1/m$ at each point $\varepsilon_1, \varepsilon_2, \varepsilon_3, \dots, \varepsilon_m$.

(2) Draw a random sample of size m from \hat{F} with \hat{F} fixed, as,

$$X_i^* = \varepsilon_i^*, X_i^* \sim \hat{F} \quad i = 1, 2, \dots, m \quad (4)$$

Call this the bootstrapped sample j where $X^* = (X_1^*, X_2^*, \dots, X_m^*)$, $\varepsilon^* = (\varepsilon_1^*, \varepsilon_2^*, \dots, \varepsilon_m^*)$ [29].

Two common questions, which arise during the bootstrap process, are: (1) determining how large of a sample is required (m) to fully specify the SDF, and (2) figuring out how many bootstrap samples are needed to construct confidence intervals for the resulting SDF. Both of these issues are addressed by Follen et al. [25] and in the discussion below.

6 Histograms of Maximum Strain Outputs from Recorded Truck Events

An important aspect measured data quality is the noise that is present during measurements. Because the maximum strain measurement from each sensor is used for each truck event in this method, the signal-to-noise ratio is always high. As long as the signal-to-noise ratio is high in the

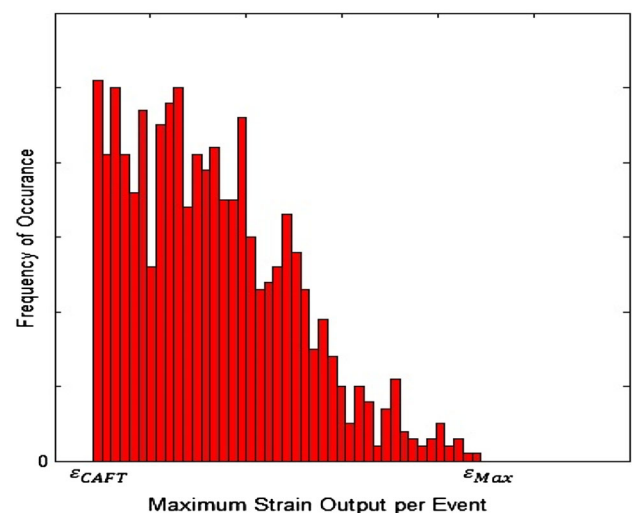


Fig. 1 Schematic histogram of maximum strains for measured truck events

measurements that make up the signature distribution, measurement noise is unimportant [25]. Figure 1 illustrates an example histogram of the maximum strain output per event. Based on the histogram, a heavy truck event is defined as an event from which the maximum strain output is greater than $\varepsilon_{\text{CAFT}}$, with corresponding live load stress level of σ_{CAFT} . This histogram represents the PDF of maximum strain output of heavy truck events, and defines the PDF $f(\varepsilon)$, where ε is the measured strain. The shape of such a PDF is extremely complex. To avoid the need for specifying a theoretical PDF, the bootstrap is employed as a nonparametric alternative because the bootstrap can reproduce the properties of any PDF, no matter how complex.

7 Defining Heavy Truck Events Using the Strain Threshold

The strain monitoring system is currently set up to depict strain data for vehicles weighing more than $\varepsilon_{\text{CAFT}}$. As stated, fatigue damage is cumulative and can occur at different stress levels based on the number of cycles. Highway trucks apply different weights based on truck type and cargo weight. As a result, the stress levels received at a critical location on a steel component may vary from cycle to cycle. The significant feature of the cumulative damage concept lies in the hypothesis that failure occurs when $\sum \frac{n_i}{N_i} = 1$. Where n is number of cycles for each truck event, which can be equal to 1, 1.5, 2 or 5 [30]. N is the number of cycles to fatigue failure applied at a specified stress level. It is noted, if there is a continuous time history for measured strain data, a rainflow method will be used for counting number of fatigue cycles. The rainflow method would be beneficial for counting the actual number of induced cycles [31].

8 Construction of SDF of Maximum Strain Outputs

For m heavy truck events at a hot spot and $i = 1$ to m , the absolute maximum strain values per event, $\varepsilon_{(i)}$, are ranked such that $\varepsilon_{(1)}$ is the largest observed value (ε_{max}) and $\varepsilon_{(m)}$ is the smallest ($\varepsilon_{\text{CAFT}}$), as shown in Fig. 2. The SDF is a plot of the ranked values of absolute maximum strain output per heavy truck event against its probability of exceedance (p_i) based on a Weibull plotting position $p_i = i/(m+1)$, where m is the sample size, and i is the rank of the observation. The Weibull plotting position is suitable because it provides an unbiased estimate of the exceedance probabilities regardless of the theoretical PDF from which the observations arise [32].

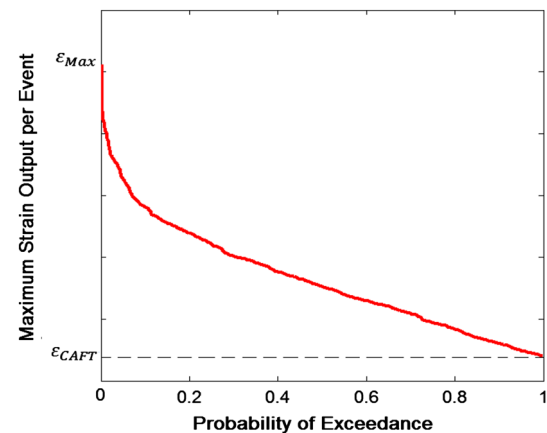


Fig. 2 Typical SDF of maximum strain outputs

9 Sample Size Needed for Statistically Stable and Independent SDFs

A stable SDF results when the strain value at a certain probability of exceedance does not change significantly when more data from the same distribution are added [25]. Figure 3 reports estimates of various SDF quantiles as a function of number of events, m and shows that the quantile estimates become more stable as m increases. Such a sample size m , will lead to stable estimates of the SDF in future Bootstrap experiments. The authors conclude from Fig. 3 that the approximate value of m needed to obtain stable estimates of the SDF is equal to L as shown in the figure, because estimates of the SDF quantile appear to stabilize for bootstrap samples of that size. Each bridge SDF is unique based on the bridge topology, traffic patterns, truck types, truck weights; thus, one would need to calculate the minimum sample size that results in stable SDFs for other bridges.

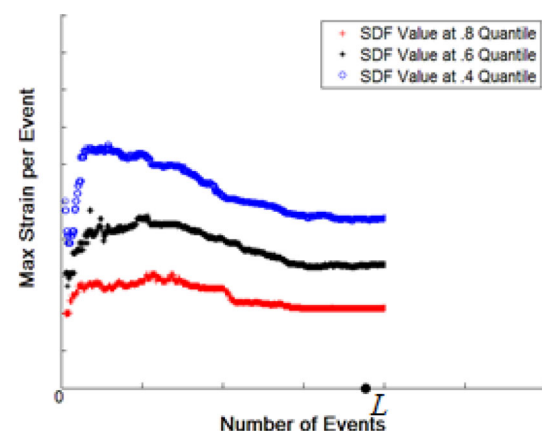


Fig. 3 Typical SDF values versus number of events

10 SDF of Maximum Stress Outputs for Measured Strains

The relation between stress and strain for most steel materials used in steel bridges is a linear elastic behavior, known as Hooke's Law. The relation between the strain amplitude and fatigue life cycles is usually given as stress-number of cycles curves (S–N curves); therefore, it is necessary to compute stress levels using measured strains. As a result, stresses are defined as a function of measured strains. Recall that Fig. 2 illustrates, for L heavy truck events ($i = 1$ to L), the SDF of maximum stress output for each event is defined as the ordered values of the maximum stress output per heavy truck event ($\sigma_{(i)}$) plotted against their probability of exceedance (p_i) using a Weibull plotting position $p_i = i/(L + 1)$ as shown in Fig. 4. Here, values of $\sigma_{(i)}$ are ranked such that $\sigma_{(1)}$ is the largest observed stress associated with ε_{\max} and $\sigma_{(L)}$ is the smallest associated with $\varepsilon_{\text{CAFT}}$. Figure 4 provides the first SDF, which is termed g1, based on the necessary sample size L .

11 Conversion of stresses to maximum stress based on Miner's rule

All stresses in Fig. 4 are converted into their maximum $\sigma_{(1)}$ using Miner's rule to calculate N_{g1}^* . Then, all the cycles associated with each stress level are converted into a reference number of cycles (N_{g1}^*) which is given as,

$$N_{g1}^* = (n_1)_{g1} + \sum_{i=1}^L \frac{(N_1)_{g1}}{(N_i)_{g1}} (n_i)_{g1} \quad (5)$$

where, $(n_1)_{g1}$ = number of stress cycles applied at a given stress level σ_1 associated with the heaviest truck event, $(N_1)_{g1}$ = number of cycles until fatigue failure applied at

stress level σ_1 according to S–N curve, $(n_i)_{g1}$ = number of stress cycles applied at a given stress level σ_i , $(N_i)_{g1}$ = number of cycles until fatigue failure applied at stress level σ_i associated with each truck event.

Now, $(N_1)_{g1}$ and N_{g1}^* are compared. If $\frac{N_{g1}^*}{(N_1)_{g1}} \geq 1$, then N_{g1}^* will be used to calculate the service life, otherwise, the algorithm will continue to generate more number of cycles until total damage reaches 100 percent; therefore, the first point of life index graph is determined as $((\sigma_1)_{g1}, N_{g1}^*)$. Again, $(\sigma_1)_{g1}$ is the largest observed stress associated with ε_{\max} in the first graph illustrated in Fig. 4.

12 Development of Heavy Truck Events Based on Bootstrap Method

The goal of this section is to develop numerous SDF's of maximum stress outputs using the bootstrap method. The bootstrap method is used to develop new sets of resampled data comprising maximum stress outputs from the measured maximum stress data. Each new bootstrap sample is then used to develop an SDF corresponding to that bootstrap sample similar to the approach suggested by Follen et al. [25]. Similar to Fig. 4, the SDF of bootstrapped maximum stress outputs is plotted as a new graph, g2. Figure 5 illustrates two estimates of the SDF of maximum stress outputs, one is derived from use of the bootstrap and one is based on the original sample. The two estimates are based on the same sample size L . The SDF's are sorted in descending order as shown in Fig. 5 where j is the number of each graph after sorting. Previous sections will repeat for the new graph. At first, N related to maximum stress in the new graph will be calculated according to S–N curve, referred to as $(N_1)_{g2}$. Then, stresses will be converted into

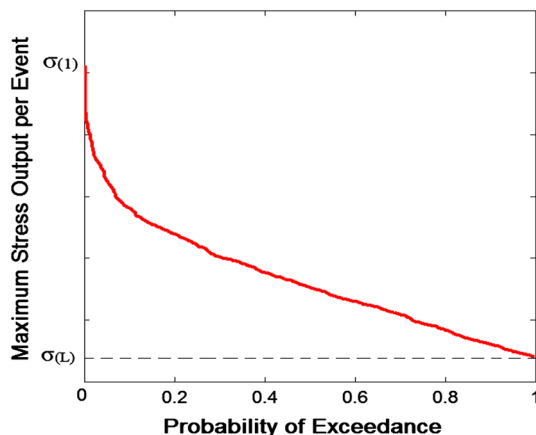


Fig. 4 Typical SDF of maximum stress outputs based on required sample size (g1)

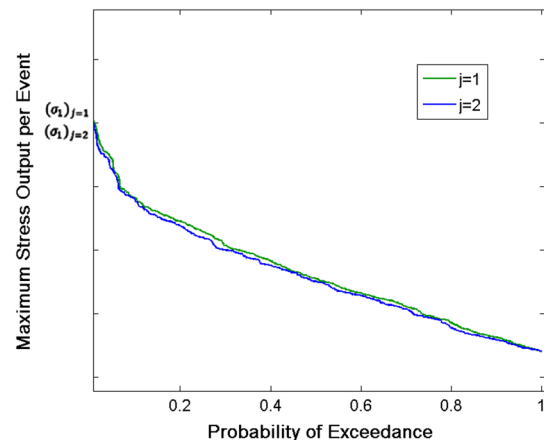


Fig. 5 Typical decreasing SDFs of maximum stress outputs

maximum stress $(\sigma_1)_{g2}$ to calculate of N_{g2}^* . In Fig. 5; $(\sigma_1)_{j=1} = (\sigma_1)_{\text{larger}}$ and $(\sigma_1)_{j=2} = (\sigma_1)_{\text{smaller}}$.

N_{g2}^* is a conversion of all cycles for each stress level into a reference number of cycles based on the specified number of cycles of stress data points, which is expressed as,

$$N_{g2}^* = (n_1)_{g2} + \sum_{i=1}^L \frac{(N_1)_{g2}}{(N_i)_{g2}} (n_i)_{g2} \quad (6)$$

where, $(n_1)_{g2}$ = number of stress cycles applied at a given stress level σ_1 in bootstrapped graph, $(N_1)_{g2}$ = number of cycles until fatigue failure applied at stress level σ_1 in bootstrapped graph, $(n_i)_{g2}$ = number of stress cycles applied at a given stress level σ_i in bootstrapped graph, $(N_i)_{g2}$ = number of cycles until fatigue failure applied at stress level σ_i in bootstrapped graph.

Then, the calculated number of cycles using Miner's rule are compared. If $\frac{(N^*)_{j=1}}{(N)_{j=1}} + \frac{(N^*)_{j=2}}{(N)_{j=2}} \geq 1$, the $(N^*)_{j=1}$ and $(N^*)_{j=2}$ will be used to estimate the bridge connection service life. Otherwise, the algorithm will continue to generate more cycles until total damage reaches 100 percent. In this section, the second point of the life index graph is determined as $((\sigma_1)_{g2}, N_{g2}^*)$. As a result, the algorithm will continue until $\sum_{j=1}^k \frac{(N^*)_j}{(N)_j} = 1$, where j is the number of sorted graphs in descending order as; $j = 1$ is the largest graph and $j = k$ is the smallest graph and k is the number of repetitions of the stress history to failure using bootstrap method. $(\sigma_1)_j$ are sorted decreasing graphs including $(\sigma_1)_{gi}$ as $i = 1, 2, 3, \dots, k$.

13 Life Index and Cumulative Number of Cycles

According to the obtained points, a graph of the maximum stresses vs. cumulative number of cycles will be plotted. Therefore, for all the points the absolute maximum stress values and dependent number of cycles will be ranked from the largest to the smallest. Then $N_{\text{cumulative}}$ is given as,

$$N_{\text{cumulative}} = N_{j=1}^* + \sum_{j=1}^k \frac{(N)_{j=1}}{(N)_{j=k}} N_{j=k}^* \quad (7)$$

where, $N_{j=1}^*$ = number of stress cycles applied at the largest maximum stress level $(\sigma_1)_{j=1}$, $(N)_{j=1}$ = number of cycles until fatigue failure applied at the largest maximum stress level $(\sigma_1)_{j=1}$, $N_{j=k}^*$ = number of stress cycles applied at the smallest maximum stress level $(\sigma_1)_{j=k}$, $(N)_{j=k}$ = number of cycles until fatigue failure applied at the smallest maximum stress level $(\sigma_1)_{j=k}$.

The service life index (μ_j) is defined by mapping all the stresses on a range of [0, 1] as,

$$\mu_j = \frac{(\sigma_1)_j - (\sigma_1)_{\text{max}j}}{(\sigma_1)_{\text{min}j} - (\sigma_1)_{\text{max}j}} \text{ for } j = 1, 2, 3, \dots, k \quad (8)$$

where, $(\sigma_1)_j$ is the maximum stress level for each bootstrapped graph, similar to Fig. 5. The min j and max j indices values are equal to 1 and k , respectively.

Aging of a steel bridge over a period of time can be calculated by the piecemeal decrease of life index. This means that the service life index will gradually decrease as the steel bridge ages until fatigue failure.

The service life index starts from unity. Unity is the first point of life index, which shows a steel bridge is undamaged and no repair is deemed necessary. On the other hand, when the service life index is less than one, the steel bridge is subjected to fatigue cycles, with a collapse predicted as μ_j , which is equal to zero, and approaches $N_{\text{cumulative}}$. The service life index can be used as a reliable fatigue signature to evaluate the age condition of existing steel bridges under load cycles and can also be used to predict the remaining service life. This is documented below how the service life index can be used as an indicator for steel bridge service life prediction subjected to cyclic loadings.

14 Determination of Service Life Based on Regression Analysis Using Service Life Function

A curve is fitted through the points (μ_j vs. $N_{\text{cumulative}}$) using ordinary least squares regression to fit the function $f(\mu)$. The function $f(\mu)$ is defined as the service life function. Regression analysis identifies and quantifies the function $f(\mu)$ that determines the number of stress cycles applied at the maximum stress levels. This function represents actual changes of average daily traffic (ADT), a unique feature of this research. Average daily traffic is equal to the total heavy truck traffic volume during a given time period, ranging from one day to one year, divided by the number of days in that time period. It should be noted that this value will vary year to year. In fact, due to an increasing demand, the ADT for a given bridge generally increases. Hence, the number of cycles can change throughout the service life of steel bridges. When the life index of a specific bridge is calculated based on measured stresses, and then the number of cycles related to actual changes of traffic will be determined by substituting the value of calculated life index into the service life function. The measured stresses are experienced based on actual traffic loads. The following inverse exponential function $f(\mu)$ is proposed for modeling

service life because it captures the shape relationship between the service life indices and cumulative number of cycles.

$$f(\mu) = \left(\frac{a - \ln(1 - \mu)}{b} \right)^c \quad (9)$$

where, constants a , b , and c are specific values for each steel bridge and $f(\mu)$ represents the number of stress cycles applied at the maximum stress levels for a given service life index μ .

The function $f(\mu)$ in Eq. (9) is also useful as an approximating function for possibly an algebraically complex a nonlinear relationship in terms of the life index. It is applicable to data sets, which are naturally related to bending curvature, and can be used to fit trends with complex curvature with no particular theoretical function. The estimated function $f(\mu)$ can be used for service life predictions. If daily strain values for truck events are measured on a bridge, then the actual change in ADT can be determined for each year. Hence, the number of cycles can change throughout a bridge's service life. To consider the actual change in ADT, the extracted, measured, maximum stress level of the bridge will be calculated due to heavy truck events after a specific time interval. Then, a life index corresponding to this stress level is calculated using Eq. (8). The induced number of cycles at this stress level is determined by Eq. (9) based on the actual change of ADT. Steel bridge remaining service life at the equivalent point is estimated as,

$$T = \frac{(N_{\text{cumulative}}) - f(\mu)}{(N_{\text{ADT}})_{\text{Heavytrucks}}} \quad (10)$$

where, (N_{ADT}) represents the number of cycles for average daily traffic in one year for heavy trucks. The presented theory for service life prediction of existing steel bridges using measured strain data is summarized in the flowchart as shown in Fig. 6.

In summary, for the application of the presented procedure for service life prediction to a full-scale steel bridge, first, all the critical components are determined. Then, measured strains are gathered for all the critical locations on the critical components. Probability density function, cumulative distribution function, and survival distribution function of measured strain data are determined. After, determining the required sample size for a stable statistical survival distribution function, maximum stresses are calculated from measured strain data for each truck passage. SDF of maximum stress data are plotted and all the stress data are converted into their maximum $(\sigma_1)_{g1}$ using Miner's rule. Also, the number of cycles associated with each maximum stress level is converted into a reference number of cycles, N_{g1}^* . Using the bootstrap method, maximum stress data are extended to more data as future events. Similar to SDF of maximum stress data, all the SDFs of bootstrapped stress data are plotted. Then, the maximum stress data associated with each bootstrapped SDF is converted into its maximum stress for each SDF. Maximum stress values and associated number of cycles

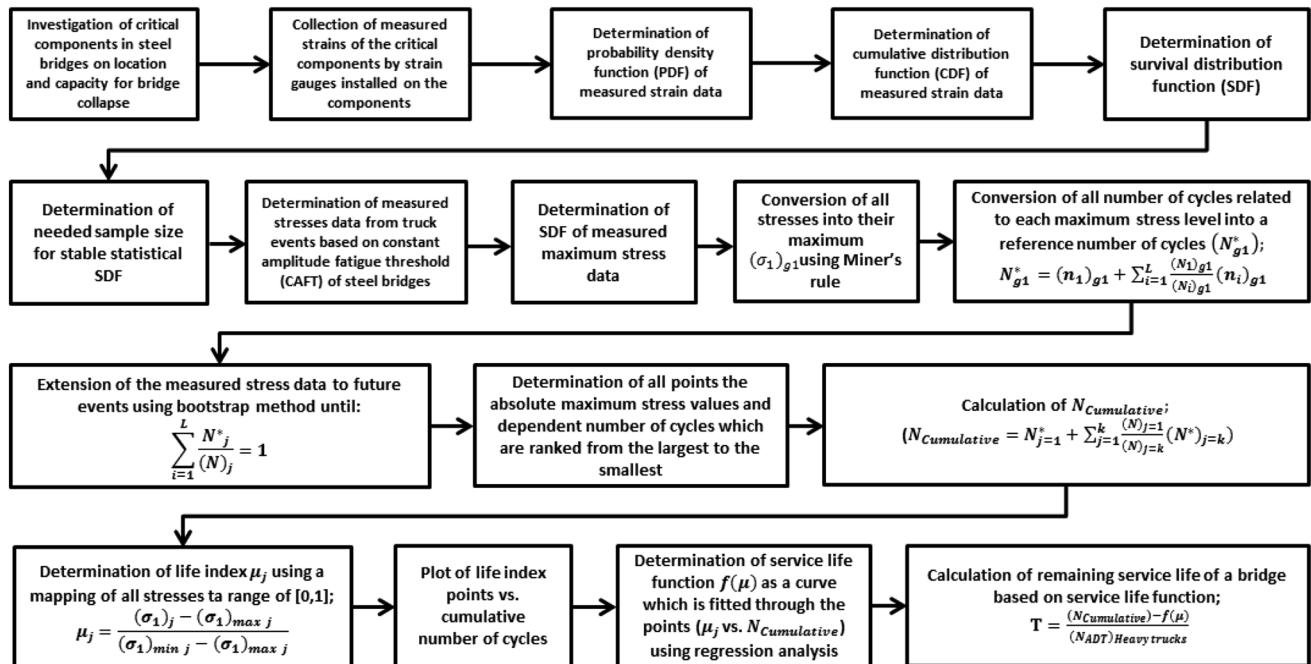


Fig. 6 Procedure for steel bridge service life prediction

N_{gi}^* , which is labeled N_j^* are ranked from the largest to the smallest. The cumulative number of cycles is calculated from the associated number of cycles for each truck passage and then life indexes are determined by a mapping the stresses into a range of [0, 1]. After plotting the life index points vs. cumulative number of cycles, a service life function is fitted through the points using regression analysis. Finally, remaining service life of the steel bridge is determined using the cumulative number of cycles, the service life function, and the average daily traffic volume related to the bridge.

15 Conclusions

A simple and reliable statistical method is presented for service life prediction of steel bridges which is based on measured strain data gathered from a real-time structural health monitoring system over a specified time period. The following innovations were used in the proposed method:

1. A nonparametric bootstrap method is employed for generation of new samples of measured strain data, which are then used to simulate stresses of steel bridges under daily traffic loads. This paper presents describes how the bootstrap method can be used to predict possible future fatigue cycles as a nonparametric statistical tool. This method uses computer simulations to replace the complex theoretical probabilistic assumptions and models required for most statistical approaches used to summarize probability distributions.
2. A service life index is introduced based on the survival distribution function of the maximum stresses, using Miner's rule according to the steel linear elastic behavior. This quantitative index enables the prediction of the ultimate service life of existing steel bridges based on the number of cycles.
3. Also, a service life function as a nonlinear service life function is proposed for the prediction of remaining service life of steel bridges. This function can be used for modeling relationships between life index and cumulative number of cycles using regression analysis. The proposed service life function can predict the remaining service life for any arbitrary future time period within the range of values considered in the experiments. The fitted service life function was capable of considering the actual changes in the average daily traffic for the prediction of remaining service life.
4. In a structural health monitoring program, service life of a steel bridge can be calculated using the proposed function based on regression analysis which presents a

powerful tool for determining accuracy of statistical functions. As a result, this method predicts the number of cycles under fatigue behavior which a steel bridge can endure in its service time period. The proposed service life prediction can contribute to effective management of steel bridges.

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