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The sensitivity of bridge safety to spatial correlation of load and resistance

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ABSTRACT

Random Field theory has emerged in recent years to model the statistical correlation of resistance in concrete structures and to determine its influence on the probability of structural failure. A major shortcoming in the work carried out to date is the spatial variability and corresponding correlation associated with applied traffic loads. In this paper the influence of spatial correlation of both traffic load and resistance is considered in the context of bridge safety assessment. The current study, explores, the nature of the problem by three theoretical examples. As a general trend, examples show that while traffic loads are weakly correlated, load effects are strongly correlated as the same heavy vehicle often causes extremes of load effect in different parts of the bridge which is due to the transverse sharing of load (measured here using a load sharing factor).

It is found that the strength of correlation of load effect depends greatly on the load sharing factor which is treated in a simple way in many studies. In a more sophisticated beam-and-slab bridge example, load sharing factors are derived from a finite element analysis to assess transverse load sharing, and are shown to vary by girder number, girder segment and by load location. Despite the fact that load effect at points along the length of a bridge is strongly correlated, the combined influence of correlation in load and resistance on probability of failure is small.

1. Introduction

An accurate assessment of the remaining service life of a structure requires information about the structure and its load and a simulation model which is able to incorporate this information into a safety analysis. The simulation should account for various sources of uncertainty in modelling such as time-dependent variation of structural performance, randomness in loading, and variability of material and geometrical properties. This requires the use of probabilistic methods in a structural safety analysis. Two types of uncertainty, namely the aleatory and the epistemic, are necessary for an accurate probabilistic analysis [4]. Whereas randomness (or aleatory uncertainty) cannot be reduced, improvement in knowledge or in the accuracy of predictive models will reduce the epistemic uncertainty [3]. Probabilistic reliability analysis permits the inclusion of these uncertainties into a safety analysis.

In recent times, probabilistic and reliability-based approaches have been widely used to quantify bridge safety [1,6,9,12,13,28,40–45,49,54]. While the focus of much of this work has been on the probabilistic description of homogeneous properties, less effort has been directed towards the modelling of the spatial correlations of load and resistance. It is well established that the material properties of a structure and structural dimensions are spatially variable, associated with workmanship and environmental conditions. This results in spatially distributed damage mechanisms such as corrosion-induced cover cracking and spalling. Traffic load and particularly the stresses due to the load, are also spatially correlated.

Allowing for spatial correlation in probabilistic calculation is achieved by Random Field (RF) theory, and the terms RF and spatial variability are used synonymously in the literature. In the RF analysis, the random field is discretised into large numbers of spatially correlated discrete random variables. The structural member is divided into small segments and spatial variation within a segment is neglected. It is implicit that deterioration at a point increases the probability of deterioration at adjacent points. Recent work has demonstrated the advantage of incorporating spatial variability into stochastic models to predict the likelihood and extent of corrosion damage in reinforced concrete (RC) structures [18,23,38,40,41,43,46].

Engelund and Sørensen [10] consider spatial variation of the variables associated with the critical threshold for initiation of corrosion of reinforcement, i.e., the coefficient of diffusion of chloride and surface chloride concentration. They estimate the distribution of the time to initiation of corrosion using the First Order Reliability Method (FORM) and Second Order Reliability Method (SORM) analyses. Stewart [37] considers the spatial variability of pitting corrosion in RC beams. RC beams are discretised into series of segments in one-dimension (1D) random fields and maximum pit depths are generated for each reinforcing steel bar in each element.

Malioka and Faber [25] suggest that corrosion initiation and propagation are spatially variable due to the general trend seen within

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concrete batches and workmanship during construction of RC structures. The authors then present a random field approach to model the spatial variability of concrete permeability and use this within a reliability analysis to predict the percentage of a structure that will exhibit degradation at a specified point in time.

Spatial variability research carried out to date has been mainly focused on predicting the performance of corroding structures and spatial variability of the common parameters such as material, dimension and environmental properties [2,7,17,18,24,26,38,52,55]. A major shortcoming in the work to date is that the spatial variability and corresponding correlation associated with applied loads and load effects has not been allowed for.

Analysis of measured traffic data shows there are patterns of correlation and interdependence between vehicle weights, speeds and inter-vehicle gaps, both within lanes and between adjacent lanes in same-direction traffic [31]. Correlation between weights of successive vehicles can arise from a number of causes. There are times of the day at which heavy vehicles are more likely to travel, and these intra-day patterns are one reason why there is a weak but non-zero level of correlation between vehicle weights within each lane. Furthermore, heavy vehicles from the same company can sometimes travel together.

In the work by Nowak [29], a number of simplifying assumptions are made – for instance, that one in 15 heavy trucks has another truck side-by-side, and that for one in 30 of these multiple-truck events, the two trucks have perfectly correlated weights. A heavy truck is defined as one with a Gross Vehicle Weight (GVW) in the top 20% of measured truck weights. It is calculated that the maximum load effect in 75 years is caused by two trucks side-by-side, with each truck having a GVW of 85% of the maximum individual GVW in 75 years. As Kulicki et al. [20] note, the assumptions used are based on limited observations, and no data is utilised for the assumptions on weight correlation; they are entirely based on judgment.

Sivakumar et al. [35] refine the definition of side-by-side events to include two trucks with headway separation of ± 18.5 m (60 ft), and also consider the influence of the bridge length. Sivakumar et al. [34], citing Gindy and Nassif [14], extend this further by classifying multiple-presence events as side-by-side, staggered, and following or multiple. They present statistics, derived from weigh-in-motion (WIM) measurements, for the frequency of occurrence of these events for different truck traffic volumes and bridge spans. They describe a method for estimating site-specific bridge loading which uses multiple-presence probabilities calculated either directly from WIM data or estimated from traffic volumes using reference data collected at other sites. It is assumed that there is no correlation between weights in adjacent lanes and that the GVW distribution is the same in both lanes. The latter assumption, in particular, has been shown to be inconsistent with measurements [31].

OBrien and Enright [31] introduce 'scenario modelling' as a method of simulating traffic that is relatively simple to apply. It is found that, even though traffic load is very slightly correlated, load effects are strongly correlated and gaps in adjacent lanes are closely linked. The correlated traffic is found to give a better fit to the measured data than models which assume no correlation. A least squares measure is used to quantify the goodness of fit of the two simulation models to the measured load effects. For this purpose, ratios which compare the goodness of fit of simulated daily maximum load effects from the uncorrelated and smoothed bootstrap model are averaged across all relevant load effects and bridge lengths. In this comparison ratios significantly greater than 1 mean that the smoothed bootstrap model gives a better fit. It is found that in most cases the ratio is higher than 1.5 [31].

In this paper, three numerical examples are presented, of varying complexity, to explore the spatial variability of load and load effect and the spatial variability of resistance, and examine the effect of these correlations on the probability of failure. First, a single-span 'bridge' consisting of two side-by-side beams is considered (i.e., transverse interaction is ignored). Correlation of resistance and load is examined for a segment at mid-span of the bridge. Single point loads are applied on each beam. In the second example, point loads are again used on a single-span bridge made up of two side-by-side beams. However, in this case, the loads are assumed to travel across the bridge and their relative position is allowed to vary randomly to better simulate actual traffic loading. The effect of considering all segments, rather than just the mid-span, is also investigated. Finally, a more realistic example is considered that illustrates the same concepts identified in the simpler examples. In this final example, a probabilistic load model is applied to a 2D beam and slab (girder) bridge. Like the HL-93 model, there is a moving three-axle truck combined with a uniformly distributed load (UDL). The truck weight and the intensity of the UDL are assumed to be from Weibull distributions with parameters that give an approximate match with measurements collected on 20 m bridge in The Netherlands. In other words, these three examples investigate the following unanswered issues: (1) effect of load correlation on load effect correlation and hence probability of failure; (2) effect of load sharing factor on load effect correlation and hence probability of failure; (3) the effect of combined load and resistance correlation on probability of failure; (4) sensitivity of probability of failure to correlation coefficient of load and resistance and order of magnitude; and (5) effect of considering the possibility of element failure which are not necessarily at the mid-span for a simply supported bridge.

For this study, the authors combine models that allow for the spatial variability of resistance and the spatial variability of load and load effect. The influence of load correlation on probability of failure is investigated and its interaction with correlation of resistance.

2. Nature of correlation

2.1. Correlation coefficient for load and resistance

In the three examples considered in the current study, the random variables include the following: (i) loads on each lane, and (ii) resistances for each segment of each lane. For example, in the second example, a two-lane bridge has 14 segments in each lane, and two loads (one each on lanes 1 and 2) giving twenty eight resistances. Each random variable is assigned a probability density function (PDF) $f_{Xi}(x_i)$. In this study, the Pearson coefficient of linear correlation, ρ_{ij}, is used as a measure of the degree of linear dependence between the two variables and is referred to as the "coefficient of correlation" throughout this paper. In the current paper, the traffic load is assumed to be independent of distance and it is correlated using the constant correlation coefficient, ρ_P. In this study, P stands for load, S for load effect resulting from P, and R refers to resistance. For resistance, two different correlation terms are included: constant and distance-dependent:

$$\rho_R(\tau) = \rho_{R0} + (1-\rho_{R0})\exp\left(-\left(\frac{\tau_x}{d_x}\right)^2 - \left(\frac{\tau_y}{d_y}\right)^2\right) \quad (1)$$

where ρ_{R0} represents the constant component of correlation (e.g., workmanship will vary from site to site). The second term relates to inter-segment distances: $d_x = \theta_x/\sqrt{\pi}$; $d_y = \theta_y/\sqrt{\pi}$, where θ_x and θ_y are termed 'scales of fluctuation' and quantify the extent of the spatial correlation in the x and y directions respectively. The terms, $\tau_x = x_{j+1} - x_j$; $\tau_y = y_{j+1} - y_j$ are distances between centres of segments j and $j+1$ in the x and y directions respectively [24]. Eq. (1) is referred to as the autocorrelation function [15,18,24,50]. It determines the correlation coefficient between two segments separated by distance τ and is representative of the spatial correlation between the segments. As the distance between correlated segments increases, the correlation coefficient reduces.

To illustrate the effect of the distance-dependent term in Eq. (1), Fig. 1 shows the one-dimensional form of the function. It can be seen that the distance-dependent term has almost zero effect for segments