Building Tomorrow's Society
Bâtir la Société de Demain

Fredericton, Canada
June 13 – June 16, 2018/ *Juin 13 – Juin 16, 2018*

MODELING OF CONCRETE BRIDGE DECKS DETERIORATION USING A HYBRID STOCHASTIC MODEL

Mohammed Abdelkader, Eslam [1, 4], Marzouk, Mohamed[2] and Zayed, Tarek[3]
[1] Ph.D. student, Department of Building, Civil, and Environmental Engineering, Concordia University, Montreal, QC, Canada. Corresponding author
[2] Professor of Construction Engineering and Management, Structural Engineering Department, Faculty of Engineering, Cairo University, Egypt
[3] Professor, Award Co-ordinator for MSc/PgD in Construction and Real Estate, Academic Advisor, The Hong Kong Polytechnic University, Hong Kong
[4] eslam_ahmed1990@hotmail.com

Abstract: Infrastructure systems represent a very important aspect of life on Earth. Existing Infrastructure is subjected to degradation while the demands are growing for a better infrastructure system in response to the high standards of safety, health, population growth, and environmental protection. Bridges play a crucial role in the urban development by providing access for people to services such as health care units, schools, markets, etc. Bridges are vulnerable to high levels of deterioration because of some factors such as deferred maintenance actions, extreme weather conditions, variable traffic loading, etc. A reliable deterioration model is required for the successful development of Bridge Management Systems (BMSs) which helps in performing accurate maintenance, repair, and rehabilitation activities. This paper presents a hybrid Bayesian model that is capable of predicting the condition ratings of the concrete bridge decks along its service life. Bayesian belief networks (BNs) are utilized to model the factors that affect the condition rating of the bridge decks. BNs are used to calculate the transition probabilities based on the severity of five bridge defects which are: corrosion, delamination, cracking, spalling and pop-out. Finally, a Markovian model is used to predict the future performance of the concrete bridge decks. A case study of the concrete bridges in Quebec is presented to demonstrate the capabilities of the proposed model.

1 Introduction

Bridges are vital links in transportation networks that should be safe, functional and serviceable during their service life to facilitate the mobility of people and transportation of goods which results in sustainable economic development. Concrete bridges are prone to high level of deterioration because of the variable traffic loading, extreme weather conditions, cycles of freeze and thaw, etc. The bridges in Canada are subjected to harsh conditions whereas 22% of the bridges are in a "Fair" condition, 3% of the bridges are in a "Poor" condition, and 1% of the bridges are in a "Very Poor" condition based on Canada's infrastructure report card (Felio, 2016). One-third of Canada's bridges have structural or functional deficiencies with short remaining service life where 20 million light vehicles, 750,000 trucks, and 15,000 public transits use the Canadian bridges annually (National Research Council Canada, 2013). The average age of the bridges is 24.5 years in 2007 compared to a mean service life of 43.3 years. This means that the bridges in Canada have passed 57% of their useful lifetime (Statistics Canada, 2009a). Bridges in Quebec province have the highest average age of 31 years followed by Nova Scotia with an average age of 28.6 years, which means that they require extensive maintenance and repair (Statistics Canada, 2009b).

The degradation in the condition rating of Canada's infrastructure systems occurs because of two main reasons: 1) the decline in the public investment, and 2) the increase in the average age of the infrastructure systems. The public investment peak was 3% of the gross domestic product (GDP) in the late 1950s and it declined steadily until the mid of 2000s. The decline in the investment is over 40 years from the late of the 1950s to the mid of 2000s. Most of the decline was in the first 20 years where the investment dropped from 1.6% of GDP in 1959 to 0.4% of GDP in 1979) (Mackenzie, 2013). American Association of State Highway and Transportation Officials (AASHTO) and Intermodal Surface Transportation Efficiency Act (ISTEA) defined five main components for BMS which are (Czepiel, 1995): 1) database for data storage, 2) condition rating model, 3) deterioration model, 4) cost model, and 5) optimization model for running system. The structure of BMS is shown in Figure 1 (Elbehairy 2007). Deterioration model is one of the main pillars of the BMS because it enables the asset managers to forecast the future condition of bridge elements. The objective of the present study is to develop a stochastic time-based model that overcomes the limitations of the previously developed models and can provide reliable prediction results. The proposed model is compared with the weibull distribution to illustrate the capabilities of the proposed model.

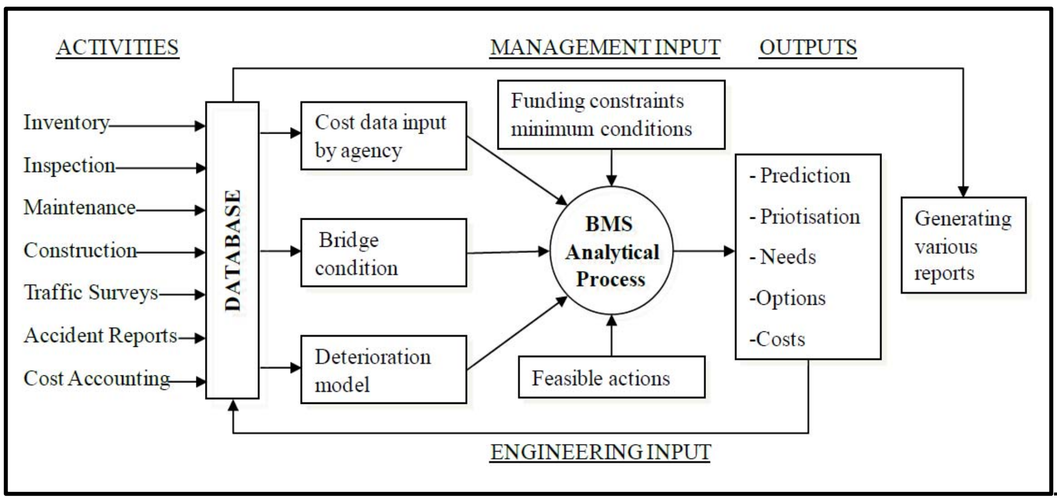

Figure 1: Typical structure of a Bridge Management System

2 Deterioration Models

The deterioration models can be divided into: deterministic and stochastic models. Deterministic models establish a relationship between the factors affecting the deterioration process and the bridge condition rating based on mathematical and statistical techniques such as straight-line extrapolation, multiple regression, curve fitting, artificial neural networks, support vector machines, etc. Deterministic models assume that the relationship between the future condition ratings of the bridge is certain over time (Ranjith et al. 2013). Stochastic models are capable of capturing the randomness and uncertainties associated with the deterioration process of bridges where the predicted condition rating of bridges is subjected to inherent uncertainties such as traffic loads, weather conditions, properties of materials, exposure to damaging agents, etc.

3 Literature Review

This section provides an overview for the previously developed deterioration models. Agrawal (2010) compared between Markov chain approach and weibull-based approach to predict the deterioration of group of bridge elements based on historical data from the New York State Department of Transportation (NYSDOT). The transition probabilities were calculated based on non-linear optimization by minimizing the sum of the absolute difference between the condition rating obtained from the regression model and the condition rating obtained from the Markov chain. They concluded that weibull-based approach performed better than the Markov chain-based approach. Huang (2010) developed an artificial neural network (ANN) to predict the deterioration of bridge decks. The ANN was based on back-propagation approach multilayer perceptron (BP-MLP) classifier. He identified 11 significant factors that affect the deterioration of the bridge decks such as age, deck area, length of deck, number of spans, average annual daily traffic (AADT), design load, etc. These factors were used as an input for the ANN model and they are selected based on the P-value.

Callow et al. (2013) applied time-delay neural network (TDNN) to model the deterioration of bridge elements. Genetic algorithm optimization was employed to optimize the backward prediction model (BPM) output while case-based reasoning (CBR) was implemented to retrieve similar cases. Bu et al. (2015) developed a model that incorporated both time-based model and state-based model with backward prediction models (BPM) for long-term deterioration prediction of bridge components. The state-based model utilized Markov chain and Elman neural networks (ENN) to calculate the transition probabilities while the time-based model was based on Kaplan and Meier (K-M) estimate to calculate the non-parametric probability distribution function of transition times. Zambon et al. (2017) compared between a group of stochastic models which are: Markov chain with exponentially-distributed and weibull-distributed sojourn times, and gamma process. They concluded that the gamma process has better prediction capabilities when compared to the Markov chain models.

Wu et al. (2016) presented a life-cycle optimization model based on the semi-Markov decision process. The developed model was based on the 2012 NBI for the state of Texas. They highlighted that the predicted deterioration curve matched the deterioration curve of the 2012 NBI with 10.8% mean absolute error. Mašović and Hajdin (2013) modeled the deterioration of the bridge elements in Serbia based on the Markov chain. They employed expectation maximization algorithm (EM) to estimate the transition probabilities. They highlighted that the EM algorithm provided reasonable deterioration curve even if the inspection records were limited.

4 Research Methodology

The element-level inspection obtained from the Ministry of Transportation in Quebec (MTQ) defines the status (extent of damage) of the bridge elements based on four condition states which are: 1) condition state 1 (good), condition state 2 (fair), 3) condition state 3 (poor), and 4) condition state 4 (very poor). The definition of the condition states is the first step of the proposed methodology. The deterioration model is constructed based on a historical data of element-level bridge inspections of concrete bridge decks.

The second step is to calculate the condition index for each inspection record (event). The proposed model utilizes a defect-based methodology that integrates both Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Grey Relational Analysis (GRA). The integrated bridge deck condition index (IBDCI) can be calculated as follows.

$$[1]\ IBDCI = \frac{(CT + CG)}{2}$$

Where;

CT, CG are the condition ratings obtained from TOPSIS and GRA, respectively.

The third step is to define the transition events and censored events based on the inspection data. Transition events (un-censored events) are defined based on sequential change in condition rating of concrete bridge decks. Censored events mean that the observed event which is the sequential change in the condition state does not occur during the observation period (Morcous and Lounis 2010). The transition event may not be observed within the analysis period for two main reasons (Destefano and Grivas 1998): 1) the element may be replaced while it is in its initial condition state, therefore it will not transit to the next condition state, and 2) the analysis period may be not long enough to allow transition to the lower condition state.

The developed deterioration model is only based on transition events (complete data) in order to provide more reliable results. Transition time is the time taken by the facility to deteriorate from a certain condition state to the next lower condition state. The transition time varies from one facility to another because of the stochastic nature of the deterioration process (Morcous and Lounis 2007). The transition event is assumed to occur at the middle of the inspection period (Destefano and Grivas 1998).The proposed model is concerned with five types of bridge defects which are: corrosion, delamination, cracking, spalling, and pop-out. The marginal probabilities are calculated, for instance, the probability that the corrosion is in a poor category, or the probability that the spalling is in a good condition. There are three types of transition events which are: $TE(1,2)$, $TE(2,3)$, and $TE(3,4)$. Therefore, there are three in-state probabilities which are : P_{11}, P_{22}, and P_{33}. These in-state probabilities are obtained based Bayesian belief networks (BBNs). It is worth mentioning that a BBN is constructed for each in-state probability. For each node in the BBN, a set of mutually exclusive events is assigned. For instance, there are four condition states which are: “Good”, “Medium”, “Poor”, and “Very poor” assigned to each bridge defect. For the in-state probability, there are two states which are: “Yes”, and “No”. After the calculation of the transition probabilities, the transition probability matrix is constructed and consequently the future condition of the concrete bridge decks can be calculated. The proposed model is validated by comparing its performance with the performance of the weibull distribution using three performance indicators which are: root mean square error, mean absolute error, and chi-squared statistic.

4.1 Bayesian Belief Networks

Bayesian belief networks (BBN) are probabilistic models that are based on directed acrylic graphs (DAG), which allows the modeling of probabilistic relationships between set of variables. BBN is usually formulated as follows $BBN = (P, G)$, whereas P indicates the parameters of the marginal probabilities while G indicates the model structure. G is formulated as follows $G = (V, A)$, and it represents the DAGs, which is composed of a finite set of nodes as well as directed arcs between pairs of nodes (Liang and Ghazel, 2017). The relationships between the nodes in BBN are demonstrated in the form of family relationships, whereas X and Y are regarded as parents of Z, and Z is considered as the child of both X and Y if a link goes from X to Z, and Y to Z. The conditional probabilities are divided into two categories which are: known conditional probabilities and missing conditional probabilities. Known conditional probabilities are the ones that can be calculated from the available dataset. On the contrary, missing conditional probabilities cannot be calculated from the current data set.

For the known conditional probabilities, the best-fit distribution of the transition time is defined using Anderson Darling test (A^2). Anderson Darling test is based on comparing the fit of an observed cumulative distribution function to an expected cumulative distribution function. Anderson darling test assumes more weight to the distributions’ tail than the Kolmogorov-Smirnov test. Anderson Darling Statistic can be calculated as follows (Love at al., 2013). The parameters of the best-fit distribution are obtained based on the maximum likelihood estimation (MLE) approach.

$$[2]\ \mathrm{A}^2 = -\mathrm{n} - \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} (2\mathrm{i} - 1) \times (\ln \mathrm{F}(\mathrm{x_i}) + \ln(1 - \mathrm{F}(\mathrm{X}_{\mathrm{n-i+1}})))$$

For the missing conditional probabilities, maximum entropy approach is used to calculate the conditional probabilities using the genetic algorithm (Pendharkar, 2008). The structure of the BBN is shown in Figure 2.

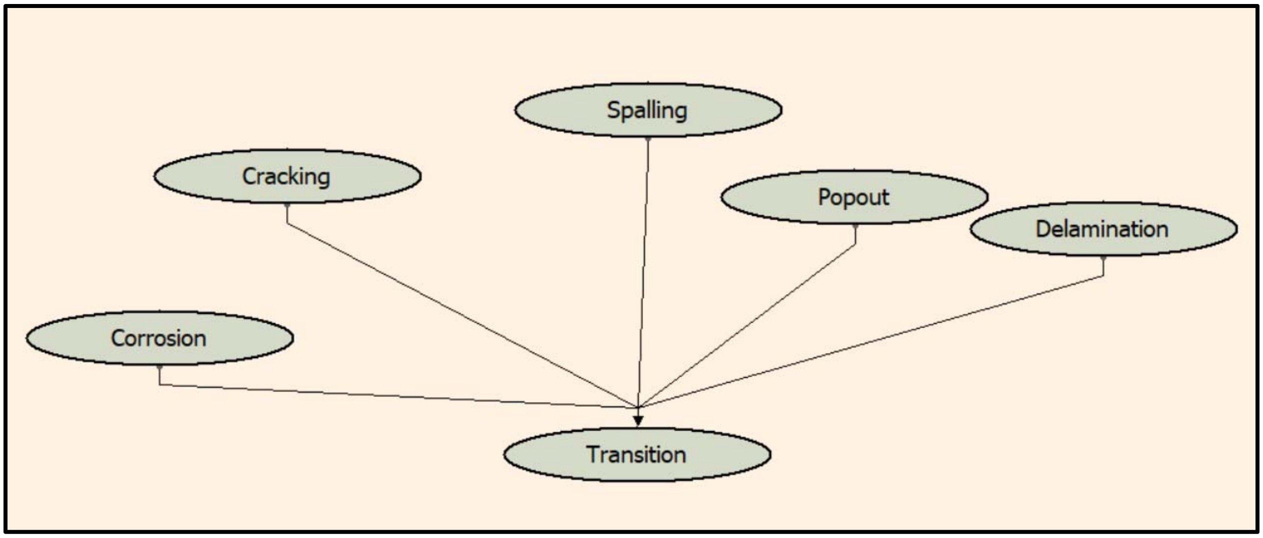

Figure 2: Developed Bayesian belief network

BBN is based on Bayes' theorem, which is an efficient method to represent the conditional probabilities between a set of random variables. In a BBN, for a set of mutually exclusive events $\{A_1, A_2, A_3, \dots\dots\dots\dots. A_m\}$, and a given observed event B, the updated probability can be computed as follows (Kabir et al., 2015).

$$[3]\ P(A_j|B) = \frac{P(B|A_j) \times P(A_j)}{\sum_{i=1}^{m} P(B|A_j) \times P(A_j)}$$

Where;

$P(A_j|B)$ represents the posterior occurrence probability of A given that the condition B has occurred. $P(B)$ indicates the marginal probability. $P(A)$ indicates the prior probability. $P(B|A)$ is the conditional probability of occurrence of B given that the even A has occurred. The implemented approaches to compute the future performance are discussed in the following sections.

4.2 Markovian Model

After the calculation of the transition probabilities, it is time to forecast the future performance of the concrete bride decks using Markov chain. Markov chain is considered as a special case of the Markov process and it can be defined as a series of transitions between condition states. A stochastic process is regarded as a first-order Markov chain if the probability in the future state depends on the present state not on the past state (Bu et al. 2015).

The condition rating using Markov decision processes can be calculated using the following equation.

$$[4]\ \mathrm{E(t)} = \mathrm{Q(0)} \times \mathrm{P^{t,t+1}} \times \mathrm{R'}$$

Where;

$\mathrm{E(t)}$ represents the estimated condition rating using Markovian-chain method. $\mathrm{Q(0)}$ represents the initial state vector where $\mathrm{Q(0)} = [100\% \quad 0 \quad 0 \quad 0]$. $\mathrm{R'}$ represents the transpose of a vector of condition ratings where $\mathrm{R} = [100\% \quad 71.71\% \quad 64.04\% \quad 43.49\%]$. $\mathrm{P^{t,t+1}}$ denotes the transition probability matrix.

4.3 Performance Indicators

The proposed model incorporates three performance indicators to compare between the two deterioration models. The three performance indicators are: root-mean square error ($RMSE$), mean absolute error (MAE), chi-squared statistic (x^2). $RMSE$, MAE, and x^2 can be calculated as follows (Nazari et al., 2015; Ranjith et al., 2013).

$$[5]\ \mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{K}}\sum_{\mathrm{i}=1}^{\mathrm{K}}(\mathrm{O_i} - \mathrm{P_i})^2}$$

$$[6]\ \mathrm{MAE} = \frac{1}{\mathrm{K}}\sum_{\mathrm{i}=1}^{\mathrm{K}}|(\mathrm{O_i} - \mathrm{P_i})|$$

$$[7]\ \mathrm{x}^2 = \sum_{\mathrm{i}=1}^{\mathrm{K}}\frac{(\mathrm{O_i} - \mathrm{P_i})^2}{\mathrm{P_i}}$$

Where;

$\mathrm{O_i}$ indicates the observed condition of the bridge deck. $\mathrm{P_i}$ indicates the predicted condition of the bridge deck. K represents the number of observations (bridge decks).

5 Model Implementation

The proposed methodology utilizes 181 inspection records from the Ministry of Transportation in Quebec (MTQ), Canada. One hundred fifty six are used for training the model, while the remaining twenty five records are used for testing the model. Out of the 156 inspection records, there are 104 transition events and 52 censored events. The transition probability matrix is shown in the following equation, whereas P_{11}, P_{22}, and P_{33} equal to 97.1062%, 97.303%, and 98.8712%, respectively. The parameters of the weibull distribution are computed using maximum likelihood estimation algorithm. The scale and shape parameters of the weibull distribution are 84.2378, 5.0643, respectively. The deterioration curve of the hybrid Bayesian model is shown in Figure 3. A comparison between the hybrid Bayesian model and the weibull distribution is illustrated in Table 1.

$$[8]\ P^{t,t+1} = \begin{bmatrix} 97.1062\% & 2.8938\% & 0 & 0 \\ 0 & 97.303\% & 2.697\% & 0 \\ 0 & 0 & 98.8712\% & 1.1288\% \\ 0 & 0 & 0 & 100\% \end{bmatrix}$$

Table 1: Comparison between deterioration models

Deterioration model	RMSE	MAE	x^2
Hybrid Bayesian model	0.8572	0.542	62.5
Weibull distribution	1.4527	0.9834	356

As shown in Table 1, $RMSE$, MAE, and x^2 of the Bayesian model are 0.8572, 0.542, and 62.5, respectively. $RMSE$, MAE, and x^2 of the weibull distribution are 1.4527, 0.9834, and 356, respectively. The chi-squared critical values at 180 degrees of freedom and a significance level of 5% equals to 212.304 Thus, the weibull distribution fails to pass the chi-squared test. Based on the previous statistics, the hybrid Bayesian model significantly outperformed the weibull distribution model.

The proposed model is a defect-based model. Thus, it was capable to simulate the deterioration process of the bridge deck. One of the main reasons of the inaccurate performance of the weibull distribution is its incapability to model the deterioration process. Moreover, based on the weibull distribution the bridge deck remains in condition state 1 for a long time while it takes a very short time to deteriorate from condition state 2 to condition state 3 as well as from condition state 3 to condition state 4. On the other hand, the hybrid Bayesian model predicts that the bridge decks remains in each condition state for a reasonable time.

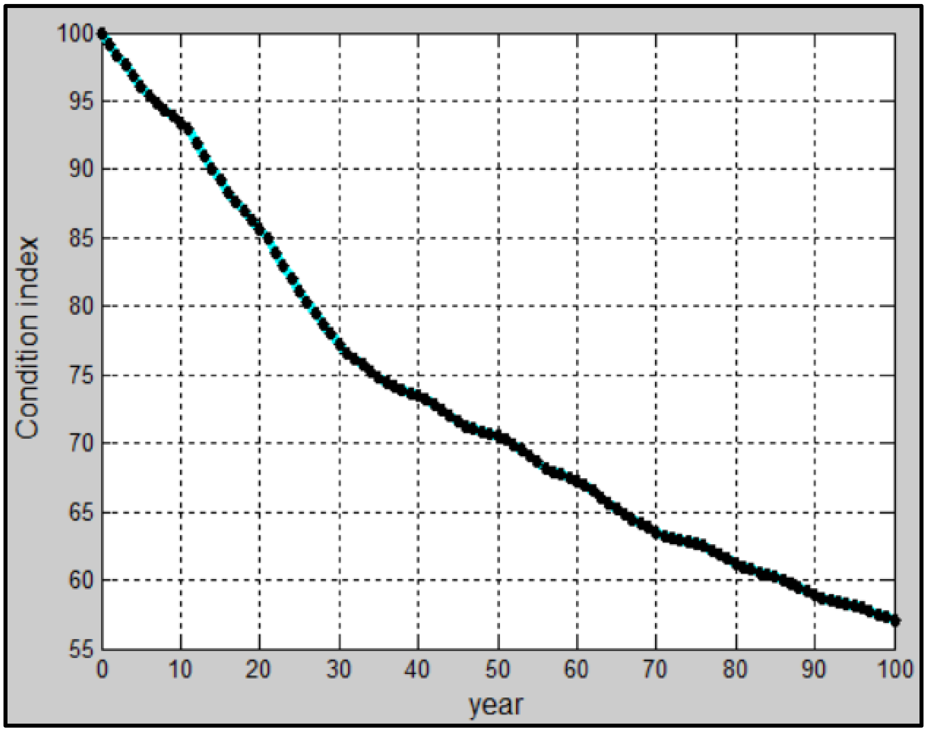

Figure 3: Deterioration model of the hybrid Bayesian model

6 Conclusions

This paper presents a stochastic time-based model that is capable of predicting the future condition of the concrete bridge decks. The proposed model utilizes a combination of the Bayesian belief networks and Markov decision process to forecast the future the performance. The Bayesian belief network is used to calculate the in-state probabilitiesP_{11}, P_{22}, and P_{33} according to the severity of the bridge defects. Five bridge defects are considered which are: corrosion, delamination, cracking, spalling, and pop-out. After the construction of the transition probability matrix, the Markovian decision process is used to calculate the future condition ratings. Finally, the proposed model is compared with the weibull distribution to illustrate its prediction capabilities based on three performance metrics. The proposed model outperformed the weibull distribution because it is a defect-based model. Thus, it is capable to model the deterioration of the bridge decks.

References

Agrawal, a. K., Kawaguchi, A., and Chen, Z. 2010. Deterioration rates of typical bridge elements in New York. *Journal of Bridge Engineering*, **15**(4): 419–429.

Bu, G. P., Lee, J. H., Guan, H., Loo, Y. C., and Blumenstein, M. 2015. Prediction of Long-Term Bridge Performance: Integrated Deterioration Approach with Case Studies. *Journal of Performance of Constructed Facilities*, **29**(3).

Callow, D., Lee, J., Blumenstein, M., Guan, H., and Loo, Y. 2013. Development of hybrid optimisation method for Artifi cial Intelligence based bridge deterioration model — Feasibility study. *Automation in Construction*, Elsevier B.V., **31**: 83–91.

Czepiel, E. 1995. *Bridge Management Systems Literature Review and Search*. Northwestern University BIRL Industry Research labaratory, United States of America.

Destefano, P. D., and Grivas, D. A. 1998. Method for estimating transition probability in bridge deterioration models. *Journal of Infrastructure Systems*, **4**(2): 56–62.

Elbehairy, H. 2007. Bridge Management System with Integrated Life Cycle Cost Optimization. PH.D thesis, Waterloo University, Canada.

Felio, G. 2016. *Canadian Infrastructure Report Card: Informing the Future*. Canadian Construction

Association, Canadian Public Works Association, Canadian Society for Civil Engineering, and Federation of Canadian Municipalities, Canada, <http://www.canadainfrastructure.ca/downloads/Canadian_Infrastructure_Report_2016.pdf> (12.20.2016).

Huang, Y.-H. 2010. Artificial neural network model of bridge deterioration. *Journal of Performance of Constructed Facilities*, **24**(6): 597–602.

Kabir, G., Sadiq, R., and Tesfamariam, S. 2015. A fuzzy Bayesian belief network for safety assessment of oil and gas pipelines. *Structure and Infrastructure Engineering*.

Liang, C., and Ghazel, M. 2017. A risk assessment study on accidents at French level crossings using Bayesian belief networks. *International Journal of Injury Control and Safety Promotion*.

Love, P. E. D., Wang, X., Sing, C., and Tiong, R. L. K. 2013. Determining the Probability of Cost Overruns. *Journal of Construction Engineering and Management*, **139**: 321–330.

Mackenzie, H. 2013. *Canada's Infrastructure Gap: Where It Came from and Why It Will Cost So Much to Close*, Canadian Centre for Policy Alternatives, Canada. <https://www.policyalternatives.ca/sites/default/files/uploads/publications/National%20Office/2013/01/Canada's%20Infrastructure%20Gap_0.pdf> (12.20.2016).

Mašović, S., and Hajdin, R. 2014. Modelling of bridge elements deterioration for Serbian bridge inventory" *Structure and Infrastructure Engineering*, **10**(8): 976–987.

Morcous, G., Lounis, Z., and Cho, Y. 2010. An integrated system for bridge management using probabilistic and mechanistic deterioration models: Application to bridge decks. *KSCE Journal of Civil Engineering*, **14**(4), 527–537.

Morcous, G., and Lounis, Z. 2007. Probabilistic and Mechanistic Deterioration Models for Bridge Management. *Computing in Civil Engineering*, 364–373.

National Research Council Canada. 2013. Critical Concrete Infrastructure: Extending the Life of Canada's Bridge Network. <http://www.nrc-cnrc.gc.ca/ci-ic/article/v18n1-5> (12.20.2016).

Nazari, A., Rajeev, P., and Sanjayan, J. G. 2015. Offshore pipeline performance evaluation by different artificial neural networks approaches. *Measurement*, Elsevier Ltd, **76**: 117–128.

Ranjith, S., Setunge, S., Gravina, R., and Venkatesan, S. 2013. Deterioration Prediction of Timber Bridge Elements Using the Markov Chain. *Journal of Performance of Constructed Facilities*, **27**(3): 319–325.

Statistics Canada. 2009a. Age of Public Infrastructure: A Provincial Perspective. < http://www.statcan.gc.ca/pub/11-621-m/11-621-m2008067-eng.htm> (12.20.2016).

Statistics Canada. 2009b. Average age of public infrastructure by province and type of infrastructure, 2007. < http://www.statcan.gc.ca/pub/11-621-m/2008067/tables/5002061-eng.htm#archived> (12.20.2016).

Wu, F., and Chen, C. C. 2009. Bayesian updating ofparameters for a sediment entrainment model via Markov chain Monte Carlo. *Journal of Hydraulic Engineering,* **135**(1): 22–37.

Zambon, I., Vidovic, A., Strauss, A., Matos, J., and Amado, J. 2017. Comparison of stochastic prediction models based on visual inspections of bridge decks. *Journal of Civil Engineering and Management*, **23**(5): 553–561.