Title	Probabilistic modelling of bridge safety based on damage indicators
Authors(s)	Heitner, Barbara, O'Brien, Eugene J., Schoefs, Franck, Yalamas, Thierry, Décatoire, Rodrigue, Leahy, Cathal
Publication date	2016-10-01
Publication information	Heitner, Barbara, Eugene J. O’Brien, Franck Schoefs, Thierry Yalamas, Rodrigue Décatoire, and Cathal Leahy. “Probabilistic Modelling of Bridge Safety Based on Damage Indicators.” Elsevier, October 1, 2016. https://doi.org/10.1016/j.proeng.2016.08.279.
Conference details	The 9th International Conference on Bridges in Danube Basin: New Trenda in Bridge Engineering and Efficient Solution for Large and Medium Bridges 2016, Žilina, Slovakia, 30 September - 1 October 2016
Publisher	Elsevier
Item record/more information	http://hdl.handle.net/10197/7997
Publisher's version (DOI)	10.1016/j.proeng.2016.08.279

Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 00 (2016) 000–000

Procedia Engineering

www.elsevier.com/locate/procedia

9th International Conference „Bridges in Danube Basin 2016“, BDB 2016

Probabilistic modelling of bridge safety based on damage indicators

Barbara Heitner[a,b]*, Eugene J. OBrien[b], Franck Schoefs[c], Thierry Yalamas[a], Rodrigue Décatoire[a], Cathal Leahy[d]

[a]*Phimeca Engineering, 34 Rue Sarlieve, Cournon-d'Auvergne, 63100, France*
[b]*School of Civil Engineering, University College Dublin, Newstead, Belfield, Dublin 4, Ireland*
[c]*Research Institute of Civil Engineering and Mechanics, Université de Nantes, 1 Rue de la Noë BP 92101, 44321, Nantes cedex 3, France*
[d]*Roughan O'Donovan Innovative Solutions, Arena House, Arena Road, Sandyford, Dublin 18, Ireland*

Abstract

This paper introduces the various aspects of bridge safety models. It combines the different models of load and resistance involving both deterministic and stochastic variables. The actual safety, i.e. the probability of failure, is calculated using Monte Carlo simulation and accounting for localized damage of the bridge. A possible damage indicator is also presented in the paper and the usefulness of updating the developed bridge safety model, with regards to the damage indicator, is examined.

Keywords: Reliability; Safety; Bridges; Probabilistic; Bayesian Updating; Damage Indicator

1. Introduction

Probabilistic assessment of bridges has been the subject of various studies in recent decades [1][2][3][4]. It has been widely accepted that evaluating an existing bridge according to the standards and codes used for new structures can lead to unnecessary demolition or repair, and thus to high economic cost and an increase in the associated environmental impact. Using a probabilistic way and understanding the realistic risks related to the state of the bridge helps to avoid unnecessary costs and emissions. Nevertheless, decreasing the level of uncertainty is beneficial and so in the present paper a probabilistic model is presented that incorporates data, which can be obtained through bridge monitoring.

* Corresponding author. Tel.: +33789044595.
E-mail address: heitner@phimeca.com

1.1. Bridge Safety models

In several studies in the literature, researchers developed a complete or partial bridge safety model based on probabilistic assessment of load and/or resistance. The main focus of these studies however varies widely. Rocha et al. [1] focus on the safety assessment of short span railway bridges for identifying critical train speeds and the associated probability of failure. Hajializadeh et al. [2] primarily study the effect of spatial correlation of both load and resistance on the probability of failure of concrete road bridges. The principal aim in Zhou et al. [3] is to quantify the effect of projected traffic growth on the time-dependent reliability of a reinforced concrete (RC) bridge, accounting for structural deterioration caused by chloride induced corrosion. Marsh & Frangopol [4] also concentrate on the deterioration model of an RC bridge deck but improve the model by incorporating corrosion rate sensor data.

These works can also be distinguished through the simplifications, idealizations and the application levels. In the present work both load and resistance of a one-directional (single lane) bridge are modelled in a probabilistic context, accounting for localized damage and the bridge safety is found by combining them and calculating the probability of load exceeding capacity. The structural model of the bridge is greatly simplified and loads other than dead and traffic loads are ignored, since the emphasis is placed on the probabilistic assessment, the introduction of damage and the global methodology.

1.2. Bayesian updating

Bayesian updating is a powerful technique for combining a probabilistic model with a limited volume of information from measurement to enhance the existing model. It has already been used for several different problems in the field of structural engineering, such as for estimating bridge characteristic load effects [5], for prediction of the effects of corrosion on RC beam bearing capacity [6] or for updating either fatigue reliability of steel structures [7] or degradation of RC structures [8] using non-destructive test data. In the framework of this paper, a simple deflection-based damage indicator (DI) will be used as the measurement data for updating the bridge safety model and thus for obtaining a better measure of the actual condition of the studied RC bridge. It is acknowledged that more realistic damage indicators exist – deflection is used here simply to demonstrate the concept.

2. Initial bridge safety model

2.1. Resistance model

The resistance of the bridge is defined as the bending moment capacity of an RC deck cross-section. This resistance is calculated using both deterministic and random variables for the geometric, concrete and steel reinforcement properties. The incorporated random variables (explained in section 4) and their descriptions have been taken from the literature [9][10][11][12]. The bridge is represented by a simplified 1D beam model. Spatial variability is not accounted for along the length of the beam, however localized damage is introduced.

2.2. Dead load model

As for the resistance, the dead load model incorporates random variables that can be defined according to findings reported in the literature (e.g. after Akgül [13]). It accounts for the weight of concrete and the surface asphalt layer. Other bridge equipment is not taken into account as the corresponding load and its variation are relatively small. It can also be noted here that other loads, such as wind, thermal and seismic, are not considered in the current study.

2.3. Traffic load model

The traffic load model for this study is based on Weigh-in-Motion (WIM) data. The raw WIM data was cleaned and filtered for quality assurance purposes. There are different techniques for cleaning WIM data [14][15][16] and the final result depends on individual subjective decisions. For the purpose of this study it is decided to focus on trucks that can travel without special permit on roads, i.e., standard vehicles. The calculation of the relevant load effects, which are defined as the daily maximum values induced by the traffic load, and the related statistical interference method, are explained in more detail in section 4.

2.4. Probability of failure

In the present study the failure of the bridge is defined as the failure of any of its segments (one or more at a time). There are several possible ways to obtain this general probability of failure. However due to the complexity of civil engineering structures, analytical solutions can rarely be derived. Hence, Monte Carlo simulation is widely preferred and its suitability has already been proven in several studies [4][19][22] for computing probabilities of structural failure. Assuming full correlation between the segments, the results are independent from the discretisation of the bridge as shown in the following formulas:

$$Pf_{MC} = \frac{\sum_{j=1}^{N_{sim}} I_j}{N_{sim}} \tag{1}$$

where N_{sim} is the total number of simulations, j is the actual simulation and I_j can be expressed as:

$$I_j = \begin{cases} 1, \ if \ \ G_j \leq 0 \\ 0, \ otherwise \end{cases} \tag{2}$$

where the limit state function, G, of the j^{th} simulation is written as:

$$G_j = \min \left[C_{ij} - Ed_{ij} - Et_{ij} \right] \tag{3}$$

where i=1…k and k is the number of segments in the bridge.

3. Bayesian updating

3.1. Prior distribution of bar area loss

The aim of the methodology is to evaluate ageing bridges or bridges subject to intervention where the occurrence of damage cannot be ignored. In most of the studies to date, damage of reinforced concrete bridges is accounted for through a corrosion process that results in a loss of area of the reinforcement and hence gives a time-dependent resistance model as presented by Enright & Frangopol [23]. Additionally, in many recent studies the spatial variability of resistance is also accounted for [4][22][24].

In the next step of the methodology it is assumed that localized corrosion damage is discovered on the bridge. Therefore the presence of damage is not in question, but its severity is unknown. Corrosion is one of the most common sources of damage of RC bridges and hence this study focuses uniquely on it. The time that is needed for corrosion initiation and the speed of the corrosion propagation are highly dependent on the environment the bridge is located in, e.g. on the humidity of the environment, the present pollution or the amount of salt using for de-icing on or under the bridge. Using the appropriate formulas it is possible to approximate a bar area loss due to corrosion as a function of time [4][22][23][24][25]. In the present paper the descriptors of the distribution of the bar area loss are taken from [26].

3.2. Damage indicator

The prior distribution of bar area loss that is solely based on the literature, involves high levels of uncertainty and therefore it may be advantageous to update it with the use of real-time data. These data can be of several kinds, e.g. Ma et al. [6] use field measurements in a demolished RC bridge of concrete cover thickness, concrete strength and reinforcement loss, to update their probabilistic strength degradation model. However the aim of the present paper is to demonstrate a methodology that can be used for bridge maintenance. Thus it is not realistic to involve data that can be obtained only after demolishing the bridge. For this purpose it is proposed to apply Bayesian updating based on a damage indicator (DI). There are various DIs that can be used in the proposed model. The important point is to find DIs which are:

- Easy and fast to measure;
- Lead to no restriction on the traffic flow;
- Give relevant information about possible damage extent;
- And damage location in the bridge.

To find reliable and appropriate DIs that suit all these requirements is a real challenge. Therefore it has been decided to first establish the methodology and analyse the results using very simple DIs based on the deflection data of the bridge. In this case the deflections have been calculated from an assumed moving reference (as from a moving vehicle) but similar results would be expected from a fixed reference such as a laser measurement device fixed to the bridge. The location of the damage, as was mentioned before, is to be known and the question of interest is the extent, i.e. the severity of it. The chosen DIs are defined as the areas under the moving reference deflection curves for the two axles of the vehicle. These measures are able to provide information about the actual stiffness loss of the bridge relative to the bridge's original health condition, corresponding to the prior calculation of bridge reliability.

3.3. Connection between stiffness loss and moment capacity loss

Accounting for the bar area loss due to corrosion is a suitable way to consider damage not only because of its obvious contribution to capacity loss but also because it similarly affects the stiffness of the bridge. The stiffness of the bridge is approximated accounting for both concrete and steel properties, while neglecting the cracked part of concrete, as is shown in equation 4. In this sense while decreasing the area of steel, the stiffness decreases as well. The connection between the bar area loss and the bending moment capacity loss is well established in many textbooks so no further explanation is provided here.

$$S = E_c \cdot I_i \tag{4}$$

where E_c is the modulus of elasticity of the concrete, while I_i is the second moment of area of the idealized composite steel and concrete cross-section.

Fig 1 shows that in the probabilistic model a nearly linear correlation can be derived between stiffness and bar area loss and between capacity and bar area loss. This finding verifies the concept of transforming the stiffness loss, which information is implicit in the DIs, indirectly into a capacity loss. The correlation between stiffness and bar area loss is approximated by a linear model and the bar area loss prior distribution is updated with the data obtained through this linear model and based on the stiffness loss data coming from the DIs.

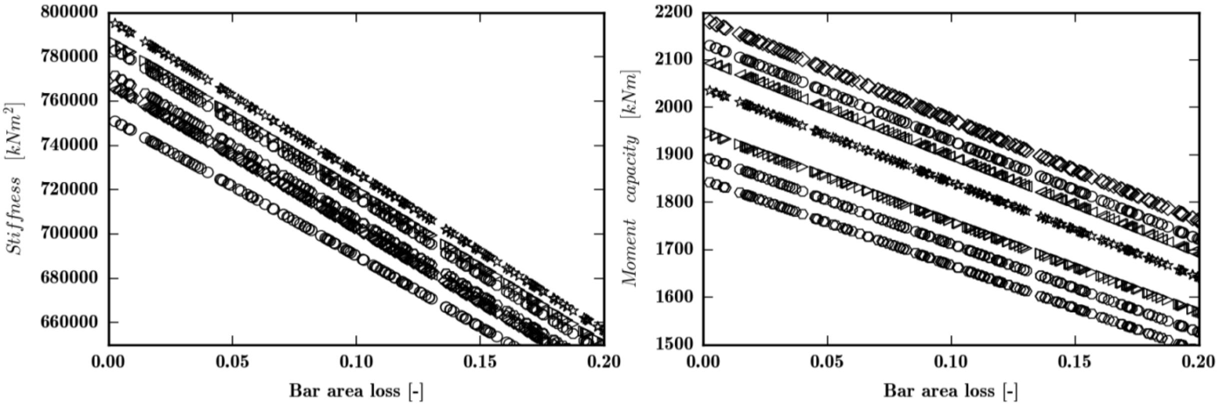

Fig 1. Linear correlation between the bar area loss and stiffness and the bar area loss and the moment capacity for short span RC bridges that slightly differ in material and geometric properties.

4. Example application

4.1. Bridge resistance and dead load models

In this example the bridge is assumed to be a simply supported RC solid slab bridge, whose geometry is presented Fig 2. To build the resistance and dead load models, several parameters are taken stochastically, using parameters found in the literature and their distributions (Table 1). All variables are considered to be normally distributed except for the yield strength of steel which is lognormally distributed according to [12]. Segment no. 8 is assumed to have a corrosion problem and so this segment's resistance is decreased by involving an extra parameter; the bar area loss. The bar area loss distribution, which follows a gamma distribution, corresponds to data of naturally corroded 27 year old RC beams [26].

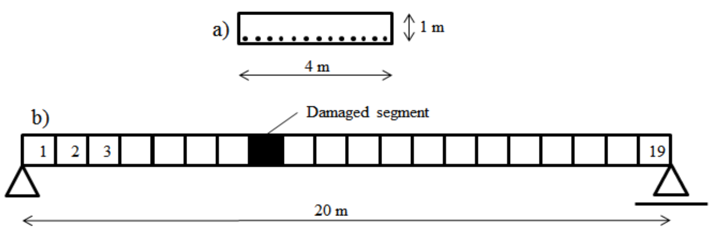

Fig 2. Example RC solid slab bridge's a) cross-section and b) longitudinal view.

Table 1. Stochastic parameters.

Parameter	Nominal value	Unit	Mean value	Standard deviation
Slab depth	1000	[mm]	+ 0.8	3.6
Concrete cover	50	[mm]	+ 6	11.5
Concrete compressive strength	45	[N/mm^2]	+ 7.4	6
Steel yield strength	400	[N/mm^2]	+36	21.3
Unit weight of concrete	23.68	[kN/m^3]	x 1.05	x 0.11
Unit weight of asphalt	22.73	[kN/m^3]	x 1.0	x 0.25
Thickness of asphalt	80	[mm]	+ 0	40
Bar area loss		[%]	Shape: 1.5	Scale: 8.9

4.2. Daily maximum bending moment due to traffic load

An extensive database of Weigh in Motion (WIM) data was available, courtesy of the Federal Highway Administration's Long Term Pavement Performance (LTPP) program [15]. For the purpose of this study one year (2011) of data from 19 sites in the USA are reviewed and after some preliminary investigation, a typical site is chosen: Illinois, I57. The total number of heavy vehicles in this database is 832,307 for 253 days (all working days in 2011) with an average daily truck traffic in the monitored lane of 3281.

Using this population of trucks, the bending moment can be calculated at each segment of the bridge induced by each vehicle at each instant in time. However it would not be efficient and useful to calculate and store all these load effects. Therefore it is decided to calculate daily maximum values in accordance with the Block Maximum approach as its efficiency is well known [3][17][18]. A drawback of this method is that only one load effect per day/block is considered, regardless of the heaviness of the actual day’s traffic. This approach has the disadvantage of possibly ignoring some extreme trucks in the database. This study considers a short span bridge and hence the daily maximum load effects can be obtained from 1-truck loading events based on the assumption that these events are independent and identically distributed (iid).

There are several ways to approximate extreme data (such as daily maximum load effect) through the use of inferential statistics. For maximum bridge load effects, some of the most used tail fitting (and other) methods are studied in detail in Hajializadeh’s work [19]. For bending moments induced by the passage of the trucks of the database, the focus, in terms of safety, needs to be placed on the tail of this distribution, i.e., based on extreme value theory. This tail however can be defined in several ways. Some authors suggest the top $2\sqrt{n}$ data [20], where n is the number of data, some the top 30% [14] while Hajializadeh [19] uses the top 10% of the data as a compromise between the previous two definitions. In the current case it is decided to use the top $2\sqrt{n}$ data of the daily maximum bending moments for tail fitting. For fitting this block maximum data, the Generalized Extreme Value (GEV) distribution is chosen after Castillo [19]. GEV is a family of three distributions: Gumbel (type I), Fréchet (type II) and (negative) Weibull (type III), and is written as [21]:

$$G(x;\mu,\sigma,\xi) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{5}$$

where μ is the location parameter, σ is the scale parameter and ξ is the shape parameter. Depending on the individual cases, any of the above three distribution can be confidently fitted to the collection of extreme data, though some authors [19] argue that Fréchet is unsuitable for bridges given the natural limit on the space available and the capacity of axles. Using a Gumbel probability paper plot it is possible to obtain an idea about which GEV distribution the daily maximum data follows most closely. Applying the maximum likelihood method, both Gumbel and Weibull distributions are fitted for the tail assumed to contain $2\sqrt{n}$ number of data points and based on the results of the Kolmogorov-Smirnov test, the better one is selected.

4.3. Probability of failure

The probability of failure is calculated through equations 1-3 using Monte Carlo simulation with a sample size of 10^6 and accounting for full spatial correlation for both the moments due to dead load and traffic load along the bridge. This is on the basis that if one segment of the bridge experiences an extremely large induced bending moment, then it is very probable that all the others will do so as well. The calculated general probability of failure of the studied bridge, assuming corrosion damage is present in segment 8, is $1.41\cdot10^{-3}$ (see Table 2).

4.4. Bayesian updating

The updating is performed on the prior distribution of the rebar area loss for segment 8 (of 19 segments) and the stiffness loss data obtained from a population of vehicles passing, using the areas under the deflection curves as

DIs. This DI is directly related to a stiffness loss that can be converted into rebar area loss through the linear model presented in Fig 1. The posterior distribution of the rebar area loss can then be found by applying the Markov Chain Monte Carlo method (MCMC) with the Metropolis-Hastings algorithm [27]. The effect of updating depends highly on the measured DI, i.e. the actual state of the bridge. If the actual state differs strongly from the defined prior distribution, then the effect of updating is significant. The descriptors of the prior and the posterior distributions of the rebar area loss in the cases of an a) lightly, b) moderately or c) severely damaged bridge can be found in Table 2, while in Fig 3 the prior and posterior gamma distributions are shown.

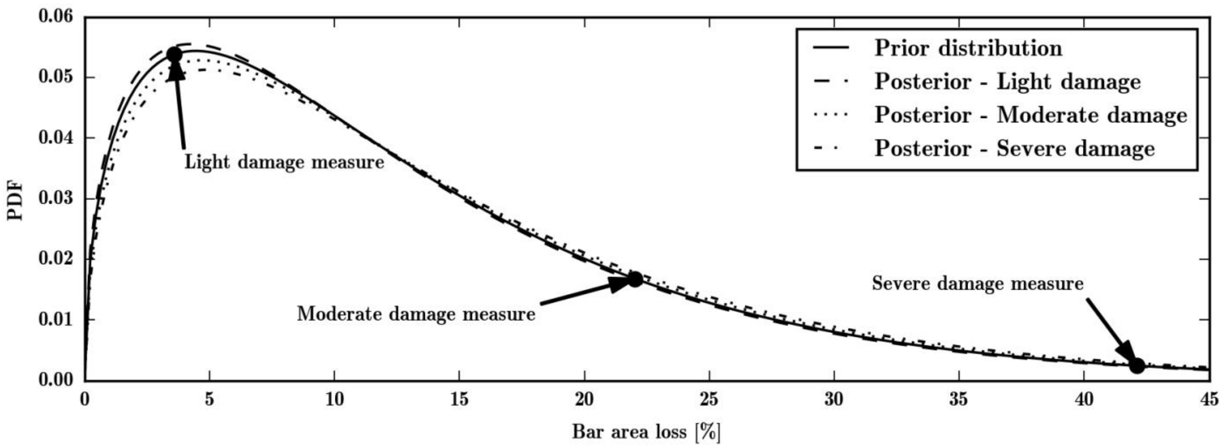

Fig 3. Probability density functions of prior and posterior gamma distributions of bar area loss

Using the updated rebar distribution, the probability of failure of the bridge is recalculated. The results of the probability of failure before updating and after the three different updatings, which represent three different severities of damage, are presented in Table 2. The initial (prior) distribution indeed strongly influences the results of the posterior distributions. This is due to having only one measurement at a time. The effect of choosing the prior distribution and the related sensitivities will be discussed during the presentation.

Table 2. Results of Bayesian updating in case of three different damage level.

Damage level	Stiffness loss obtained through the DI [%]	Corresponding bar area loss [%]	Gamma distribution		Probability of failure [$\cdot 10^{-3}$]	
			Shape parameter	Scale parameter	Mean	$CI_{95\%}$
Using the prior distribution [26]		-	1.50	8.90	1.41	[1.34 ; 1.48]
Light	3.23	3.59	1.48	8.85	1.23	[1.16 ; 1.29]
Moderate	19.83	22.03	1.52	9.03	1.59	[1.51 ; 1.67]
Severe	37.91	42.12	1.53	9.24	1.89	[1.80 ; 1.97]

4. Conclusions

A general bridge safety model is presented in this paper. Three main parts of the model can be distinguished: moment capacity, moment induced by the dead load and moment induced by the traffic load. The model involves localized damage due to corrosion that, through introducing the bar area loss parameter, leads to decreased capacity of the affected segment. This initial model is then updated using a deflection based damage indicator and the correlation between the bar area loss and the stiffness loss. Table 2 summarizes the results of the initial model and of the updated model accounting for three different level of corrosion damage. It can be seen that, although the distribution of bar area loss changes slightly between the different cases, the probability of failure of the bridge is already affected. Moreover in case of more data (for example using continuous measurements over consecutive years), the updating would influence more heavily the bar area loss distribution and so the probability of failure. This simple example proves the usefulness of updating bridge safety models.

Acknowledgements

The research this paper is supported by funding received from the European Union's Horizon 2020 research and innovation programme under Marie Sklodowska-Curie grant agreement No. 642453. The Federal Highway Administration (FHWA) of the United States is also thanked for providing access to their WIM database.

References

[1] J.M. Rocha, A.A. Henriques, R. Calçada, Probabilistic safety assessment of a short span high-speed railway bridge, Engineering Structures 71 (2014) 99-111.
[2] D. Hajializadeh, E.J. OBrien, M.G. Stewart, The sensitivity of bridge safety to spatial correlation of load and resistance, Structures 5 (2015) 22-34.
[3] X.Y. Zhou, F. Schmidt, F. Toutlemonde, B. Jacob, Applying Weigh-in-motion traffic data to reliability based assessment of bridge structures, ICOSSAR2013, 11th International Conference on Structural Safety & Reliability, Jun 2013, New York.
[4] P.S. Marsh, D.M. Frangopol, Reinforced concrete bridge deck reliability model incorporating temporal and spatial variations of probabilistic corrosion rate sensor data, Reliability Engineering & System Safety 93 (2007) 394-409.
[5] B. Enright, C. Leahy, E.J. OBrien, A Bayesian approach for estimating characteristic bridge traffic load effects Civil Engineering Research in Ireland, Belfast, UK, 28-29 August 2014.
[6] Y. Ma, J. Zhang, L. Wang, Y. Liu, Probabilistic prediction with Bayesian updating for strength degradation of RC bridge beams, Structural Safety 44 (2013) 102-109.
[7] R. Zhang, S. Mahadevan, Model uncertainty and Bayesian updating in reliability-based inspection, Structural Safety 22 (2000) 145-160.
[8] R. Décatoire, Optimisation of inspection plans for structures submitted to a stochastic degradation context: application on RC structures, PhD Thesis. Université de Nantes, Faculté des Sciences et des Techniques, 2015.
[9] S.A. Mirza, J.G. MacGregor, Variations in dimensions of reinforced concrete members, J Struct Div. 105(4) (1979) 751-766.
[10] R.W. McGee, On the service life modelling of Tasmanian concrete bridge, PhD Thesis, University of Tasmania, Hobart, Australia,2001.
[11] M.M. Attard, M.G. Stewart, A two parameter stress block for high strength concrete, ACI Structural Journal 95 (3) (1998) 305-317.
[12] D. Seo, S. Shin, B. Han, Reliability-based structural safety evaluation of reinforced concrete members, Journal of Asian architecture and building engineering 9(2) (2010) 471-478.
[13] F. Akgül, Lifetime system reliability prediction for multiple structure types in a bridge network, PhD thesis, University of Colorado, Boulder, Colorado, 2002.
[14] B. Enright, Simulation of traffic loading on highway bridges, PhD Thesis. College of Engineering, Mathematical and Physical Sciences, University College Dublin, Ireland, 2010.
[15] C. Leahy, Using weigh-in-motion data to predict extreme traffic loading on bridges, PhD thesis, College of Engineering and Architecture, University College Dublin, Ireland, 2013.
[16] B. Sivakumar, M. Ghosn, F. Moses, Protocols for collecting and using traffic data in bridge design, NHCRP report 683, National Academy of Sciences, Washington, 2011.
[17] C.C. Caprani, E.J. OBrien, G.J. McLachlan, Characteristic traffic load effects from a mixture of loading events on short to medium span bridge, Structural Safety 30 (2007) 394-404.
[18] E.J. OBrien, A. Bordallo-Ruiz, B. Enright, Lifetime maximum load effects on short-span bridges subject to growing traffic volume's, Structural Safety 50 (2014) 113-122.
[19] E.J. OBrien, F. Schmidt, D. Hajializadeh, X.-Y. Zhou, B. Enright, C.C. Caprani, S. Wilson, E. Sheils, A review of probabilistic methods of assessment of load effects in bridges, Structural safety 53 (2015) 44-56.
[20] E. Castillo, Extreme value theory in engineering, Academic Press, New York, 1988.
[21] S. Coles, An introduction to statistical modeling of extreme values, Springer-Verlag, London, 2001.
[22] M.S. Darmawan, M.G. Stewart, Spatial time-dependent reliability analysis of corroding pretensioned prestressed concrete bridges, Structural Safety 29 (2007) 16-31.
[23] M.P. Enright, D.M. Frangopol, Probabilistic analysis of resistance degradation of reinforced concrete bridge beams under corrosion, Engineering Structures 20(11) (1998) 960-971.
[24] M.G. Stewart, A. Al-Harthy, Pitting corrosion and structural reliability of corroding RC structures: Experimental data and probabilistic analysis, Structural Safety (93) (2008) 373-382.
[25] D.V. Val, M.G. Stewart, E. Melchers, Effect of the reinforcement corrosion on reliability of highway bridges, Engineering Structures 11 (1998) 1010-1019.
[26] M.M. Kioumarsi, M.A.N. Hendriks, J. Kohler, M.R. Geiker, The effect of interference of corrosion pits on the failure probability of reinforced concrete beam, Engineering Structures 114 (2016) 113-121.
[27] W. Hastings, Monte Carlo sampling methods using Markov chains and their application, Biometrika, 57 (1) (1970) 97-109.