AN INTEGRATED DETERIORATION METHOD FOR PREDICTING LONG-TERM PERFORMANCE OF BRIDGE COMPONENTS: CASE STUDIES

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ABSTRACT

An integrated deterioration prediction method has been developed to predict long-term performance of bridge elements for various situations in terms of the quantity and distribution of available condition rating data. The method employs a categorisation and selection process in conjunction with the Backward Prediction Model (BPM) as well as the time-based and state-based models. To check the accuracy of the proposed integrated method, a series of case studies are carried out based on the U.S. National Bridge Inventory (NBI) datasets. A total of 40 bridges with 464 bridge inspection records are selected from the New York State region. Of these, 315 records are used as input for the proposed method to predict the long-term performance of the concerned bridges. The predicted bridge condition ratings are compared with the actual condition ratings - i.e. the remaining 149 inspection records. The accuracy of the prediction is reasonable. To demonstrate the superiority and merits of the proposed method, a detailed comparison is made between the proposed integrated method and the standard Markovian-based procedure.

Keywords: Integrated deterioration method, Backward Prediction Model (BPM), time-based model, state-based model, long-term performance.

1. INTRODUCTION

The optimal budgeting and efficient use of maintenance funds for the well-being of bridges require a sophisticated bridge asset management technology including its effective implementation. A Bridge Management System (BMS) is essential to help bridge authorities with the complex decision-making process for the optimum Maintenance, Repair and Rehabilitation (MR&R) strategies. The objective of adopting such a system is to improve and maintain the optimal health status of concerned bridge networks; such also provides effective analytical predictions in terms of condition ratings and deterioration rates etc as well as decision making on budgeting for upcoming

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maintenance and the optimal maintenance strategies. Reliable long-term prediction of bridge performance is crucial and can be used as input information for various key functions in a BMS including cost-related and MR&R planning. However, the reliability of current deterioration models in predicting the long-term bridge performance is still in doubt due to some fundamental shortcomings such as lack of usable condition rating records due to late uptake in BMS implementation and incompatible inspection data (Lee 2007). The situation has been further aggravated by the randomness of data distribution related to various maintenance issues and inconsistent bridge inspection processes (Bu et al. 2013a).

To overcome the abovementioned shortcomings, an integrated deterioration method has been developed to predict reliable long-term performance of bridge elements for various situations in terms of the quantity and distribution of available condition rating data (Bu et al. 2013a and 2013b). The proposed deterioration method consists of a categorisation process, a selection process, and time-based and state-based deterioration models. It takes into account environmental conditions, bridge and material types, construction eras and traffic conditions in the categorisation process. The selection process is used to identify the status of the given condition rating data and in turn select the more appropriate deterioration model. In addition, the Backward Prediction Model (BPM) (Lee et al. 2008) is employed to generate the missing historical inspection records when the input data is insufficient.

The proposed integrated method has been demonstrated to provide improved performance as compared to the stand-alone state-based or time-based model using selected examples (Bu et al. 2013a and 2013b). In order to further validate the reliability of the proposed integrated method, a series of cases studies are presented herein using the New York State region datasets obtained from the National Bridge Inventory (NBI) database. A total of 40 bridges are selected for long-term performance predictions. The outcomes are checked by a cross-validation method where the predicted condition ratings are compared with the actual records. Further, the predicted outcomes by the proposed integrated method are also compared with those predicted by the standard Markovian-based deterioration procedure (Jiang and Sinha 1989). The outcomes of the comparison demonstrate that the proposed method provides more reliable long-term predictions than does the standard Markovian-based procedure.

2. INTEGRATED DETERIORATION METHOD

The proposed integrated method consists of a categorization process, a selection process in conjunction with Backward Prediction Model (BPM), time-based and state-based models. The proposed method is based on element level inspection records to predict the long-term performance of each bridge element. The element level inspection records are presented as Overall Condition Ratings (OCRs) using the percentage scale. On the other hand, the condition ratings (CRs) obtained from the NBI dataset are scaled from 0 to 9 for bridge components (e.g. CR0 represents a “failed” condition rating, and CR9 represents an “excellent” condition rating). To satisfy the requirements of

the proposed method, the NBI data need to be calibrated into the percentage scale (e.g. CR9 =100%, CR8 = 90%, and CR0 = 10%).

The categorization process is used to group similar elements/components together, thereby identifying the common deterioration patterns. The selected bridge network is categorised by location, component types, material types, traffic volume and the construction era. Generally, the NBI dataset includes three major types of bridge structural component: the deck, the superstructure and the substructure. According to FHWA (1995), the material types can be classified as concrete, steel, prestressed concrete, timber, masonry, aluminium and others. The Average Daily Traffic (ADT) volume generally can be classified based on the roadway classification. Table 1 presents the roadway classification and the corresponding ADT.

Table 1: 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

Source: Peshkin and Hoerner 2005

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. 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 finds an appropriate deterioration model. It should be noted that the BPM is used as an alternative when the input data are insufficient. Detailed implementation of the BPM is presented elsewhere (Lee et al. 2008). Two deterioration models - the time-based and state-based models - are available in the proposed integrated method. 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 (DeStefano and Grivas 1998). On the other hand, the state-based model has fewer restraints. In this study, the selection process ensures that the sample data only satisfy the requirements of the state-based model. 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. Also as part of the proposed method, the ENN technique is used in place of the standard regression process (Bu et al. 2013b) to generate the performance curves of the bridge components based on the given NBI dataset. The transition probability can be generated using Equation (1) below by

minimising the difference between the average condition ratings *A(t)* from the ENN and the estimated condition ratings *E(t, P)* by the Markov chain method. Thus

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

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; *E(t, P)* = the condition ratings at time t and estimated by the Markov chain method, in which

$$E(t,P) = Q(0) \times P^{t} \times R^{'} \quad (2)$$

Note that the vector of condition ratings is R = [9, 8, 7, 6, 5, 4, 3] and the transition probability matrix

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

where $q(i)$ = 1-$p(i)$, $p(i)$ corresponds to $p_{i,i}$ and $q(i)$ corresponds to $p_{i,i+1}$. In Equation (3), $p(1)$ 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 noting that the lowest condition rating before a bridge is repaired is CR3 (Jiang, 1990). Hence, the corresponding probability, $p(7)$, is assumed to be one.

3. CASE STUDIES

A total of 464 inspection records are selected from 40 bridges within the construction era of 1971-2010 from the New York State region. These records are for bridge substructures of prestressed concrete construction and without any MR&R improvement works. Of these, 315 inspection records are selected as input for both the proposed integrated method and standard Markovian-based deterioration procedure. The remaining 149 records are compared with the predicted condition ratings from both the proposed integrated method and the standard Markovian-based procedure to cross-validate the accuracy of the prediction.

3.1. Transition probabilities for the proposed integrated method

The sample data can be divided into the four different classification groups as part of the proposed integrated procedure. According to the roadway classification and construction era the sample data

are grouped as collector roads of construction eras from 1991 to 2010 and from 1971 to1990 and freeways of the same corresponding construction eras. The selection process ensures that these sample data only satisfy the requirement of the state-based model. As a result, four different long-term bridge performance curves are generated by the Elman Neural Network (ENN) in the proposed method. In this study, the "freeway" bridge network (see Table 1) of the 1991-2010 construction era is selected as one example to illustrate the deterioration phenomenon. Figure 1 presents the inspection records and the long-term performance curves generated via the ENN and Markov chain routines. As shown in the figure, the condition ratings for the (1991-2010) freeway network change from 9 to 7 between years 1 to 13, and a 17-year prediction is generated. The figure also shows that the ENN generated long-term performance curve agrees well with that estimated by the Markov chain method.

In addition, a Chi-square goodness of fit test is performed to validate the accuracy of the generated transition probabilities. The outcome of the Chi-square test indicates that the calculated χ^2 value from the proposed method is 0.8 which is much smaller than the critical value 43 at a significance level of $\alpha = 0.05$. This suggests that the difference in long-term performance predictions due to the ENN process and the Markov chain routine are insignificant.

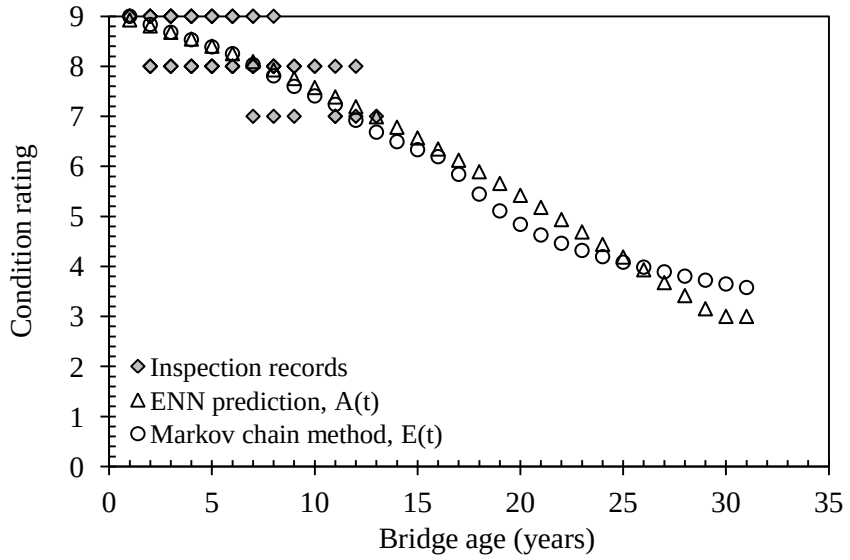


Figure 1: Data distribution and bridge performance curves for freeway network of the 1991-2010 construction era

The transition probabilities for freeway with construction era of (1991-2010) then can easily be generated and presented in Table 2. The values in each age group represent the probability of the condition rating remaining in each condition state. For example, 83.5% of the condition rating will remain at CR9, and only 16.5% will drop to CR8, over a one-year period.

Table 2: Transition probabilities for the freeway bridges 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

3.2. Transition probabilities for standard Markovian-based procedure

The standard Markovian-based deterioration procedure estimates the transition probabilities of the bridge condition by minimising the difference between the average condition ratings from the third-order polynomial regression function and the estimated condition ratings from the Markov chain method. The same amounts of input data are used by the standard Markovian-based procedure to generate the transition probabilities which are given in Table 3.

Table 3: 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

4. VALIDATIONS

Once the transition probabilities are confirmed, future prediction can be performed readily. A cross-validation method is employed herein to measure the accuracy and reliability of the predicted condition ratings. This is done by comparison with the actual condition ratings i.e. the 149 records identified in Section 3.0 above. The same basis for validation is also used for the standard Markovian-based procedure. The validated outcomes from the proposed method are compared with those from the standard Markovian-based procedure to demonstrate that the proposed method provides more accurate predictions.

It is found in the above comparative study 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. Table 4 shows an example of the validation outcomes for the freeway bridges of the 1991-2010 construction era. It covers the bridge ID, number of input data, validation year, actual NBI data, prediction outcomes from both the proposed and standard

procedure, as well as the prediction errors for both the proposed method and the standard procedure. It is obvious that most prediction errors of the proposed method are smaller than those of the standard Markovian-based procedure. For example, the prediction errors for bridge ID104xx9 of the proposed method are 0.433, 0.138 and 0.180, which are smaller than the corresponding errors of the standard procedure at 0.804, 0.709 and 0.523.

Table 4: Validation outcomes for the freeway bridges of the 1991-2010 construction era

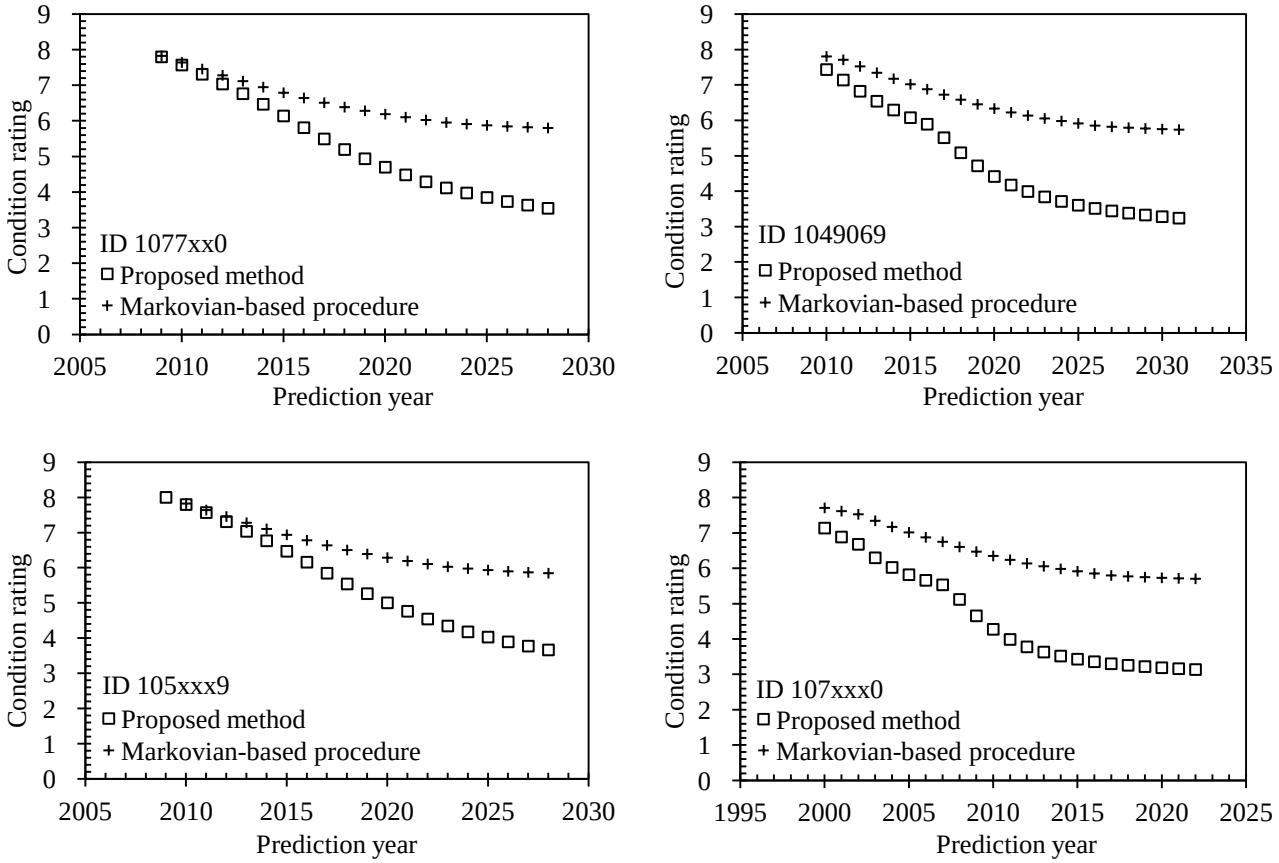
Bridge ID	No. of input data	Validation Year	Actual NBI	PM	SP	PM Error (%)	SP Error (%)
103xxx2	8	2010	9	8.888	8.872	0.112	0.128
		2011	9	8.760	8.748	0.240	0.252
		2012	8	8.612	8.627	0.612	0.627
104xxx9	8	2010	7	7.433	7.804	0.433	0.804
		2011	7	7.138	7.709	0.138	0.709
		2012	7	6.820	7.523	0.180	0.523
105xxx9	8	2010	8	7.797	7.825	0.203	0.175
		2011	8	7.568	7.640	0.432	0.360
		2012	8	7.309	7.455	0.691	0.545
107xxx0	7	2000	7	7.138	7.709	0.138	0.709
		2001	7	6.884	7.617	0.116	0.617
		2002	7	6.678	7.527	0.322	0.527
		2003	7	6.297	7.343	0.703	0.343
1074xx0	9	2005	7	7.568	7.640	0.568	0.640
		2006	7	7.309	7.455	0.309	0.455
		2007	7	7.035	7.279	0.035	0.279
1077xx0	10	2009	8	7.797	7.825	0.203	0.175
		2010	8	7.568	7.640	0.432	0.360
		2011	8	7.309	7.455	0.691	0.545
550xxx9	10	2009	7	7.509	7.720	0.509	0.720
		2010	7	7.242	7.535	0.242	0.535
		2011	7	6.963	7.355	0.037	0.355
		2012	7	6.690	7.186	0.310	0.186
103xxx1	7	2009	9	8.888	8.872	0.112	0.128
		2010	9	8.760	8.748	0.240	0.252
		2011	9	8.612	8.627	0.388	0.373
		2012	8	8.447	8.510	0.447	0.510
1034xx1	3	2011	9	8.835	8.808	0.165	0.192
		2012	9	8.679	8.653	0.321	0.347
1044xx9	5	2010	9	8.835	8.808	0.165	0.192
		2011	9	8.700	8.686	0.300	0.314
		2012	9	8.542	8.567	0.458	0.433

Note: Proposed Method: PM; Standard Markovian-based Procedure: SP

5. LONG-TERM PREDICTION

Once the predicted condition ratings are validated, long-term bridge performance can be predicted using the generated transition probabilities. In this study, the freeway bridges of the 1991-2010 construction era and categorised using the proposed method have been selected as an example for predicting the long-term performance of a bridge substructure. 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 3 presents 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 routine (Section 3.0). The results show that the predictions by both methods have similar predictions at the beginning stage. They then deviate in longer term predictions: the proposed method can predict the condition ratings reaching the threshold rating of CR3 whereas the standard Markovian-based procedure stops at CR6. For example, the proposed method predicts that the condition ratings of bridge ID177xx0 gradually decrease from CR8 to CR3 during a 20-year prediction period. On the other hand, the standard Markovian-based procedure predicts only a decrease from CR8 to CR6 and then remains constant at CR6. The comparison outcomes of the long-term predictions confirm that the proposed method is able to provide bridge deterioration patterns of longer time-range than the standard Markovian-based procedure.



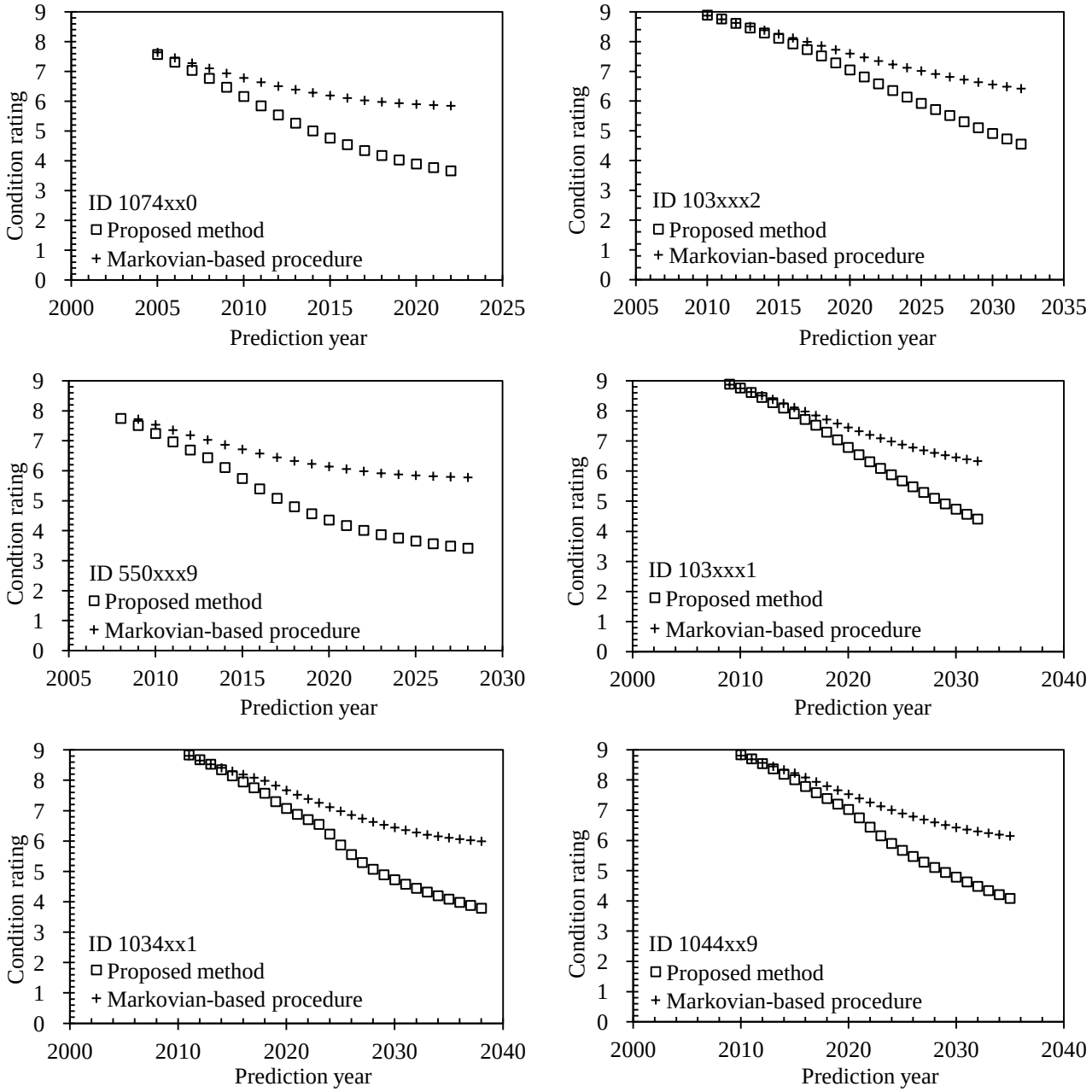


Figure 3. Comparisons of long-term deterioration predictions

6. CONCLUSION

This paper presents a series of case studies to underscore the reliability of the proposed integrated deterioration method. The proposed method is developed by integrating the state-based and time-based deterioration models with the authors' previously published Backward Prediction Model (BPM). A total of 40 bridges (or 464 NBI inspection records) are selected from the New York State network as a basis to conduct a comparative study on bridge deterioration predictions by the proposed method and the standard Markovian-based procedure. The accuracies of the short-term predictions by both methods are confirmed using the cross-validation process. The proposed

method on the other hand is superior to the standard procedure in predicting the long-term bridge performance over a period of up to 25 years.

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