An Integrated Method for Probabilistic Bridge Deterioration Modelling

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ABSTRACT
In order to minimise the shortcomings of long-term predictions of bridge deterioration due to insufficient data, this paper presents an integrated method to build a reliable transition probability for predicting long-term performance of bridge elements. A selection process is developed in this method to automatically select the suitable prediction approach for a given situation of condition data. An Artificial Neural Network (ANN)-based Backward Prediction Model (BPM) is also employed for effective performance prediction when element inspection records are insufficient. A benchmark example is presented in this paper to demonstrate how the BPM-generated missing historical data together with available inspection data can be used as input for a state-based model in the integrated method. The outcome demonstrates that BPM-generated historical data, together with available data, can improve the reliability of transition probabilities, and in turn improve the reliability of long-term predictions.

KEYWORDS
Integrated method; State-based model; Artificial Neural Network (ANN); Transition probability; Backward Prediction Model (BPM); Long-term performance.

INTRODUCTION
Bridge deterioration models are used to estimate the remaining bridge service life and help make future Maintenance, Repair and Rehabilitation (MR&R) decisions. The quality of the MR&R decisions is highly dependent on the accuracy and reliability of the prediction outcomes of the deterioration models. Generally, a large number of historical bridge condition ratings are required for a deterioration model to achieve reliable prediction outcomes. However, routine inspection records which are compatible with the Bridge Management Systems (BMSs) are usually insufficient, thereby unable to satisfy the basic requirements of running the deterioration model in the current BMSs. Therefore, to develop an advanced bridge deterioration model is an issue of utmost urgency.

The most current BMSs adopt the routine and visual bridge inspection technique. This technique employs a discrete condition rating or state to represent defects of the bridge elements. These discrete condition ratings are normally used to develop probabilistic deterioration models for bridge elements (Morocus et al., 2010). The probabilistic models can be classified into two types namely the state-based and time-based models. The state-based models predict the bridge condition ratings using transition probability obtained from the difference between the two condition states at a given discrete interval. Markov chain models are one of the most common examples of the state-based models (Morcous and Akhnoukh, 2006). Several approaches have been developed in the past to calculate the transition probabilities, such as the expected-value method (Jiang, 1990), Poisson regression (Madanat and Wan Ibrahim, 1995), and ordered profit model (Madanat et al., 1995).

However, these approaches have a most critical common shortcoming in that they are only workable when the given condition data has an ideal distribution over the time (Mishalani and Madanat, 2002). On the other hand, the time-based models employ a probability density function of time, referring to as the state duration time required for a bridge element to deteriorate from an initial condition state to its next lower state. Parametric, semi-parametric and non-parametric models have been proposed to generate the probability distribution function of transition time (Morcous and Akhnoukh, 2006). However, these models require frequent inspection of condition rating over a long period and exhibit obvious transition changes in a given condition data. Moreover, an element-level inspection record usually suffers the problem of various situations of condition rating data distributions due to insufficient inspection records. Therefore, a stand-alone model, such as the state- or time-based model, has difficulty in predicting reliable long-term bridge performance due to the shortcomings of each model mentioned above.

In order to minimise the above-mentioned shortcomings, this paper presents an integrated method incorporating both the state- and time-based models. This method is proven to be more effective compared to the stand-alone model (i.e. state- or time-based model) because a selection process is embedded to automatically choose a suitable prediction approach for a given situation of available condition data. A previously developed Artificial Neural Network (ANN)-based Backward Prediction Model (BPM) (Lee et al., 2008) is also employed. In this study, a benchmark example is presented. This example is based on the state-based model using the BPM-generated data together with the available inspection data to estimate the transition probability and thereby predict long-term bridge element performance. The outcome of this example is used to demonstrate the advantages of incorporating BPM in the integrated method.

METHODOLOGY

The major components and procedures of the proposed integrated method are presented in Figure 1. The figure illustrates the core process of the integrated method, which includes categorisation, Overall Condition Rating (OCR) calculation, a selection process, and four different prediction alternatives.

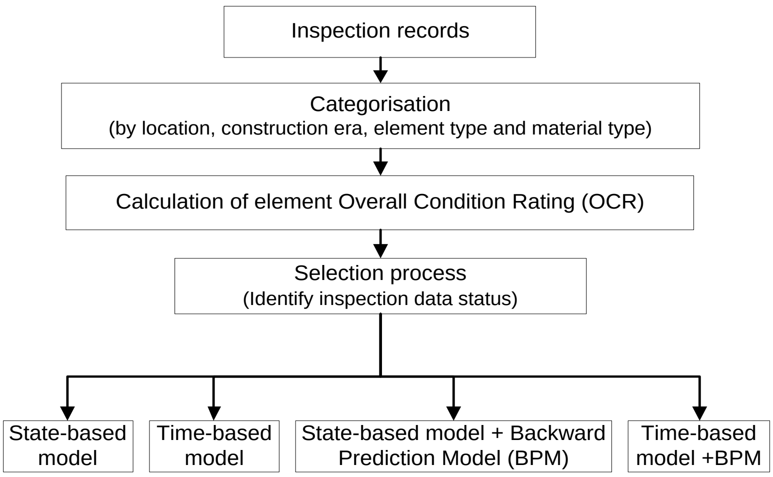


Figure 1. The components and procedures of the proposed integrated method

The inspection records were obtained from the Queensland Department of Transport and Main Roads (QTMR), Australia. Categorisation of bridge inspection records is carried out according to the classification of structural deterioration obtained from the QTMR. In this research, the available inspection records only deal with classifications in relation to bridge location, construction era, element type and material type. Note that construction era is also considered as one categorisation because the quality of construction materials and construction methods in the last few decades has continuously been improved as compared to the earlier constructed structures. Once the categorisation process is completed, the OCRs are calculated using the following equation:

$$OCR = \frac{q_1 w_1 + q_2 w_2 + q_3 w_3 + q_4 w_4}{q_1 + q_2 + q_3 + q_4} \tag{1}$$

where, q_1, q_2, q_3 and q_4 are the element quantities in condition states (CSs) 1, 2, 3 and 4, respectively, and w_1, w_2, w_3 and w_4 are the weighting factors for each condition state (Thompson and Shepard, 2000). Four CSs are in the order of 1 to 4 (excellent to very poor), and in this study they represent the bridge condition ratings from 100%, 70%, 50% and 20% in a descending order.

The selection process is subsequently used to identify the status of available inspection records and to determine the most suitable prediction approach. Four types of deterioration modelling alternatives are: (a) state-based model, (b) time-based model, (c) state-based model together with BPM and, (d) time-based model together with BPM. Note that the decision of using the BPM or otherwise is also incoporated in the selection process. Alternative (a) is used when the available inspection records are only workable using the state-based model. Alternative (b) is employed when the available inspection records satisfy the input requirement of a time-based model. Alternatives (c) and (d) involve the use of BPM-generated data together with the available inspection records. In this paper, Alternative (c) is selected as a benchmark example. When the available inspection records are insufficient, the BPM may be required to generate missing historical condition ratings thereby enhancing the historical condition depreciation patterns. The BPM procedure is depicted in Figure 2. Based on the Artificial Neural Networks (ANN), the BPM establishes a correlation between the available condition rating records (year t_p-t_{pn}) and the corresponding years' non-bridge factors. This correlation can then be applied to generate the missing historical condition ratings (year t_1-t_{p-1}) using the corresponding years' non-bridge factors (Lee et al., 2008). The BPM-generated historical condition data together with the available inspection records can then be employed to generate the transition probability using the state-based model. The procedure of the state-based model is presented in Figure 3. Note that the collection of inspection records, categorization and Overall Condition Rating (OCR) calculation as described above are necessary before performing the predictions using the state-based model. This model constitutes five steps: Step (1) - generate a performance curve using a 3rd-order polynomial regression function. Step (2) - generate the theoretical OCRs using the Markov chain method which forecasts the bridge condition ratings based on the concept of defining states of bridge condition transition from one state to another during one transition period (Jiang, 1990). Step (3) - obtain the transition probability by minimising the difference between the average condition ratings A(t) from the regression function and the estimated condition ratings E(t) by the Markov chain method. This is described in Equation (2) in the form of a non-linear programming objective function.

$$\text{Min} \sum_{t=1}^{N} \left| \mathrm{A}(t) - \mathrm{E}(t) \right| \text{ subject to } 0 \le \mathrm{p}(i) \le 1,\ i = 1, 2, \ldots, U. \tag{2}$$

Step (4) - validate the accuracy of the transition probability based on the closeness of the average OCRs and the OCRs predicted by the Markov chain method. The Chi-square goodness of fit test is used to validate the accuracy of the transition probability. The calculation formula for the Chi-square method is given below:

$$\chi^2 = \sum_{i=1}^{k} \frac{(\mathrm{E}_i - \mathrm{A}_i)^2}{\mathrm{E}_i} \tag{3}$$

where, χ^2 has a Chi-square distribution with k-1 degrees of freedom, E_i provides a value of the condition rating in year i as predicted by the Markov chain method, A_i is the value of condition rating in year i as predicted by the regression, and k is the number of prediction years. Upon establishment of the transition probability matrices and the initial state vector defined from the inspection records, Step (5), predicting the bridge element condition ratings, can be effortlessly undertaken. Other details about the integrated method can be found elsewhere (Bu *et al. submitted*).

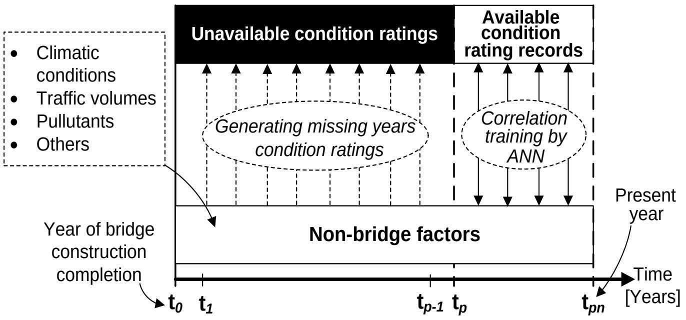


Figure 2. Procedure of BPM (Lee et al., 2008)

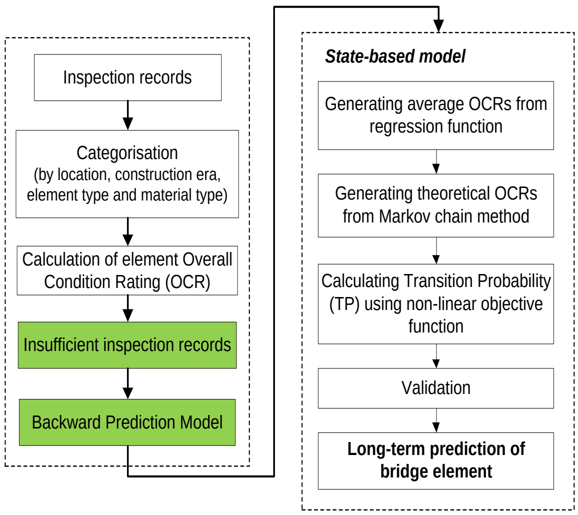
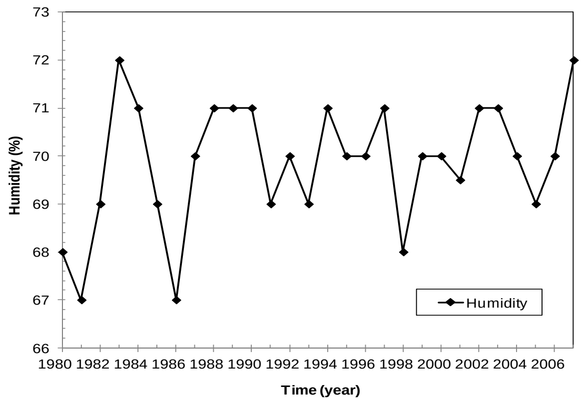


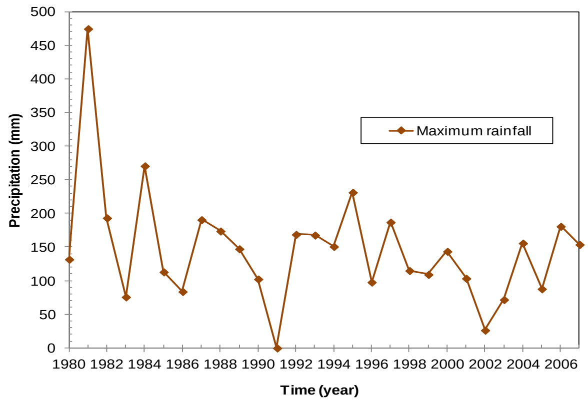
Figure 3. Procedure of the state-based model

BENCHMARK EXAMPLE

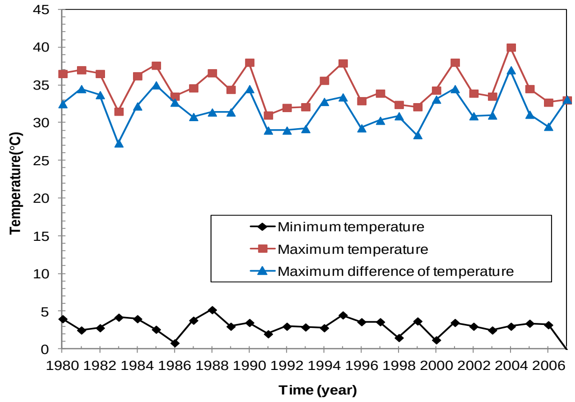
In this study, the state-based model is presented for prediction of long-term bridge element performance using the BPM-generated data together with the available data. The inspection records of the chosen bridge element type 4C (footway) are only available from bridge ages 10 to 20 years. The missing inspection records for ages 0 to 10 years are generated by the BPM. Figure 4 shows the non-bridge factors that are obtained from the local weather station from the years 1980 to 2007, including humidity, maximum rainfall, minimum and maximum temperatures, and maximum difference of temperature. These non-bridge factors are used in the BPM to generate the missing historical condition ratings.



(a) Humidity



(b) Maximum rainfall



(c) Temperatures

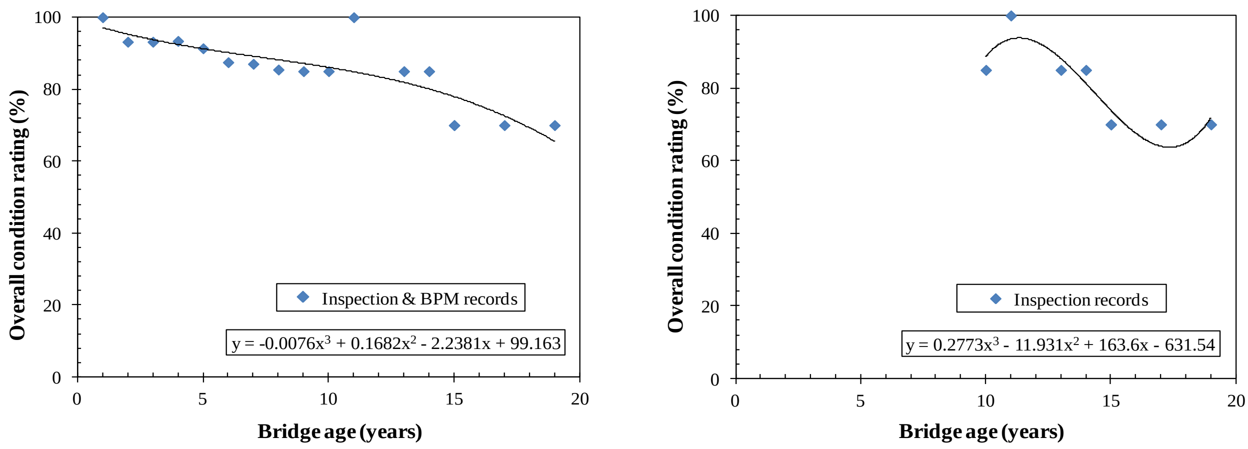
Figure 4. Non-bridge factors for BPM

The bridge element type 4C are collected from a total of 4 bridges and 8 inspection records. Amongst the four bridges, only Bridge#XX47XX satisfies the requirement of using the BPM in generating the missing historical condition ratings. Note that for this particular bridge, the BPM generates the missing condition ratings from years 1991 to 1999, and the forward predictions for years 2000, 2003 and 2007 for cross-validation. The results of cross-validation is summarised in Table 1. It shows a comparison between the predicted and the actual number of elements for different CSs in years 2000, 2003 and 2007. For years 2000 and 2003, the prediction differences for CS1 and CS2 are ±0.3, respectively, out of 42 total quantities. For year 2007, the prediction differences are 0.6 for CS1 and 1.3 for CS3, out of 42 total quantities. These prediction differences are considered insignificant. Therefore, using the BPM generated data can lead to satisfactory prediction.

Table 1. Cross-validation of predicted and actual number of elements

Year	Condition State (CS)	Prediction results (%)	Predicted Number of Elements	Actual Number of Elements
2000	CS1	50.76	21.3	21
	CS2	49.24	20.7	21
	CS3	0	0	0
	CS4	0	0	0
				Total quantities 42
2003	CS1	50.76	21.3	21
	CS2	49.24	20.7	21
	CS3	2	0	0
	CS4	0	0	0
				Total quantities 42
2007	CS1	1.52	0.6	0
	CS2	95.45	40.1	42
	CS3	3.03	1.3	0
	CS4	0	0	0
				Total quantities 42

Upon validation, the input data combining the BPM results together with the available condition ratings is then used to generate the transition probabilities. Figure 5(a) illustrates that the use of the available inspection records in conjunction with the BPM-generated missing condition data can provide a more reliable and reasonable bridge element deterioration pattern within a network region. This is however not the case for Figure 5(b) where the regression curve is meaningless without using the BPM-generated data.



(a) Regression curve with BPM (b) Regression curve without BPM

Figure 5. Regression performance for element type 4C with and without BPM-generated data

RESULTS AND DISCUSSION

The purpose of this study is to verify the proposed integrated method based on the probabilistic deterioration modelling. One typical bridge situation is selected as a benchmark example to demonstrate the capability of the integrated method. Detailed results of this typical example are presented in this section. Figure 6 presents the transition probability matrices of each age group (at a 6-year interval) for element type 4C. The values in each group age represent the probability of the element quantities that are remained in the current condition state. For example, for bridge element type 4C with age group (1-7), 93.3% of the element quantities remain in CS1 for each of the six years.

	1	**2**	**3**	**4**
1	0.933	0.067	0	0
2	0	1.000	0	0
3	0	0	1.000	0
4	0	0	0	1.000

Transition matrix for age group (1-7)

	1	**2**	**3**	**4**
1	0.998	0.002	0	0
2	0	0.937	0.063	0
3	0	0	0.512	0.488
4	0	0	0	1.000

Transition matrix for age group (8-13)

	1	**2**	**3**	**4**
1	0.956	0.044	0	0
2	0	0.838	0.162	0
3	0	0	0.672	0.328
4	0	0	0	1.000

Transition matrix for age group (14-19)

	1	**2**	**3**	**4**
1	0.826	0.174	0	0
2	0	0.626	0.374	0
3	0	0	0.614	0.386
4	0	0	0	1.000

Transition matrix for age group (20-25)

Figure 6. Transition probability matrices for bridge element type 4C

Figure 7 shows the comparison between the 3rd-order polynomial regression function and the Markov chain method in generating the Overall Condition Ratings (OCRs) A(*t*) and E(*t*), respectively. The above transition probabilities are used in the Markov chain method. The comparison demonstrates that the predicted OCRs E(*t*) from the Markov chain method are very close to the OCRs A(*t*) obtained from the regression function. Further, Table 2 summaries the degree of freedom, the critical x^2 value of 36.415 at the significance level α = 0.05 and that estimated from the Markov chain method, i.e. x^2 = 0.0684 which is much smaller. This suggests that the generated transition probabilities using the integrated method are well acceptable to predict long-term bridge performance.

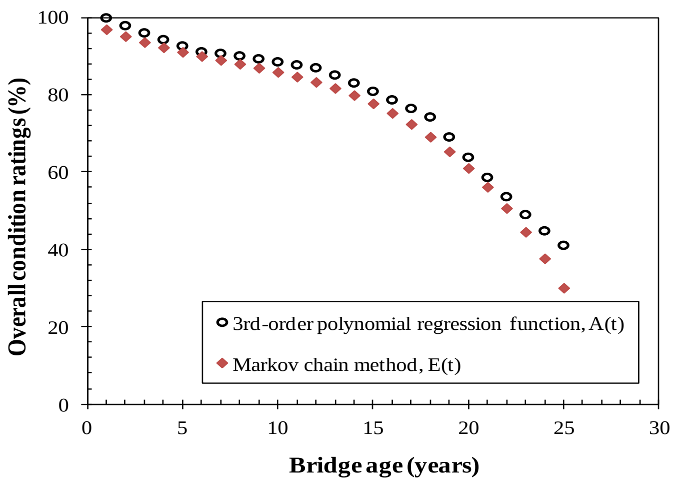


Figure 7. Comparison between the average A(*t*) from the 3rd-order regression function and estimated E(*t*) from the Markov chain method

Table 2. Comparison of the x^2 values at significance level α = 0.05

Element type	Construction era	Degree of freedom	$x^2_{critical}$ (α=0.05)	x^2 value
4C	1980-2000	24	36.415	0.0684

Once the transition probabilities are validated, the long-term bridge element prediction can be simply conducted. Figure 8 shows the long-term prediction for element type 4C of another bridge #XX54XX, out of the four selected bridges. It presents the future condition ratings of the bridge element in terms of the element quantities and OCRs. The long-term prediction is based on the latest inspection record as an initial condition state vector from a given bridge element, by which the element condition ratings for the future 25 years are predicted. It is evident in the figure that the predicted condition ratings gradually decrease as the bridge age increases. This suggests that the transition probabilities correctly reflect the bridge deterioration pattern.

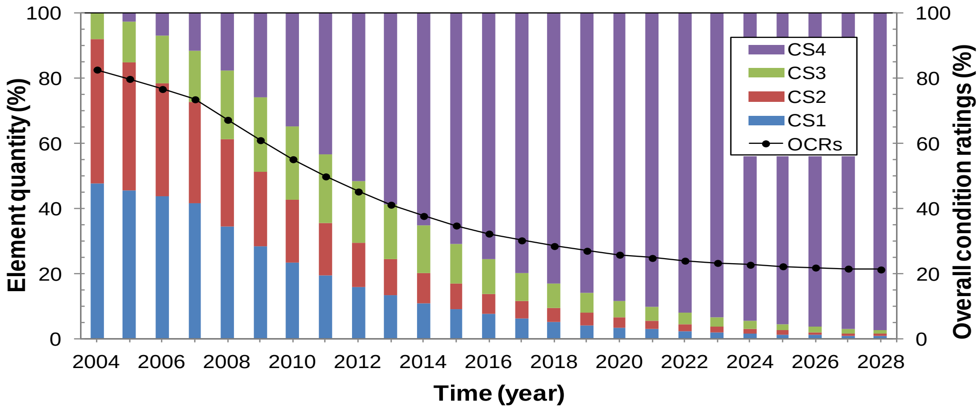


Figure 8. Long-term prediction for Bridge#XX54XX-element type 4C

Through this study, the advantages of the integrated method in predicting long-term bridge element performance are summarised as follows: (1) it categorises the bridge elements by bridge location, construction era, element types and material types, by which similar elements are grouped together to identify common deterioration patterns; (2) it uses the BPM-generated missing historical condition ratings to establish workable transition probabilities when the inspection records are insufficiently available.

CONCLUSIONS

This study presents an integrated method using typical probabilistic bridge deterioration modelling techniques to provide alternative workable solutions for various situations of available condition data. The integrated method employs a combination of the state-based and time-based models which are the most prominent techniques to predict bridge performance. The selection process embedded in the integrated method provides a flexibility of choosing the most appropriate alternatives and leads to more effective prediction outcomes as compared to the stand-alone model. The BPM is also employed in the integrated method to generate the missing historical data for insufficient data scenarios.

In this paper, one of the alternatives, i.e. the state-based model together with BPM is chosen to verify the proposed integrated method. A benchmark example representing a particular bridge element type is investigated where the historical condition ratings are insufficient. This requires the use of the BPM to generate the missing data thereby establishing workable transition probabilities and prodcuing more reliable and reasonable bridge element deterioration patterns within a network region. Upon validation, a long-term prediction of bridge element deterioration is also successfully conducted. On the basis of this study, further investigation on various situations of condition rating data distributions is necessary in order to comprehensively validate the reliability and accuracy of the proposed integrated method.

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