Prediction of Long-Term Bridge Performance: An Integrated Deterioration Approach with Case Studies

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Abstract: A bridge deterioration approach is to predict the condition ratings and the deterioration pattern of bridge elements for determining optimal maintenance strategies and estimating future funding requirements. To effectively predict long-term bridge performance, an advanced integrated deterioration approach has been developed which incorporates a time-based model, a state-based model with the Elman Neural Network (ENN) and a Backward Prediction Model (BPM). The proposed method involves the categorisation of the selected inspection records by bridge components, material types, traffic volume and the construction era. The main advantage of such categorisation is to group similar components together, thereby identifying the common deterioration patterns. A selection process embedded in the proposed method offers the ability to automatically select the most appropriate model for predicting future bridge condition ratings. To demonstrate the advantage of the proposed method in predicting long-term bridge performances, case studies are performed using the New York State inspection records available from the U.S. National Bridge Inventory (NBI) database. To compare the performance of the proposed method against the standard Markovian-based deterioration procedure in predicting future bridge condition ratings, a total of 40 bridges with 464 bridge substructure inspection records are selected and used

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as input. The predicted outcomes are validated by a cross-validation process, which demonstrates that the proposed method is more accurate than the standard Markovian-based procedure.

CE Database subject headings: Bridge; Deterioration; Performance, Prediction.

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Introduction

To effectively manage a large infrastructure asset, Maintenance, Repair and Rehabilitation (MR&R) work must be timed to actively satisfy the safe condition of structures and to maximise the financial benefits to bridge owners. The planning of MR&R activities for bridges is based on measured and predicted condition ratings. Currently, most bridge owners only rely on bridge inspection results with instant follow-up measures taken to decide the maintenance strategies (Lee et al. 2005). This can be effective for managing small number of bridge networks, but it is neither efficient nor economical for managing large bridge networks (Lee et al. 2005). A computer-based Bridge Management System (BMS) is normally used to help determine the best possible MR&R strategy for a large bridge network with a given budget. The BMS is based on the results of a deterioration model to provide various important future estimations for the planning of MR&R activities (Lee et al. 2008).

In the past two decades, many bridge deterioration models, including deterministic, probabilistic and Artificial Intelligence (AI) techniques, have been developed in an attempt to achieve reliable long-term performance predictions (Veshosky et al. 1994; Jiang 1990; and Sobanjo 1997). Despite these research achievements in the development of deterioration models, some fundamental problems still remain. The most critical one is that bridge inspection records are inadequate for the BMS input. For example, to be reliable deterministic and probabilistic models usually require some minimum amounts of bridge condition rating data together with a well-distributed deterioration pattern over the life to date of the bridge (Bu et al. 2012). The AI-based techniques require a large bridge information input, including condition ratings and non-bridge factors (e.g. traffic volume, climate change and exposure class). However, the BMS-compatible routine condition inspection records are usually insufficient for several reasons: (1) commercial BMS software has been used for less than 20 years, and even those bridge agencies that implemented BMSs from an early stage have only 7 to 9 inspection records available for developing long-term performance models; (2) bridge condition ratings usually do not change much over short periods; (3) previously conducted inspections are incompatible with what is required as input by many typical BMSs; and (4) frequent maintenance on bridge elements causes variations in the distribution of inspection records (Lee et al. 2008; and Bu et al. 2013a). These limitations are especially responsible for the inaccurate prediction of the long-term performances of bridge elements.

To achieve reliable long-term performance of bridge elements based on limited BMS condition ratings (Level-2 or element-level inspection records), an integrated method has been developed by incorporating the two commonly used approaches viz the state- and time-based models, and the Backward Prediction Model (BPM) (Lee et al. 2008). The proposed method improves the prediction accuracy compared to the stand-alone state- or time-based model (Bu et al. 2013a,b). In this investigation, case studies are conducted using the National Bridge Inventory (NBI) dataset to demonstrate the advantages of the proposed method in predicting long-term bridge performance.

A total of 40 bridges with 464 inspection records on substructures are selected from the New York State network. Among these records, 315 are used as input to predict the bridge condition ratings using both the proposed method and the standard Markovian-based procedure. The predictions are cross-validated with the actual condition ratings – i.e. the remaining 149 inspection records. For long-term prediction, both methods are also compared which further confirms the superiority and merits of the proposed integrated method.

Calibration of the NBI dataset

The most widely used inspection process for a BMS operation is the element-level bridge inspection (Lee 2007). The proposed integrated method is based on element-level inspection records, by which the long-term performance of each bridge element can be predicted. These element-level inspection records are presented as Overall Condition Ratings (OCRs) using a percentage scale. On the other hand, the Condition Ratings (CRs) obtained from the NBI dataset are scaled from 0 to 9, which is a commonly used numerical condition rating for bridge components by the FHWA (1995). Table 1 summarises the FHWA bridge condition ratings. To be compatible with the proposed method, the NBI data is necessary to be calibrated into the percentage scale. Figure 1 illustrates the scale of the NBI data and the corresponding percentage scale for the proposed method.

Integrated deterioration method

An advanced integrated deterioration approach has been developed to effectively predict long-term bridge performance. It incorporates a time-based model, a state-based model with the Elman Neural Network (ENN) and a Backward Prediction Model (BPM). The proposed approach contains a categorisation process and a selection process. It also incorporates the Backward Prediction Model (BPM), and the commonly used state- and time-based models. The categorisation process is used to group similar components together, thereby identifying the common deterioration patterns. The selected bridge network is categorised by component types, material types, traffic volume and the construction era. In general, the NBI dataset covers three major types of bridge structural components: deck, superstructure and substructure. According to the (FHWA 1995), the material types can be classified as concrete, steel, prestressed concrete, timber, masonry, aluminium and others. The Average Daily Traffic (ADT) volume can generally be classified based on the roadway classification (Peshkin and Hoerner 2005). Table 2 presents the roadway classification and the corresponding ADT.

Note that the construction era is also considered in the categorisation process. This is to encompass the fact that the quality of construction materials and construction processes have continuously improved over the past several decades (Bu et al. 2013a). To obtain more reliable prediction outcomes, the construction era classification is considered herein and is grouped into a period of 20 years viz, group 1 (1991-2010) and group 2 (1971-1990).

After the categorisation process, the selection process offers the ability to identify the status of the given inspection records and then automatically selects the most appropriate deterioration model (state- or time-based with or without BPM) to be used. It should be noted that the BPM is used when the input data are insufficient. Detailed implementation of the BPM can be found elsewhere (Bu et al. 2013a). The time-based model requires sequential changes in the condition ratings over a long observation period to define state transition events and the corresponding transition times. The state-based model, on the other hand, has fewer restraints. Note also that, in this study, the selection process ensures that the inspection records only satisfy the requirements of the state-based model.

Time-based models employ a probability density function of time, i.e. the duration required for each bridge component to deteriorate from an initial condition state to its next lower state. The Kaplan and Meier (K-M) method is used to estimate the non-parametric reliability function with respect to the cumulative transition probabilities and the corresponding transition times and events (DeStefano and Grivas 1998). According to DeStefano and Grivas (1998), the equations for calculating the reliability of a bridge component and estimating the cumulative transition probabilities take the form:

$$\hat{R}(t_x) = [(r_x - 1)/r_x] \times R_{x-1} \tag{1}$$

$$\mathrm{TP}(t_x) = 1 - \hat{R}(t_x) \tag{2}$$

where $\hat{R}(t_x)$ = the estimated reliability of a bridge component at time t_x (years); r_x = the reversed rank order of all time values observed within the sample interval; $\mathrm{TP}(t_x)$ = the cumulative transition probabilities for all x = 1, 2, 3,….yth sample observations in ascending order of time; and $R_0 = 1$ at $t = 0$.

State-based models predict long-term bridge performance using transition probabilities obtained from the difference between the two condition states at a given discrete time interval (Bu et al. 2013a). Also as part of the proposed integrated method, the Elman Neural Network (ENN) technique is used in place of the standard regression process to generate the performance curves of the bridge components based on the given NBI dataset (Bu et al. 2013b). This is followed by the calculation of the transition probabilities using a non-linear programming objective function developed by Jiang and Sinha (1989):

$$Min\sum_{t=1}^{N}\left|A(t)-E(t)\right| \text{ subject to } 0 \le P(i) \le 1, i = 1,2,3....,U. \quad (3)$$

where N = the number of years in one age group; U = the number of unknown probabilities; $A(t)$ = the condition ratings at time t and generated by the ENN; and $E(t)$ = the condition ratings at time t and estimated by the Markov chain method.

By the Markov chain method, the estimated condition rating is generated by:

$$E(t) = Q(0) \times P^t \times R' \quad (4)$$

where $Q(0)$ is the initial state vector; P^t is the transition probability matrix P to the power of t; and R' is the transpose of a vector of condition ratings, R = [9, 8, 7, 6, 5,4, 3].

The transition probability matrix P is defined as

$$P = \begin{bmatrix} p(1) & q(1) & 0 & 0 & 0 & 0 & 0 \\ 0 & p(2) & q(2) & 0 & 0 & 0 & 0 \\ 0 & 0 & p(3) & q(3) & 0 & 0 & 0 \\ 0 & 0 & 0 & p(4) & q(4) & 0 & 0 \\ 0 & 0 & 0 & 0 & p(5) & q(5) & 0 \\ 0 & 0 & 0 & 0 & 0 & p(6) & q(6) \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (5)$$

where $q(i) = 1\text{-}p(i)$, $p(i)$ corresponds to $p_{i,i}$ and $q(i)$ corresponds to $p_{i,i+1}$. In Equation (5), $p(1)$ represents the probability of bridge condition ratings remaining at CR9, and $q(1)$ denotes the probability of the bridge condition rating dropping to CR8, the next lower condition rating, and so on. It should be noted that the lowest condition rating for repair work is CR3 among the 9-0 NBI condition rating scale (Jiang 1990). Hence, the corresponding probability, $p(7)$, is assumed to be one. Figure 2 presents the process of the proposed integrated method in terms of categorisation, model selection and long-term prediction.

Case studies

The sample inspection records obtained from the National Bridge Inventory **(**NBI) database are used by the proposed integrated method to predict future condition ratings, and the predicted outcomes can then be employed to validate the prediction accuracy of the proposed method by the cross-validation process. In this study, a total of 464 inspection records are selected from 40 bridges within the construction era of 1971-2010 from the New York State network. These records are for bridge substructures of prestressed concrete construction and no MR&R improvement works (i.e. “do-nothing”) are considered in the long-term performance prediction.

A total of 315 records are selected from the above inspection data as input for both the proposed method and standard Markovian-based deterioration procedure. The remaining 149 records are used to compare with the predicted condition ratings due to both methods, through which the accuracy of the prediction is cross- validated.

Prediction using the proposed integrated method

The selected sample data are divided into the four different classification groups as part of the proposed integrated method. According to the roadway classification and construction era, the sample data are grouped as collector road bridge network of construction eras from 1971 to 1990 and from 1991 to 2010, and freeway bridge network of the same corresponding construction eras. The selection process ensures that these sample data only satisfy the requirements of the state-based model. As a result, four different long-term bridge performance curves are generated by the proposed ENN-based method. To demonstrate that the bridge deterioration rate is significantly affected by traffic volume and construction era, a comparative study is conducted with respect to bridges with an early construction era versus a later one and a high traffic volume versus a low one. Figure 3 shows the long-term bridge performance curves for collector road and freeway bridge networks with construction eras of (1971-1990) and (1991-2010). As evident in the figure, with the same type of roadway (collector road or freeway bridge network), the bridge substructure for the construction era of 1971-1990 deteriorates faster than those of 1991-2010 (Figure 3(a) and (b)). On the other hand, for the same construction eras (1971-1990 or 1991-2010), freeway bridges (i.e. those that sustain high traffic volumes) deteriorate faster than collector road bridges (with low traffic volumes) (Figure 3(c) and (d)).

The state-based model depends on the ability of the transition probabilities to predict long-term bridge performance. The transition probabilities are generated by the non-linear objective function as presented in Equation (3). Figures 4(a)-(d) present the sample inspection records and the comparisons between the ENN and the Markov chain method in generating the average condition ratings $A(t)$ and the estimated condition ratings $E(t)$, respectively, for collector road bridge network (1991-2010), (1971-1990) and freeway bridge network (1991-2010), (1971-1990).

The available data from the collector road bridge network (1991-2010) are distributed between ratings of 9 to 7 from years 1 to 16, and a 28-year prediction is generated. For the group collector road bridge network (1971-1990), the condition ratings change from 9 to 6 with years 9 to 21. A 12-

year prediction has been conducted for this group. The condition ratings for the (1991-2010) freeway bridge network change from 9 to 7 between years 1 to 13, and a 17-year prediction is presented. The last group covers the (1971-1990) freeway bridge network, and the condition ratings change from 8 to 5 and the corresponding observed times from years 8 to 20. For this group, an 11-year prediction is generated. The figures show that the ENN generated long-term performance curves agree well with those estimated by the Markov chain method.

In addition, a Chi-square goodness of fit test (Jiang and Sinha 1989) is also performed in this study to validate the accuracy of the generated transition probabilities. The formula for the Chi-square distribution is given as:

$$\chi^2 = \sum_{i=1}^{k} \frac{(E(t)_i - A(t)_i)^2}{E(t)_i} \tag{6}$$

where χ^2 = a Chi-square distribution with k-1 degrees of freedom (DOF); $E(t)_i$ = the value of the condition rating in year i, predicted by the Markov chain method; $A(t)_i$ = value of the condition rating in year i, predicted by the ENN; and k = the number of prediction years.

The outcomes of the Chi-square test are presented in Table 3 which summarises the DOFs, the critical χ^2 values at a significance level of $\alpha = 0.05$ and the values obtained from the proposed method. The calculated χ^2 values from the proposed method are much smaller than those at a significance level of $\alpha = 0.05$. This suggests that the differences in long-term performance predictions due to the ENN process and the Markov chain method are insignificant.

The transition probabilities can easily be obtained from the non-linear objective Equation (3). The generated transition probabilities for each classification group are presented in Table 4. The values in each age group represent the probability of the condition rating remaining in each condition state. For example, for collector road bridge network of the 1991-2010 construction era, 87% of the condition rating will remain at 9, and only 13% will drop to 8, over a one-year period.

The generated transition probabilities from the proposed method can be used to predict the condition ratings for each individual bridge, and then compared with the actual condition ratings to validate the prediction accuracy of the proposed method

Prediction using the standard Markovian-based procedure

The standard Markovian-based procedure estimates the transition probabilities of the bridge condition by minimising the difference between the average condition ratings from a third-order polynomial regression function and the estimated condition ratings from the Markov chain method. The discrete inspection records without categorisation are used to generate the long-term bridge performance by the third-order polynomial regression. Figure 5 presents the 315 inspection records (without categorisation), the long-term performance curve generated by the third-order polynomial regression and the corresponding estimated condition ratings by the Markov chain method. The figure shows that the generated condition ratings by the regression and Markov chain methods are very similar for the first 30 years. However, when examining the predicted future condition ratings between 30 to 50 years, the prediction error dramatically increases. The figure also shows an unrealistic long-term performance curve. This is because, without repair or rehabilitation, the bridge condition rating decreases as the bridge age increases (Jiang, 1990).

Furthermore, the outcome of the Chi-square test shows that the calculated χ^2 value obtained from the standard Markovian-based procedure is 16.48. Although the calculated value is smaller than that at a significance level of $\alpha = 0.05$, it is much larger than the calculated values resulted from the proposed method, as indicated in Table 3. This suggests that the proposed method can generate more accurate transition probabilities than the standard Markovian-based procedure. The transition probabilities for the standard Markovian-based procedure, as summarised in Table 5, are also generated using the non-linear objective function.

Validation outcomes

To validate the reliability of the predicted condition ratings, a cross-validation is conducted in which the predicted condition ratings are simply compared with the actual one i.e. the 149 records from the total 464 inspection data. The same validation process is also employed for the standard Markovian-based procedure. The validated outcomes resulting from the proposed method and the standard Markovian-based procedure demonstrate that the former provides more accurate predictions.

A comprehensive comparative study indicates that the prediction errors for both the proposed method and standard Markovian-based procedure are all within 10%. Both methods are considered satisfactory for short-term predictions. As a typical example, Table 6 presents the validation outcomes for the collector road bridge network of the 1991-2010 construction era. It covers the bridge ID, number of input data, validation year, and actual NBI data. Also summarised in the table are the prediction outcomes due to both methods as well as their respective prediction errors. As evident, most prediction errors of the proposed method are smaller than those of the standard Markovian-based procedure. For example, the prediction errors of the proposed method for bridge ID1xxx570 are 0.579, 0.350 and 0.142 for years 2010, 2011 and 2012, respectively. They are smaller than the corresponding errors (i.e. 0.640, 0.458 and 0.278) of the standard Markovian-based procedure.

In addition, Figure 6 compares the average prediction errors of the proposed method and those of the standard Markovian-based procedure. It is clear that the proposed method is more accurate. This further demonstrates the advantages of the proposed method in predicting future condition ratings or the long-term performance of the bridge components.

Long-term prediction and discussion

Once the predicted condition ratings are validated, long-term bridge performance can be predicted using the generated transition probabilities (Tables 4(a)-(d)) together with the initial inspection records of the bridge components. The collector road bridge network of the 1991-2010 construction era being categorised using the proposed method is selected as an example for predicting the long-term performance of bridge substructures. These generated long-term performance predictions are compared with those via the standard Markovian-based procedure. Note that this comparison assumes that in the prediction periods, the bridges have undergone no maintenance, renewal or rehabilitation works. Figure 7(a)-(j) present the generated long-term predictions for ten bridges from the New York region recalling that the standard Markovian-based procedure is based on the third-order regression function. The results show that the predictions by both methods have similar predictions over the first five to ten years. They then deviate in longer term predictions: the proposed method can predict the condition ratings reaching the threshold rating of CR3, whereas the prediction of the standard Markovian-based procedure remains at CR6. For example, the proposed method predicts that the condition ratings of bridge ID1xxx090 gradually decreases from CR8 to CR3 during a 28-year prediction period. On the other hand, the standard Markovian-based procedure predicts that the condition ratings for this bridge only decrease for the first ten years and then remains constant at a rating of CR6 for the remaining 18 years. The comparison outcomes of the long-term predictions confirm that the proposed method can provide bridge deterioration patterns of longer time-range than the standard Markovian-based procedure.

Conclusion

This study presents a series of case studies to underscore the reliability of the proposed integrated deterioration approach. A total of 40 bridges (or 464 NBI inspection records) are selected from the New York State network to conduct a comparative study on bridge deterioration predictions by the proposed approach and the standard Markovian-based procedure. The accuracy of the short-term predictions by both methods is confirmed using the cross-validation process. A comparative study of the proposed approach vis-à-vis the standard Markovian-based procedure demonstrate that the former is more accurate and reliable. For long-term bridge performance over a period of up to 25 years, the proposed approach is proven to be more superior to the standard Markovian-based procedure.

The proposed approach is also able to predict long-term bridge performance for most situations given various data distributions and limited inspection records. Note, however, that the proposed approch is only applicable for predicting future condition ratings for “do-nothing” bridges. Bridges that have undergone maintenance are not considered in this study. This is not unlike many other similar studies in which the maintenance issue was neglected due to its uncertainty which can further complicate the deterioration models. Taking into consideration the maintenance issue would merit further investigations.

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Table 1 FHWA bridge condition ratings (FHWA, 1995)

Condition rating	**Description**
9	Excellent condition or new condition: no noteworthy deficiencies
8	Very good condition: no repair needed
7	Good condition: some minor problems; minor maintenance needed
6	Satisfactory condition: some minor deterioration; major maintenance needed
5	Fair condition: minor section loss, cracking, spalling, or scouring for minor rehabilitation; minor rehabilitation needed
4	Poor condition: advanced section loss, deterioration, spalling or scouring; major rehabilitation
3	Serious condition: section loss, deterioration, spalling or scouring have seriously affected primary structural components; immediate rehabilitation needed
2	Critical condition: advanced deterioration of primary structural elements for urgent rehabilitation; bridge may be closed until corrective action is taken
1	Imminent failure condition: major deterioration or section loss present; bridge may be closed to traffic but corrective action can put it back into light service
0	Failed condition: out of service and beyond corrective action

Note: In the FHWA system, assuming that bridges are usable until the rating is reduced to a value of 3.

Table 2 Roadway classification and corresponding ADT

Roadway classification	**General ADT range associated with different roadway classifications (vehicles per day [vpd])**
Freeway	30,000 and above
Arterial	12,000 to 40,000
Collector road	2,000 to 12,000
Local road	≤ 2,000

Table 3 Comparison of the χ^2 values at a significance level of α = 0.05

Roadway classification	**Construction eras**	**DOF**	**χ^2 critical (α=0.05)**	**χ^2 from the proposed method**
Freeway	1991-2010	30	43.773	0.755
Collector road		45	61.656	0.756
Freeway	1971-1990	26	38.885	0.334
Collector road		25	37.652	0.770

Table 4 Transition probabilities for four different classification groups

(a) Collector road bridge network of the 1991-2010 construction era

Ages	P(1)	P(2)	P(3)	P(4)	P(5)	P(6)	P(7)
1-6	0.870	1.000	1.000	1.000	1.000	1.000	1.000
7-11	0.900	0.897	1.000	1.000	1.000	1.000	1.000
12-16	0.934	0.791	0.776	1.000	1.000	1.000	1.000
17-21	0.929	0.852	0.594	0.931	1.000	1.000	1.000
22-26	0.927	0.892	0.701	0.802	0.692	1.000	1.000
27-31	0.910	0.900	0.703	0.804	0.692	1.000	1.000
32-36	0.908	0.885	0.846	0.791	0.683	0.711	1.000
37-41	0.877	0.865	0.843	0.808	0.740	0.665	1.000
42-46	0.756	0.755	0.752	0.742	0.719	0.672	1.000

(b) Collector road bridge network of the 1971-1990 construction era

Ages	P(1)	P(2)	P(3)	P(4)	P(5)	P(6)	P(7)
9-14	0.907	0.658	0.715	1.000	1.000	1.000	1.000
15-19	0.901	0.731	0.515	1.000	1.000	1.000	1.000
20-24	0.884	0.794	0.676	0.528	1.000	1.000	1.000
25-29	0.867	0.841	0.760	0.578	0.605	0.343	1.000
30-34	0.805	0.787	0.751	0.694	0.604	0.445	1.000

(c) Freeway bridge network of the 1991-2010 construction era

Ages	P(1)	P(2)	P(3)	P(4)	P(5)	P(6)	P(7)
1-6	0.835	0.889	0.888	1.000	1.000	1.000	1.000
7-11	0.888	0.744	0.528	1.000	1.000	1.000	1.000
12-16	0.882	0.797	0.670	0.524	1.000	1.000	1.000
17-21	0.888	0.837	0.725	0.605	0.539	0.407	1.000
22-26	0.854	0.841	0.743	0.623	0.561	0.450	1.000
27-31	0.722	0.719	0.709	0.686	0.642	0.529	1.000

(d) Freeway bridge network of the 1971-1990 construction era

Ages	P(1)	P(2)	P(3)	P(4)	P(5)	P(6)	P(7)
7-12	0.000	0.870	0.699	0.540	1.000	1.000	1.000
13-17	0.000	0.813	0.729	0.546	1.000	1.000	1.000
18-22	0.000	0.835	0.737	0.592	0.776	0.771	1.000
23-27	0.000	0.811	0.801	0.712	0.623	0.484	1.000
28-32	0.000	0.721	0.714	0.693	0.648	0.568	1.000

Table 5 Transition probabilities for the standard Markovian-based procedure

Ages	P(1)	P(2)	P(3)	P(4)	P(5)	P(6)	P(7)
1-6	0.808	1.000	1.000	1.000	1.000	1.000	1.000
7-11	0.872	0.901	0.919	1.000	1.000	1.000	1.000
12-16	0.911	0.825	0.763	1.000	1.000	1.000	1.000
17-21	0.916	0.839	0.749	0.927	1.000	1.000	1.000
22-26	0.913	0.839	0.750	0.947	1.000	1.000	1.000
27-31	0.890	0.785	0.714	1.000	1.000	1.000	1.000
32-36	0.917	0.775	0.711	1.000	1.000	1.000	1.000
37-41	0.962	0.248	0.730	1.000	1.000	1.000	1.000
42-46	0.986	0.250	0.781	1.000	1.000	1.000	1.000
47-51	1.000	0.250	0.781	1.000	1.000	1.000	1.000

Table 6 Validation outcomes for collector road bridge network of the 1991-2010 construction era

Bridge ID	**No. of input data**	**Validation Year**	**Actual NBI (grade 0-9)**	**Proposed Method (PM)**	**Standard Procedure(SP)**	**PM Error (%)**	**SP Error (%)**
1xxx720	10	2009	9	8.900	8.87	0.100	0.128
		2010	9	8.819	8.77	0.181	0.228
		2011	8	8.730	8.66	0.730	0.664
		2012	8	8.633	8.55	0.633	0.550
2xxx170	7	2009	8	7.897	7.901	0.103	0.099
		2010	8	7.805	7.804	0.195	0.196
		2011	8	7.722	7.709	0.278	0.291
		2012	8	7.509	7.523	0.491	0.477
1xxx350	10	2009	9	8.900	8.872	0.100	0.128
		2010	9	8.819	8.772	0.181	0.228
		2011	8	8.730	8.664	0.730	0.664
		2012	8	8.633	8.550	0.633	0.550
1xxx090	9	2010	7	6.594	6.749	0.665	0.663
		2011	7	6.325	6.543	0.467	0.483
		2012	7	6.139	6.372	0.270	0.304
1xxx640	12	2004	8	7.791	7.825	0.209	0.175
		2005	8	7.579	7.64	0.421	0.360
		2006	8	7.375	7.455	0.625	0.545
1xxx610	15	2009	7	7.589	7.649	0.589	0.649
		2010	7	7.385	7.468	0.385	0.468
		2011	7	7.189	7.289	0.189	0.289
		2012	7	7.005	7.116	0.005	0.116
1xxx202	8	2008	7	6.776	6.763	0.224	0.237
		2009	7	6.603	6.582	0.397	0.418
		2010	7	6.331	6.406	0.669	0.594
1xxx570	9	2010	7	7.579	7.640	0.579	0.640
		2011	7	7.350	7.458	0.350	0.458
		2012	7	7.142	7.278	0.142	0.278
1xxx930	10	2008	8	7.791	7.825	0.209	0.175
		2009	7	7.579	7.640	0.579	0.640
		2010	7	7.375	7.455	0.375	0.455
		2011	7	7.185	7.279	0.185	0.279
		2012	7	7.013	7.115	0.013	0.115
1xxx160	10	2009	8	7.897	7.901	0.103	0.099
		2010	8	7.686	7.720	0.314	0.280
		2011	8	7.478	7.535	0.522	0.465
		2012	8	7.281	7.355	0.719	0.645