Evaluation of Time-Variant Bridge Reliability Using Structural Health Monitoring

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ABSTRACT

The engineering community demands critical effects of bridge deterioration over long-term to be investigated and monitored closely, especially after the recent bridge collapses in the US. Combined with reliability techniques, structural health monitoring (SHM) can provide objective and accurate assessment of existing condition and prediction of future trends based on collected data. Also, current SHM applications generate tremendous amounts of data, especially for long-term monitoring. It is crucial to develop innovative approaches for data management and timely assessment, in order to improve the benefit of future SHM applications. The authors propose generating structural reliability indices based on monitoring data. Reliability methods provide a crucial tool for SHM to add probabilistic structural evaluation function. This paper investigates a generic but comprehensive health monitoring approach for long-term data collection and assessment using reliability concepts. A simulation is used to generate sensor data for a typical highway bridge continuously, which is processed to produce reliability parameters. Deterioration effects are introduced on this bridge in order to demonstrate how degradation can be assessed and tracked. This demonstration will establish a guideline for applying reliability assessment based on monitoring data.

NOMENCLATURE

\( \mu \) : Mean value  
\( \sigma \) : Standard deviation, scale factor  
DL : Dead load  
C(t) : Corrosion penetration model  
A, B : Random variables for corrosion penetration  
\( \xi \) : Shape factor  
u : Threshold factor  
\( \beta \) : Reliability index  
Fy : Yield stress for steel  
Sx : Section modulus  
Es : Modulus of elasticity for steel
INTRODUCTION

Bridges are critical links of transportation networks. Any damage or collapse of a bridge not only results in loss of property and human fatalities but also has severe effects on the regional economy. Deterioration of civil infrastructures in North America, Europe and Japan has been well documented and publicized. In United States, 50% of all the bridges were built before 1940 and approximately 42% of those present structural deficiency [1]. As a result, many researchers have been investigating techniques and methods to evaluate the structural condition for objective decision-making. Successful visual inspection of these structures depends on considering all possible damage scenarios at all critical locations, not an easily accomplished task even for an experienced inspector. Despite all these limitations, visual inspection remains today the most commonly practiced damage detection method. To objectively evaluate the condition of existing structures and to better design new ones, researchers are exploring novel sensing technologies and analytical methods that can be used to rapidly identify the onset of structural damage [2; 3].

Definition of Structural Health Monitoring

As there is not a standard approach for SHM, there is not a unique, collectively accepted definition as well. We adopt the following: SHM is, the measurement of the operating and loading environment and the critical responses of a structure to track and evaluate the symptoms of operational incidents, anomalies, and/or deterioration or damage indicators that may affect operation, serviceability, or safety reliability. It is possible to capture long-term structural behavior with continuous or discrete intervals of monitoring, capturing seasonal and environmental changes that are not readily apparent from intermittent tests. Health monitoring concept uses integrated local and global non-destructive experimental technologies together with advanced structural analysis and modeling techniques to complement inspections and provide continuous information regarding bridge state parameters, loading environment, and state of health [4].

Reliability Methods based on Structural Health Monitoring

There have been extensive studies with different approaches towards the common aim of improving bridge network maintenance practices by increasing the accuracy of the predictions, improving the structural safety and reducing the life-cycle cost. With the exception of some recent studies by the authors, [5; 6; 7] and studies by Hong Kong researchers [8], structural reliability approach has not been fully studied by using SHM long term data to the extent of the authors’ knowledge. So far, all reliability methods reviewed make use of condition ratings based on visual inspections or theoretical/numerical models. Supplementing the reliability models with sensor data or NDE results has been suggested in some references; however, a comprehensive reliability approach using a complete SHM application needs to be further investigated.

![Figure 1 – Approaches for Bridge Management](image-url)

There is a need for integrating SHM and reliability analysis as a framework composed of a comprehensive SHM application used for probabilistic analysis of system and component reliability for efficient bridge management and decision-making. Integrating reliability analysis in a SHM framework is a tool to achieve
a comprehensive and advanced bridge management practice. The promise of integrating both approaches as complementing applications is given conceptually in Figure 1.

Current SHM technology is capable of providing rapid or even real-time condition assessment of structures. Accurate and comprehensive data is produced, which greatly eliminates the uncertainties involved in the traditional structural appraisal methods. Better accuracy means improved operational safety, as well as instant notification of unexpected distress. These tools should be complemented with probabilistic structural analysis approaches for evaluation and estimation of uncertainties, and determination of structural system reliability based on SHM data. These advances in bridge condition assessment will lead to higher level management practices by performance projections, accurate project/network level cost-benefit evaluation and life-cycle cost analysis for maintenance optimization and decision making.

While reliability methods are quite powerful for quantifying risk and uncertainty, they require a great deal of input data to execute [9]. Also, current reliability techniques depend mostly on visual inspection results, which create additional uncertainty. As indicated in recent studies [5], reliability of a structure can change significantly if data from monitoring is used.

OBJECTIVES OF THE PAPER

The authors of this paper have been researching and applying reliability methods and structural health monitoring applications with various analyses. It is understood that using reliability techniques with SHM data has tremendous promise, for introducing an advanced analysis approach, reducing uncertainties, and providing quick and efficient processing. The main objectives of this paper are:

1. To investigate structural reliability methods for bridges with long-term monitoring application.
2. To demonstrate strain gage monitoring application using simulated data.
3. To propose a methodology that allows for using monitoring data to predict lifetime reliability.

These are the initial set of objectives that aim at integrating reliability methods into structural health monitoring. The methodology is to be further developed and tested in actual SHM applications, especially by monitoring environmental inputs and responses. One of the critical response measurements is obtained by means of strain measurements. Therefore, the scope of this paper is to propose a methodology to use probabilistic analysis of strain data for calculating structural reliability, and to validate the methodology with an analytical simulation.

RELIABILITY ASSESSMENT SIMULATION ON BRIDGES

Description of the bridge

A simulation was conducted by considering a highway bridge of steel girders and concrete deck. The bridge is simply supported; spanning 100ft between its two piers with five parallel W36×280 steel beams. The elevation view and the cross-section of the bridge are shown in Figure 2, as well as strain gage application. Two types of vehicular traffic is considered on the bridge, car or truck. Both types of vehicles are assumed to be point loads with their location and magnitudes being random variables. The mean values of vehicle loads are indicated in the same figure.

![Figure 2 – Bridge elevation and cross-sections and strain gage location](image-url)
The example bridge reflects common highway bridge characteristics, which constitute a major portion of the bridge population in the US. Although this simulation considers a single strain gage measurement, which is the most basic case, the methodology is expandable to include multiple-gage measurements. This will be discussed following the simulation and results.

**Long Term Effects and Deterioration**

All structures undergo certain deterioration effects due to normal aging and overloads. For maintenance operations and bridge safety, it is crucial to estimate the future condition of bridges. Corrosion penetration and associated section loss was considered as the main factor in capacity degradation over the lifetime of the bridge. Section loss due to corrosion is a major cause of deterioration for steel profiles, especially at locations closer to salt water and with high humidity. Numerous studies exist in the literature have setup the framework for reliability analysis under deteriorating bridge sections and multiple limit states. The following corrosion penetration model was used in the simulation to define the degradation effect over time:

\[
C(t) = A t^B
\]

where \(C(t)\) is the corrosion penetration depth in \(10^{-6}\) m, \(t\) is time in years, and \(A\) and \(B\) are statistical random variables obtained from [10]. The statistical parameters of \(A\) and \(B\) are given in Table 1.

<table>
<thead>
<tr>
<th>Random Variable</th>
<th>(A)</th>
<th>(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interior Girders</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Value</td>
<td>34.0</td>
<td>0.65</td>
</tr>
<tr>
<td>Coefficient variation</td>
<td>0.09</td>
<td>0.10</td>
</tr>
<tr>
<td>Correlation Coefficient</td>
<td>0.0</td>
<td></td>
</tr>
<tr>
<td>Exterior and Interior-Exterior Girders</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Value</td>
<td>80.2</td>
<td>0.593</td>
</tr>
<tr>
<td>Coefficient variation</td>
<td>0.42</td>
<td>0.40</td>
</tr>
<tr>
<td>Correlation Coefficient</td>
<td>0.68</td>
<td></td>
</tr>
</tbody>
</table>

The corrosion penetration was assumed to be following the pattern shown in Figure 3. According to this pattern, due to pooling, the corrosion progresses along the top surface of the bottom flange and \(\frac{1}{4}\) of the depth of the web. A similar example was presented in Estes and Frangopol [11].

![Corrosion Penetration vs Time](image)

**Figure 3 – Corrosion penetration model and corrosion pattern**

Using the corrosion penetration function and the corrosion pattern, loss of section can be calculated. Mean value and standard deviation for the cross-sectional area was evaluated using a linear approximation with Taylor Series. Similarly, mean value and standard deviation of neutral axis location and the elastic section modulus were calculated with respect to time. Degradation of the elastic section modulus is shown in Figure 4.
Therefore, the long-term deterioration effects due to corrosion were modeled as statistical variables. It is noted that in the model the uncertainty increases with time, as expected.

![Figure 4 – Deterioration of elastic section modulus over time](image)

**Simulation of Strain Measurements**

For all highway bridges in the National Bridge Inventory (NBI), an average traffic load is reported, in order to estimate the demand. The average daily traffic (ADT) value for the simulation bridge was taken as 16,000, which is a common figure for bridges in urban areas. ADT of 16,000 means that on average, 16,000 vehicles cross the bridge each day. Average Daily Truck Traffic (ADTT) was taken as 5%, which means that 5 percent of all vehicles are of truck category. For simulating strain realistically, number of vehicles on the bridge at any time was randomly generated based on the ADT, assuming a standard deviation of ± 100 cars, or ±10 trucks. Similar to the number of vehicles, vehicle loads were randomly generated from normally distributed random variables, as shown in Figure 5.

![Figure 5 – Simulated effects of car and truck as statistical random variables](image)

A MATLAB code was developed to generate strain values over time. The processing of the strain data will be real-time, as considered for the actual field application.
The concern for long-term strain monitoring is the peak values, since the maximum effects govern the structural capacity. There are two approaches to analyze the extremes:

1. **Block Maxima Approach**
2. **Threshold Approach**

These two approaches both study the extreme values, which are of concern for long-term strain measurements. Extreme values of strain are observed during heavy traffic or excessive environmental effects, that the bridge suffers through its life span.

**Block Maxima Approach**

For the Block Maxima Approach, the maximum observed values over certain time spans are considered. These values are modeled through the Extreme Value Theory. Extreme value distributions are used to model the maximum values of data sets. It is worth noting that this approach was used previously in [12; 13]. The generalized extreme value function combines three simpler distributions into a single form, allowing a continuous range of possible shapes that include all three of the simpler distributions. Three types of extreme value distributions, Type I (Gumbel), Type II (Frechet) and Type III (Gumbel), are combined in the Generalized Extreme Value distribution with shape parameter $\xi$, location parameter, $\mu$ and scale parameter, $\sigma$. The probability distribution function for the Generalized Extreme Value Distribution is given as:

$$y = f(x | \xi, \mu, \sigma) = \left( \frac{1}{\sigma} \right) \exp \left( - \left( 1 + \xi \frac{x-\mu}{\sigma} \right)^{-\frac{1}{\xi}} \right) \left( 1 + \xi \frac{x-\mu}{\sigma} \right)^{-1-\frac{1}{\xi}}$$

which is valid for $1 + \xi \frac{x-\mu}{\sigma} > 0$ (2)

From the strain data, the maximum strain values were picked for each data block of 1-minute duration. The procedure is as follows: From the simulated strain values, maximum values for one-minute time lengths are obtained, which yields 1440 data values for each day. One underlying assumption is that the strain measurements used as data points are independently and identically distributed. Since, a vehicle traveling at a common speed of 40mph will take less than 2 seconds to cross the bridge span, this assumption can be accepted.
as valid. For long-span bridges where crossing can take more than a minute, longer time blocks should be taken to satisfy the assumption.

**Threshold Modeling**

Generally, for strain measurements, the measurements exceeding certain thresholds are investigated. Signal noise and other uncertainty effects create strain values even when there is no external loading on the structure. Therefore, only the data exceeding a certain threshold can be considered. For the simulation, this threshold was set to be 50 microstrain, which is a reasonable value to observe on an actual bridge during minimal loading. The peak strain values exceeding this threshold were determined and collected. Therefore, the random variable space can be described as in Eq.(2), where $Y$ is the random variable and $u$ is the threshold value.

$$P(Y > u + | Y > u)$$

(3)

This probability converges to the Pareto distribution as $u$ approaches infinity. Therefore, the Generalized Pareto distribution is used to fit the data. The probability distribution function of a Generalized Pareto distribution is given as follows:

$$y = f(x | \xi, \sigma, u) = \left( \frac{1}{\sigma} \right) \left( 1 + \frac{y - u}{\sigma} \right)^{-1 - 1/\xi} \quad \text{for } y > u$$

(4)

where $\xi$ is the shape parameter, $\sigma$ is the scale parameter, and $u$ is the threshold parameter. For this distribution, the strain values from the simulation were filtered through the threshold value and maximum strains were retrieved with a peak-detecting algorithm. The resulting histogram of maximum strain values were plotted and fitted to a Generalized Pareto Distribution.
Obtaining the Annual Probability Distribution

The approaches using block-maxima and threshold approaches yielded different probability distributions. The probability distribution of daily maximum strains was used to calculate the annual probability of exceedance. For calculating the annual distribution, daily values were used with a binomial distribution, over 365 days for the values of the random variable.

PROBABILITY OF FAILURE

Limit State Function

Probability of failure of a structure indicates the risk of exceedance of certain limit states throughout the life-time of the bridge. If the limit state function is positive, resistance is greater than the load effects, so the structure is safe. The reliability index, $\beta$, is related to the probability of failure through the following equation:

$$\beta = -\Phi^{-1}(P_f)$$  \hspace{1cm} (5)

where $P_f$ is the probability of failure, and $\Phi^{-1}$ is the inverse of the probability distribution. For illustration, first order (FORM) reliability index formulation was used to evaluate the limit state function. More advanced methods like Monte Carlo simulation are necessary for actual implementations. The limit state function to be used for the simulation similar to that used in [5] is
where $\varepsilon_{\text{measured}}$ is the measured strain values due to traffic and live load effects, $F_y$ is the yield stress, $S_x$ is the section modulus, $E_s$ is the modulus of elasticity, $\varepsilon_{DL}$ is the strain due to dead loads and $\varepsilon_T$ is the strain due to temperature effects. Probability distribution for $\varepsilon_{\text{measured}}$ is the annual PDF of maximum strains obtained from the simulated real-time strain readings. The dead load strain was calculated from the cross-section properties including the steel shape and the deck contribution, as approximately $180 \mu\varepsilon$. Temperature-induced strains, included as $\varepsilon_T$, can be determined from slow-speed gages such as vibrating wire strain gages. A recent study on long-term bridge monitoring revealed that temperature-induced strains are very influential on the structural reliability [14]. In the mentioned study, the temperature effects on strain were found to be up to $200 \mu\varepsilon$ over seasonal changes, and that value was used for the variable $\varepsilon_T$. For an actual implementation, FEM can be used to estimate the dead load strains accurately. Annual probability of failure and reliability index was calculated by evaluating the limit state based on the reduced section modulus $S_x$ due to the corrosion model. Reliability index for each year was found and combined to calculate 75 year failure probability, and the reliability index for 75 years, which is the assumed lifetime of the bridge.

![Figure 10 – Reliability Index for 75-year Life Span](image)

The result shows the change of reliability index based on the strain measurements, over 75 years. The decrease in the reliability index is a result of deterioration effects, as well as increasing uncertainty over long term. The reliability index, $\beta$, is given in Table 2 for the years shown.

<table>
<thead>
<tr>
<th>Year</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9.08</td>
</tr>
<tr>
<td>5</td>
<td>9.07</td>
</tr>
<tr>
<td>10</td>
<td>9.05</td>
</tr>
<tr>
<td>20</td>
<td>8.98</td>
</tr>
<tr>
<td>50</td>
<td>8.36</td>
</tr>
<tr>
<td>75</td>
<td>7.09</td>
</tr>
</tbody>
</table>

The prediction of the reliability index over the lifetime of a bridge enables maintenance decisions carried out more effectively. The bigger impact will be on the bridge safety, since the reliability curve based on strain measurements indicates the remaining life and reflects any structural problems that the bridge undergoes, therefore, reducing unexpected failures.
CONCLUSIONS AND FUTURE WORK

The study shows that structural health monitoring data is very applicable to reliability analysis of bridge structures. The prediction tools used for determining the time-variant reliability are based on previous statistical studies on corrosion, which has to be updated, as more data from monitoring is available. Bayesian Updating techniques are to be used for each new point in time to refine the prediction.

System reliability is a major concept in reliability analysis, because individual limit state functions are assembled together in a system model. The failure conditions are determined by the system model, since failure of one or two members may not be important due to redundancy. On the other hand, there may be critical components (fracture-critical) which have to stay intact for the structural integrity of the whole system. System reliability can be modeled with certain assumptions, which is assembling the failure limit states as parallel or series links after determining the failure modes. System reliability can be used for monitoring-based reliability assessment. Further efforts in this direction are necessary.

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REFERENCES


