Improving Reliability of Markov-based Bridge Deterioration Model using Artificial Neural Network

Author

Bu, Guoping, Lee, Jaeho, Guan, Hong, Blumenstein, Michael, Loo, Yew-Chaye

Published

2011

Conference Title

IABSE-IASS 2011 Symposium - Taller, Longer, Lighter

Improving Reliability of Markovian-based Bridge Deterioration Model Using Artificial Neural Network

Guoping Bu
PhD Candidate
Griffith School of Engineering (GSE), Griffith University, Australia
g.bu@griffith.edu.au

Jaeho Lee
Research fellow,
Griffith School of Engineering (GSE), Griffith University, Australia
j.lee@griffith.edu.au

Hong Guan
Associate Professor,
Griffith School of Engineering (GSE), Griffith University, Australia
h.guan@griffith.edu.au r

Michael Blumenstein
Associate Professor,
Executive, Dean (Research) SEET, Griffith University, Australia
m.blumenstein@griffith.edu.au

Yew-Chaye Loo
Professor,
Executive, International and Professional Liaison (Director), SEET, Griffith University, Australia
y.loo@griffith.edu.au

Summary

Bridge Management Systems (BMSs) as a Decision Support System (DSS), have been developed since the early 1990's to reliably manage a bridge network. Forecasting long-term performance of bridge by deterioration model is a crucial component in a BMS. Markovian-based models are one of the most typical methods to predict long-term bridge performance. It has been used by a number of BMS software including the popularly used PONTIS, BRIDGIT and OBMS. The Markovian-based model is based on transition matrix obtained from overall condition rating of bridges in a network. The change in condition ratings with time provides typical deterioration rates, which can normally be determined from a non-linear regression analysis. Reliable regression analysis requires either large bridge network or sufficient historical condition ratings to obtain accurate transition probability for bridges. Markovian-based model prediction is a simple way to forecast long term performance of individual bridge. However, most bridge agencies do not have adequate condition rating records. This has become a major shortcoming in deterioration modelling.

In order to minimise the abovementioned problem, this paper presents modified Markovian method using previously developed Backward Prediction Model (BPM). Based on Artificial Neural Network (ANN) technique, the BPM is able to generate missing historical condition ratings thereby providing more historical trend of condition depreciation. In this study, BPM-generated condition ratings are used for regression analysis to obtain reliable transition probability required by the Markovian-based model. The results of the proposed study are compared with those of a typical Markovian-based model to identify the advantage of BPM and limitations for further development.

Keywords: *Bridge Management System (BMS); Long-term Bridge Performance, Markovian-based model, Artificial Neural Network (ANN); Backward Prediction Model (BPM).*

1. Introduction

Bridges are essential components of any road network which requires crucial and timely decision-making for Maintenance, Repair and Rehabilitation (MR&R) activities. Bridge Management Systems (BMSs) have been developed in early 1990's for effective management of large bridge networks. The reliable decision-making in BMSs highly depends on the accuracy of the deterioration model, which can predict long-term bridge performance (LTBP) based on historical bridge condition ratings. Numerous deterioration models have been developed to determine bridge life for their remaining years of use and their major MR&R needs. Most typical models are the Markovian-based deterioration model [1], the neuron-fuzzy hybrid system [2] and reliability-based deterioration model [3]. However, a number of shortcomings still remain in relation to the use of a

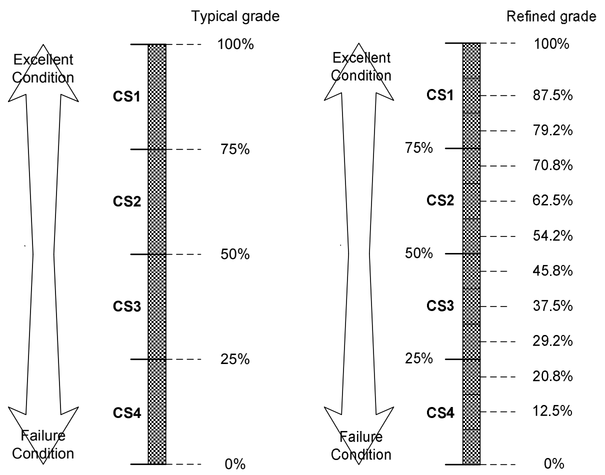
BMS from the perspective of bridge agencies: (1) most agencies only have 8 to 9 biennial inspection records available because commercial BMS software has only been used for about 20 years. (2) During short time periods, bridge condition ratings usually do not change much. (3) Approximately 60% of BMS analytical modules are heavily dependent on bridge inspection information [4]. The lack of available condition records is the major difficulty in deterioration modelling. Based only on a few sets of condition rating records, current deterioration models cannot always provide reliable LTBP predictions.

An Artificial Neural Networks (ANNs)-based Backward Prediction Model (BPM) has been developed by [5] to overcome the problem of insufficient historical condition ratings in predicting reliable bridge deterioration on an element level. This model can produce missing historical condition ratings through establishment of a correlation between existing condition ratings and non-bridge factors which influence the variation of bridge condition ratings [5]. The non-bridge factors include climate and environmental condition changes, traffic volume increases and population growth. In this paper, the BPM-generated historical condition ratings will be used as input for a typical stochastic Markovian-based deterioration model to predict the LTBP.

This study consists of two different analyses: (1) predicting on using Markovian-based model with available condition ratings (insufficient) as input; (2) BPM-generated condition ratings together with the available condition ratings (sufficient) are as input. The sample bridge element condition rating records (element#54C – headstock, cast-in-situ concrete) are obtained from the Queensland Department Transportation of Main Roads (QTMR), Australia. A total of 14 historical condition rating records are available for 5 identical types of bridge elements (headstock). These sample information obtained from large bridge network unable to provide full history of bridge depreciation to conduct a reliable long-term prediction. Therefore the available inspection records are considered insufficient, when the BPM-generated condition ratings are used together with the available condition ratings, the input becomes sufficient for the long-term prediction. Based on the two different size of input, the outcomes of the two analyses are compared to evaluate the prediction accuracy, which helps identify the advantage of BPM in conjunction with a typical deterioration model.

2. Methodology

The Overall Condition Rating (OCR) method is widely used in the Markovian-based models because of its efficiency identifies the status of bridge performance at the project level. At present, condition rating information is collected by a quantitative bridge inspection method, which is then converted into OCR in a subjective manner. A "grading" system used in current inspection method is that the magnitude of each grade is too large to be used in the deterioration models. The practical difficulties lie in the fact that the deterioration rate increased rapidly at an inflection point. Figure 1 illustrates the condition index, for example, each CS has 25% of its steps in a 4CS-grade system which implies that each CS is uniformly distributed in the scale of 100%, and that a CS1 grade is in between 75 to 100% of the scale. However, the actual position of condition ratings for CS1, depending on the level of defect severity, could be anywhere within the currently defined CS1 scale. This indeterminacy seriously increases the degree of uncertainty with time in predicting long-term bridge element's performance. To minimise the above-mentioned shortcoming, the grade system i.e. 4 grades for 4CSs is refined to 12 grades by dividing each CS into three sub-CSs. This result in a refined grading system (Fig. 1 (b)) with each grade represented by the median of each sub-CSs except for the maximum and minimum conditions.



(a) Typical 4 grades for 4CSs

(b) Modified 12 grades for 4CSs

Fig. 1: Condition index for BMS element condition rating

2.1 Artificial Neural Network (ANN)-based Backward Prediction Model (BPM)

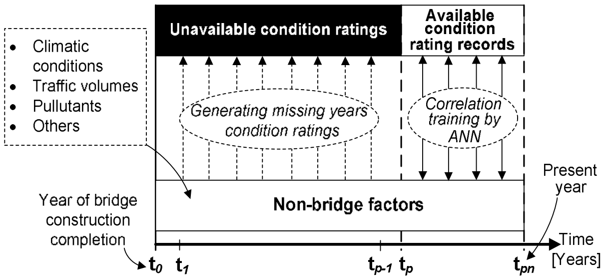


Fig. 2: Mechanism of BPM [5]

The mechanism of the BPM is shown in Figure 2. In Stage 1, An ANN technique establishes the correlation between the existing condition rating datasets (t_p-t_{pn}) and the corresponding years' non-bridge factors. The non-bridge factors directly and indirectly influence the variation of the bridge conditions thereby the deterioration rate. The correlations are then applied to generate the historical trends using the non-bridge factors from year t_0 to t_p [5]. The missing historical condition ratings for years t_1-t_{p-1} can then be generated. Each year of the BPM outcome, i.e. generated condition ratings, includes 66 data outputs which results from the combined number of learning rates (lr: 0.0-0.5) and momentum coefficients (mc: 0.0-1.0) in the neural network configurations. The number 66 also corresponds to the total quantity of a given bridge element. In Stage 2, a forward comparison method is utilised in the BPM methodology to validate the BPM results. It produces forward prediction for years t_p-t_{pn} using the BPM outcomes (years t_1-t_{p-1}). The results of the forward predictions are then compared with the actual BMS condition ratings (t_p-t_{pn}). Afterwards, the generated condition rating records are ready for use in a typical deterioration model following validation of the BPM outcomes.

2.2 Markovian-based deterioration model

The Markovian-based bridge deterioration model forecasts bridge condition ratings that are based on the concept of defining states of bridge condition transition from one state to another during one transition period [1]. Markovian-based models have been employed by most State-of-the-Art BMSs, such as PONTIS, BRIDGIT and OBMS. There are four stages in the LTBP prediction: (1) develop bridge performance curves, (2) generate the transition probability matrix, (3) predict LTBP, and (4) test prediction accuracy. Each stage is described in some detail in the following sections.

2.2.1 Stage 1

Development of a regression performance curve is required to determine the relationship between available condition rating data and bridge age for different bridge categories (materials, types, locations, etc). A third order polynomial model is utilised to obtain the regression function of the relationship. The polynomial model is expressed as follows:

$$A(t) = \beta_0 + \beta_1 t_i + \beta_2 t_i^2 + \beta_3 t_i^3 + \alpha_i \tag{1}$$

where, $A(t)$ = condition rating of a bridge at age t; t_i = bridge age; α_i = error term; and β_0 = recorded condition rating of a new bridge. Equation (1) indicates that the condition rating of a bridge, A(t), depends on the bridge age, t_i.

2.2.2 Stage 2

A refined 12 grades for 4CSs have been explained above. As shown in Figure 1 (b), 100% is considered as the best Condition Rating (CR) which is defined as Max-CS1; CR 87.5% as Mid-CS1 and CR 79.2% as Min-CS1. The same definition is applied for the remaining CSs. Without repair or rehabilitation, the bridge condition rating should decrease with time. Therefore, there is a probability of condition rating transition from one sub-CS, say *i*, to another sub-CS, *j*, during a one-year period, which is denoted by p_{ij}. According to the Markovian method, the sub-CS vector for any time *t*, Q(t), can be obtained by multiplication of initial sub-CS vector Q(0) and the transition probability matrix *P* to the power of *t*, i.e.,

$$Q(t) = Q(0) \times P^t \tag{2}$$

$$[P] = \begin{bmatrix}
p(1) & q(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & p(2) & q(2) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & p(3) & q(3) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & p(4) & q(4) & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & p(5) & q(5) & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & p(6) & q(6) & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & p(7) & q(7) & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & p(8) & q(8) & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p(9) & q(9) & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p(10) & q(10) & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p(11) & q(11) \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix} \tag{3}$$

The transition probability matrix *P* is defined in Equation (3), where q(i)=1-p(i). Hence, p(i) corresponds to $p_{i,i}$ and q(i) corresponds to $p_{i,i+1}$. Therefore, p(1) is the transition probability from CR 100% (Max-CS1) to CR 100%, and q(1), from CR 100% to CR 87.5%, and so on. It should be noted that the lowest CR before a bridge is repaired is zero. Hence, the corresponding probability p(12) is assumed to be 1. Let R be a vector of condition ratings, R = [100, 87.5, 79.2, 70.8, 62.5, 54.2, 45.8, 37.5, 29.2, 20.8, 12.5, 0], and R^T be the transpose of R, then the estimated condition ratings at age t by the Markovian-based model is,

$$E(t) = Q(t) \times R^T \quad (4)$$

Since the deterioration rate of a bridge condition is dissimilar at different bridge ages, the transition process of bridge conditions is not homogeneous with respect to the bridge age. In order to meet the homogeneity requirements of the Markovian-based model, a zoning technique approach is used to obtain the transition matrix. This approach was used previously for the development of pavement performance curves [6]. With the zoning technique approach, bridge age is separated into groups and within each age group the Markovian-based model is assumed to be homogeneous. A six-year group for bridge age is found appropriate for the available bridge inspection database and for solving equations of unknown probabilities [1]. A new bridge element (age 0) is given a condition rating of 100%. Thus, the initial state vector Q(0) for a new element is [1 0 0 0 0 0 0 0 0 0 0 0], where the 12 vector coefficients are the probabilities of having a condition rating of 100, 87.5, 79.2, 70.8, 62.5, 54.2, 45.8, 37.5, 29.2, 20.8, 12.5 and 0, respectively at age 0. Equations (2) and (4) can be solved for Age Group 1 (i.e., 1-6 yrs) using the initial state vector Q(0). The initial state vector for Age Group 2, Q(7) is taken in the same form as the last sub-CS vector of Age Group 1, Q(6). By following this analysis for all age groups, the condition ratings versus age relationship can be obtained for a particular element using the Markovian-based model [7].

The transition probability is obtained by minimising the difference between the average condition ratings from the regression function in Stage 1 and estimated condition ratings E(t) by the Markovian-based model. This is described in Equation (5) in the form of a non-linear programming objective function.

$$\mathrm{Min}\sum_{t=1}^{N}\left|A(t)-E(t)\right| \quad (5)$$

subject to $0 \leq p(i) \leq 1$, i= 1,2,$\cdots$,U.

where, N = the number of years in one age group; U= the number of unknown probabilities; A(t) = the average of condition ratings at time t, estimated by the regression function and E(t) = estimated value of condition ratings by Markovian-based model at time t.

2.2.3 Stage 3

Upon establishment of the transition probability matrix and initial state vector defined from inspection records, a long-term prediction of bridge element performance can be easily undertaken by using Equations (2) and (4).

2.2.4 Stage 4

The accuracy of the LTBP prediction depends on the closeness of the values of condition ratings predicted by the Markovian-based model and by the regression function. The Chi-Square goodness of fit test is used to measure the closeness of the predicted values of condition ratings [8]. The formula for the Chi-Square method is given below:

$$\chi^2 = \sum_{i=1}^{n} \frac{(E_i - A_i)^2}{E_i} \quad (6)$$

where, χ^2 = a Chi-square distribution with n-1 degrees of freedom, Ei = value of condition ratings in Year i predicted by the Markovian-based model, Ai =value of condition ratings in Year i predicted by the regression function, and n = number of prediction years.

3. Analysis

In this section, the sample bridge element condition rating records (element #54C – headstock, Cast-in-situ concrete) are used as an example to demonstrate the advantage of using BPM-generated condition ratings in typical deterioration modelling. Table 1 presents the fourteen OCRs for 5 bridge elements (headstock) obtained from 5 different bridges in the same bridge network. Also included in the table are construction year, inspection year, and bridge age.

Table 1: Overall Condition Ratings (OCRs) for element #54C from 5 different bridges

Bridge ID	Construction Year (age)	Inspection Year (age)	OCRs	Inspection Year (age)	OCRs	Inspection Year (age)	OCRs
x6xx	1975(0)	1999(24)	0.872	2004(29)	0.616	2007(32)	0.616
x56x	1982(0)	1999(17)	1.000	2003(21)	1.000	2007(25)	0.667
x82x	1979(0)	1999(20)	1.000	2004(25)	0.667	2007(28)	0.667
x1x2x	1978(0)	1999(21)	1.000	2004(26)	0.667	2007(29)	0.667
x1x6x	1981(0)	2002(21)	0.889	2006(25)	0.667	—	—

3.1 LTBP prediction without BPM (insufficient historical condition rating records)

Using only the available OCRs calculated from limited inspection records are considered insufficient. Figure 3 shows the plot of CR versus age for element #54C (headstock). It is observed that no historical condition ratings are available in bridge age 1-18 years. Figure 3 also shows a comparison of element condition ratings predicted by both the regression method and the Markovian-based model. It can be seen that the two predictions are not close. The condition ratings predicted by the regression method decreases as the actual condition ratings (bridge age 20-30) and increases after passing bridge age 42. This is definitely unrealistic if no maintenance work was considered. This also implies that the transition probability matrix is unreliable, based on which the prediction by the Markovian-based model cannot be accurate.

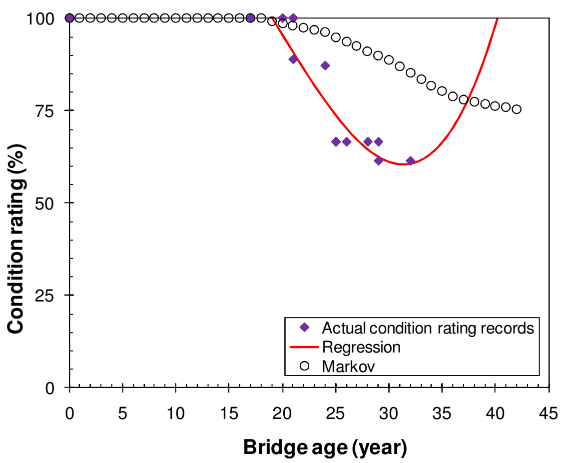


Fig. 3: Comparison of Markovian and regression condition predictions without BPM (Element #54C)

Once the transition probability matrix is obtained from Equation (5), the Markovian-based model becomes a simple multiplication of matrices. Among the five bridges in Table 1, Bridge #x1x6x is selected for the long-term prediction. This is demonstrated in Figure 4. The condition ratings are predicted from 2007 at bridge age 26 to 2023 at bridge age 42. The condition ratings decrease from 60% to 55% from year 2007 to 2011, and remain stable afterwards. The accuracy of this prediction is validated by the Chi-square method which is performed by using the values of E(t) and A(t) from t = 26 to t = 42 (n = 17). Note that a significant level of $\alpha = 0.05$ is chosen as a threshold in determining the difference between the values of the Markovian-based model and regression function. The outcome of the Chi-Square test equals 230 at the 16 (n-1) degrees of freedom. This is much greater than 26.3 obtained from the Chi-square distribution table at significant level of $\alpha = 0.05$. This further confirms that unreliable transition probabilities obtained from insufficient condition ratings cannot lead to accurate LTBP prediction at a bridge element level.

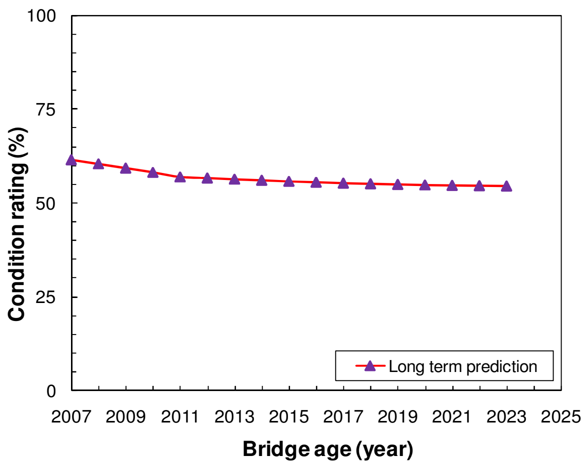


Fig. 4: Long-term prediction using OCR (Element #54C, Bridge #x1x6x)

3.2 LTBP prediction with BPM (sufficient historical condition rating records)

To minimise the uncertainty demonstrated in Section 3.1, this section uses sufficient input data to predict the long-term bridge condition ratings for the selected Bridge #x1x6x. The input data consists of BPM generated condition ratings and available condition ratings. The BPM required non-bridge factors are obtained from the local weather station from the year 1974 to 2007, including changes in humidity, minimum temperature, maximum temperature, and maximum differences of temperature and rainfall. Based on the BPM outcomes, Table 2 presents the average condition ratings for the selected bridge. Note that no elements are found in CS3 and CS4.

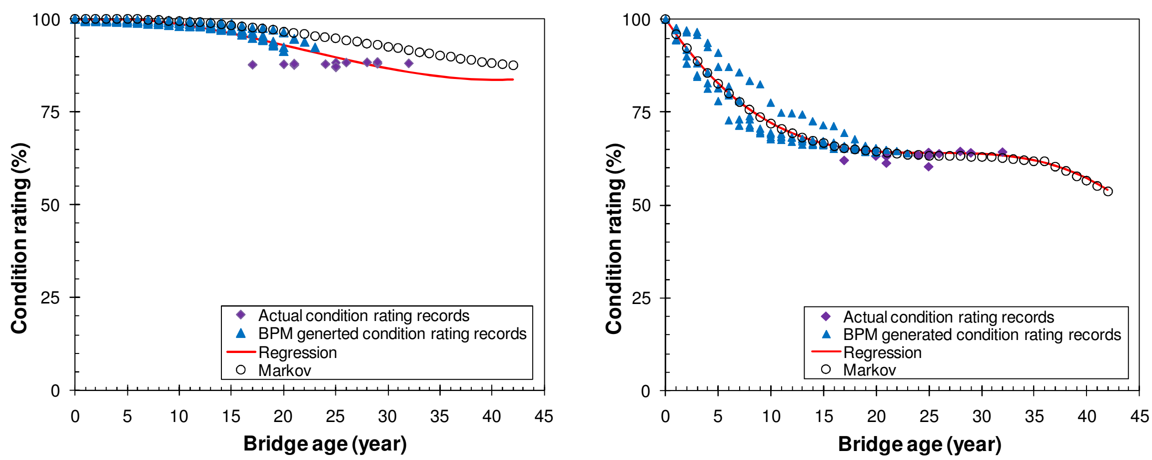
Table 2: Average historical condition ratings generated from BPM (Element #54C, Bridge #x1x6x)

	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992
CS1	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
CS2	0.98	0.96	0.96	0.94	0.91	0.87	0.86	0.83	0.82	0.78	0.75
	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2006
CS1	0.99	0.98	0.98	0.97	0.97	0.96	0.95	0.93	0.91	0.88	0.87
CS2	0.75	0.74	0.73	0.71	0.71	0.69	0.68	0.66	0.64	0.63	0.63

The results of cross-validation is summarised in Table 3. It shows a comparison between predicted and the actual number of elements in different CSs in year 2002 and 2006, respectively. Note that no prediction difference is found for 2002. However for 2006, the prediction differences for both CS1 and CS3 are 0.1 out of 3 total quantities which is considered insignificant. Therefore, using the BPM generated data can lead to satisfactory prediction. Upon validation, the input data combining BPM results together with available condition ratings is then used to generate new transition probabilities. The performance curves of CSs1 and 2 for Element #54C are shown in Figures 5 (a) and (b) respectively, which demonstrate that the sufficient condition ratings can provide more accurate regression performance curves. Furthermore, by comparing the performance deterioration rate for the two different condition states in Figure 5 (a) and Figure 6 (b), it can be seen that elements in CS1 having higher performance, deteriorate slower than those in CS2.

Table 3: Validation using BPM forward prediction compared with existing condition ratings

Year	Condition State (CS)	Prediction results (%)	Predicted Number of Elements	Actual Number of Elements
2002	CS1	67	2	2
	CS2	33	1	1
	CS3	0	0	0
	CS4	0	0	0
			Total quantities 3	
2006	CS1	3	0.1	0
	CS2	95	2.8	3
	CS3	2	0.1	0
	CS4	0	0	0
			Total quantities 3	



(a) CS1 (b) CS2

Fig. 5: Comparison of Markovian and Regression condition predictions using BPM generated historical condition rating (Element #54C)

The new transition probabilities obtained from using sufficient input data can lead to improved prediction. The new predictions for CS1, CS2 and the average value between CSs1 and 2 are presented in Figure 6. During the 17 years of long-term prediction (from year 2007 to 2023), the average condition rating decreases gradually from 75% to 65%. The Chi-Square goodness of fit method is also used in this analysis to validate the accuracy of the new prediction. Table 4 presents the validation results using the Chi-Square method. It shows that the calculated χ^2 values for both CS1 and CS2 at the degree of freedom 16 are much smaller than those obtained from the Chi-Square Table for a significant level of $\alpha = 0.05$. Therefore, the new predictions are considered satisfactory.

Table 4: Results of validation by using Chi-square goodness of fit method

	Degree of Freedom	χ^2(Calculated)	χ^2 (Chi-Square Table)	Result
CS1	16	1.23	26.3 (α=0.05)	Acceptable
CS2	16	0.28	26.3 (α=0.05)	Acceptable

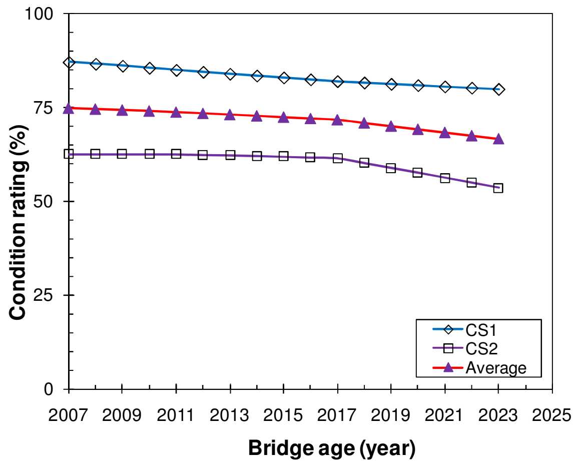


Fig. 6: Long term prediction (Element #54C, Bridge #x1x6x)

4. Discussion and Conclusion

This paper demonstrates the application of BPM to improve the reliability of Long-term Bridge Performance (LTBP) prediction. The Markovian-based model is selected for predicting bridge deterioration, because it is the most widely accepted prediction model and has been adopted by most State-of-the-Art BMSs. The paper presents two different analyses under two different input situations - insufficient and sufficient historical condition rating records. Bridge Element #54C is selected from five bridges in a same bridge network. Each bridge has two or three available inspection records which are considered insufficient. On the other hand, sufficient condition records are obtained by adding BPM-generated condition records. The outcomes of the two analyses are compared to identify the advantage of using BPM for a typical Markovian-based deterioration model.

These two analyses employ the non-linear programming objective function Eq. (5) for calculating transition probabilities. The objective function is used to generate transition probability by minimising the absolute difference between the average condition ratings obtained from the regression function and those from the Markovian-based model. Once the transition probability is obtained, a long-term performance prediction of a bridge element can be computed by the Markovian-based model. The Chi-Square goodness of fit method is used in this study to validate the accuracy of the long-term prediction. Table 5 presents the values of long-term prediction of bridge elements, both with and without using the BPM-generated condition ratings as inputs. For 16 degrees of freedom, the χ^2 value without BPM is much greater than that for the Chi-Square table with level of significance $\alpha = 0.05$. Whereas, the χ^2 value with BPM is much smaller. This confirms that far better predictions can be achieved by including BPM-generated condition ratings.

Table 5: the χ^2 value with and without using BPM-generated condition ratings

	Degree of Freedom	χ^2 without BPM	χ^2 with BPM	$\chi^2_{(\alpha=0.05)}$ Chi-Square table
Long-term prediction	16	230 (OCR)	1.23 (CS1) 0.28 (CS2)	26.3

Furthermore, using OCRs to predict future condition ratings may cause catastrophic structural failure because it ignores small quantities of elements in low condition states, such as CSs3 and 4. However, the BPM can generate missing condition ratings at element level in a quantitative-manner, and can be used to predict long-term bridge performance curves on each condition state. The advantage of predicting the LTBP on each condition state is that it can reduce the prediction uncertainty. Based on the outcome of this study, sufficient historical condition rating records can lead to reliable long-term prediction results. Consequently, the BPM-generated condition ratings can be implemented in typical stochastic deterioration models, such as Markovian, to improve the reliability of long-term prediction.

Despite the advancement of using the Markovian-based model incorporating BPM-generated condition ratings, certain assumptions and limitations still remain in the Markovian-based model. These are well recognised in the literature, (1) past conditions have no effect on future prediction [9]; (2) discrete transition time intervals, constant bridge population, and stationary transition probabilities are used [10]; (3) unable to consider the effect of major repair on the deterioration process [11]; and (4) the interactive effects among deterioration mechanisms of different bridge components are not considered [12]. Overcoming such fundamental limitations of the Markovian-based models is beyond the scope of this study. This merits further study.

5. Acknowledgement

The authors acknowledge the financial support provided by the Australian Research Council through an ARC Linkage Project (LP0883807). The authors also wish to thank the industry partners Queensland Department of Transport and Main Roads and Gold Coast City Council for their financial and in-kind support.

6. References

[1] Jiang, Y. (1990), "The Development of Performance Prediction and Optimization Models for Bridge Management Systems", *Purdue University*, Doctor of Philosophy.

[2] Kawamura, K. and Miyamoto, A. (2003), "Condition state evaluation of existing reinforced concrete bridges using neuro-fuzzy hybird system", *Computer and Structures,* 81, pp. 1931-1940.

[3] DeStefano, P. D., Grivas, D. A. and Cornelius, S. A. (1997), "A reliability-based deterioration model for bridge maintenance planning", *In Infrastructure condition assessment: art, science, and practice(Ed, Saito, M.) ASCE*, New York, pp. 31-40.

[4] Hearn, G., Purvis, R. L., Thompson, P. D., Bushman, W. H., McGhee, K. K. and McKeel, W. T. (2000), "Bridge Maintenance and Management: A look to the future.", *In the Proce. of the TRB 81st Annual Meeting: A3C06:Structures Maintenance and Management,* pp. 1-7.

[5] Lee, J. H., Sanmugarasa, K., Loo, Y. C., and Blumenstein, M. (2008). "Improving the Reliability of a Bridge Management System (BMS) using an ANN-based Backward Prediction Model (BPM)." Journal of Automation in Construction, 17(6), 758-772.

[6] Butt, A. A., Shahin, M. Y., Feighan, K. J., and Carpenter, S. H. (1987), "Pavement Performance Prediction Model Using the Markov Process", *Journal of the Transportation Research Board,* pp. 12-19.

[7] Agrawal, A. K., Qian, G., Kawaguchi, A., Lagace, S., Delisle, R., Kelly, B., Weykamp, P., Conway, T., and Dublin, E. (2006), "Deterioration Rates of Typical Bridge Elements in New York."

[8] Jiang, Y., and Sinha, K. C. (1989), "Bridge Service Life Prediction Model Using the Markov Chain", *Journal of Transportation Research Board,* pp. 24-30.

[9] Madanat, S., Karlaftis, M., and McCarthy, P. (1997), "Probabilistic Infrastructure Deterioration Models with Panel Data", *Journal of Infrastructure Management Systems,* ASCE, 3 (1), pp. 120-125.

[10] Collines, L. (1972), "An Introduction to Markov Chain Analysis", *CATMOG, Geo Abstracts Ltd,* University of East Anglia, Norwich.

[11] DeStefano, P. D. and Grivas, D. A. (1998), "Method for estimating transition probability in bridge deterioration models", *Journal of Infrastructure System, ASCE,* Vol.4, No.2, pp. 56-62.

[12] Cesare, M. A., Santamarina, C., Turkstra, C., and Vanmarcke E. H. (1992), "Modelling Bridge Deterioration with Markov Chains", *Journal of Transportation Engineering, ASCE,* Vol. 118, No. 6, pp. 820-833.