Generating Historical Condition Ratings for the Reliable Prediction of Bridge Deteriorations

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Summary

Bridge Management Systems (BMSs) have been developed since the early 1990s as a decision support system (DSS) for effective Maintenance, Repair and Rehabilitation (MR&R) activities in a large bridge network. Historical condition ratings obtained from biennial bridge inspections are major resources for predicting future bridge deteriorations via BMSs. However, available historical condition ratings are very limited in all bridge agencies. This constitutes the major barrier for obtaining reliable future structural performances. To alleviate this problem, the Backward Prediction Model (BPM) technique for generating the missing historical condition ratings has been developed, and its reliability has been verified using existing condition ratings available from the Maryland Department of Transportation, USA. The function of the BPM is to establish the correlations between the known condition ratings and non-bridge factors including climate, traffic volumes and population growth. Such correlations can then be used to obtain the bridge condition ratings of the missing years. Based on these generated datasets, the current bridge deterioration model can predict future bridge conditions. The existing 4 National Bridge Inventory (NBI) and 9 BPM-generated historical condition ratings were used as input data to compare the prediction accuracy using deterministic bridge deterioration models. The comparison results showed that prediction error decreased as more historical data became available. This suggested that the BPM can be used to generate additional historical condition ratings, which are essential for bridge deterioration models to achieve more accurate prediction results. However, there are still significant limitations identified in the current bridge deterioration models. Hence, further research is necessary to improve the prediction accuracy of bridge deterioration models.

Keywords: Maintenance, Repair and Rehabilitation (MR&R); Bridge Management Systems (BMSs); Bridge condition ratings; Backward Prediction Model (BPM); Non-bridge factors; Bridge deterioration model.

1. Introduction

This paper presents a research study conducted in an attempt to improve long-term predictions of the BMSs. Firstly, a set of missing historical bridge condition ratings was generated using the neural network based Backward Prediction Model (BPM). Deterministic deterioration models were then employed based on complete historical condition ratings obtained from the results of BPM. The future bridge condition ratings predicted by these models were then compared with the existing bridge data to determine the level of prediction accuracy.

2. Backward Prediction Model (BPM)

The BPM predicts the selected or entire periods of historical bridge condition rating to overcome the lack of existing BMS condition ratings. The function of the developed BPM is to establish the correlation between the known condition ratings and non-bridge factors including climate, traffic volume and population growth. Such correlation can then be used to obtain the bridge condition ratings of the missing years.

3. Comparison of BPM results with National Bridge Inventory

To carry out the backward comparison, 5 sets of existing NBI data were used in this study as BPM training inputs and outputs (from 1996 in 2-year increment to 2004) to generate historical condition ratings for the periods of 1968 to 1994 in 2-year increments. All the prediction errors derived from the BPM using 6 refined non-bridge factors are less than those obtained from using the original 21 non-bridge factors. This prediction accuracy improvement could be attributable to the elimination of irrelevant factors, which cause the noise level that existed in the original set of factors. The BPM with refined non-bridge factors was therefore used in the subsequent research stage.

4. Current bridge deterioration models

The current bridge deterioration models can be categorised as deterministic, stochastic and artificial intelligence. This paper focuses on the first two types of the model as they are prevalent in many BMSs currently in use worldwide. Among the deterministic models, regression analysis is a method widely used in many bridge management systems. As for stochastic technique, Markovian model is considered as the most common of this category. However, the Markovian model is not suitable for the NBI. Thus, only regression analyses were used in the current study to predict future bridge conditions based on generated historical data from the BPM methodology.

5. Comparison of deterioration models

Comparisons of prediction error were carried out by using 4 existing NBI records and 9 BPM-based generated condition ratings, for both linear and non-linear regression techniques. In case of linear regression, the average error of 33.3% from the prediction using 4 NBI records decreases to 7.0% when using 9 generated condition ratings. Similarly for the case of non-linear regression, the prediction error decreases from 25.6% to 9.0% when the number of input datasets increases. This finding indicated that, in deterministic models, the historical data generated by the BPM technique could contribute to the improvement of prediction accuracy.

6. Discussion and Conclusion

Using BPM to generate more historical condition data could contribute to improved prediction of future bridge conditions because prediction error became smaller as more input data obtained. These finding, however, should be interpreted in light of the following main limitations of the deterministic deterioration models employed in this paper: (1) their prediction is based only on an average condition of a bridge structure with no regard to the variability of condition rating distribution in each year; and (2) they disregard the interaction between the different bridge structure elements. Further research is required to address such limitations and should aim to develop a more robust deterioration model that fully exploits the benefits of BPM-generated historical condition records.

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Summary

Bridge Management Systems (BMSs) have been developed since the early 1990s as a decision support system (DSS) for effective Maintenance, Repair and Rehabilitation (MR&R) activities in a large bridge network. Historical condition ratings obtained from biennial bridge inspections are major resources for predicting future bridge deteriorations via BMSs. However, available historical condition ratings are very limited in all bridge agencies. This constitutes the major barrier for predicting reliably future structural performances. To alleviate this problem, the Backward Prediction Model (BPM) technique for generating the missing historical condition ratings has been developed, and its reliability has been verified using existing condition ratings available from the Maryland Department of Transportation, USA. The function of the BPM is to establish the correlations between the known condition ratings and non-bridge factors including climate, traffic volumes and population growth. Such correlations can then be used to obtain the bridge condition ratings of the missing years. Based on these generated datasets, the currently available bridge deterioration model can be used to predict future bridge conditions. The existing 4 National Bridge Inventory and 9 BPM-generated historical condition ratings are used as input data to compare the prediction accuracy using deterministic bridge deterioration models. The comparison results show that prediction error decreases as more historical data become available. This suggests that the BPM can be used to generate additional historical condition ratings, which is essential for bridge deterioration models to achieve more accurate prediction results. However, there are still significant limitations identified in the current bridge deterioration models. Hence, further research is necessary to improve the prediction accuracy of bridge deterioration models.

Keywords: Maintenance, Repair and Rehabilitation (MR&R); Bridge Management Systems (BMSs); Bridge condition ratings; Backward Prediction Model (BPM); Non-bridge factors; Bridge deterioration model.

1. Introduction

A bridge is usually designed to have long-term service life. In some cases, however, it could fail prematurely and, as a result, could cause losses of human life. Thus, to ensure optimum serviceability of a bridge, critical decision-making for Maintenance, Repair and Rehabilitation (MR&R) activities is required [1]. Many Bridge Management Systems (BMSs), as a Decision Support System (DSS), have been developed to manage a large bridge network. A BMS generally assists significant future MR&R strategies, which are based on a reliable bridge deterioration model.

Thus, an effective BMS highly relies on the prediction accuracy of deterioration ratings [2].

Many bridge condition ratings and deterioration models have been developed to determine the bridge life cycle for the major MR&R needs. Nevertheless, the predictions of future structural condition ratings from BMSs are still not practical for developing long-term maintenance strategies. This is largely due to several drawbacks related to their application in most bridge agencies, viz: (1) commercial BMS software has been used for two decades and bridge agencies would have roughly 8 to 9 biennial inspection records only; (2) bridge condition ratings usually do not change much during short-term periods; and (3) approximately 60% of BMS analytical process is affected by bridge inspection records. These factors mainly lead to inaccuracy in predicting the future structural performance of bridges. Coupled with these drawbacks is the major weakness in current deterioration modelling techniques, which is essentially the lack of practical data related to the bridge element's modelling performance. These modelling techniques are invariably developed based on a few set of current structural condition ratings, thus unlikely to predict reliable future bridge condition ratings [3, 4].

Two steps of research will be conducted in an attempt to improve long-term predictions of the BMS. Firstly, a set of missing historical bridge condition ratings, which indicates the trend of structural condition depreciations, will be generated using the neural network based Backward Prediction Model (BPM), based on the sample bridge data provided by the Maryland Department of Transport (DoT), USA [3, 4]. The BPM has an ability to produce missing historical condition ratings through the relationship between the real condition ratings and non-bridge factors. In this respect, well-selected non-bridge factors are critical for the BPM to be able to obtain reliable correlations. In the second step of the research, a deterioration model will be developed based on complete historical condition ratings obtained from the results of the first step. The future bridge condition ratings predicted by this model will be then compared with the existing bridge data to determine the level of prediction accuracy. This paper presents part of a progression in the first step of the abovementioned research.

2. Backward Prediction Model (BPM)

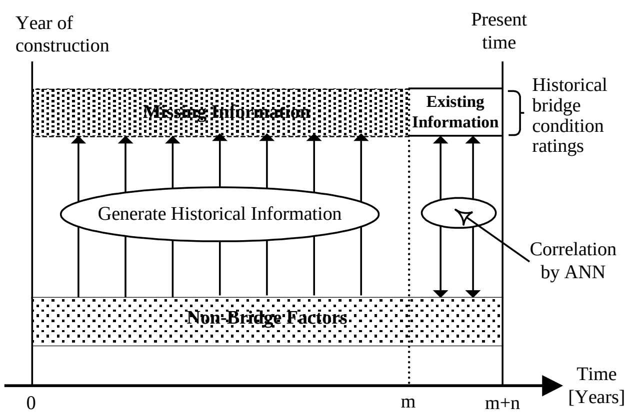


Fig. 1:Mechanism of BPM [3]

The BPM predicts the selected or entire periods of historical bridge condition rating to overcome the lack of existing BMS condition ratings. The mechanism of the BPM is shown in Figure 1. It illustrates the main function of the Artificial Neural Network (ANN) technique in establishing the correlation between the existing condition rating datasets (from year m to year $m+n$) and the corresponding years' non-bridge factors. The non-bridge factors directly and indirectly affect the variation of the bridge conditions thereby the deterioration rate. The relationships established using neural networks are then applied to the non-bridge factors (for year 0 to year m) to generate the missing bridge condition ratings (for the same year 0 to year m). Thus, the non-bridge factors, in conjunction with the ANN technique, can produce the historical trends that produce the current condition ratings [3, 4].

The structure of the ANN-based BPM consists of an input layer, hidden layer(s) and an output layer, where existing neurons in the hidden and output layers are interrelated by weighted relationship. A neuron in the hidden layer gains data from the input layer through calculation of weighted sum. Afterwards, these data are passed on to another neuron in the output layer by using a weighted connection [3, 4].

3. Comparison of BPM results with National Bridge Inventory (NBI)

The results obtained from the BPM can be validated by using either backward-manner comparison and/or forward-manner comparison. Through the backward-manner comparison, known historical data can be directly compared with the BPM outcomes to measure its prediction accuracy. The forward-manner comparison uses the BPM outcomes as input data to predict present year's bridge condition ratings, which can then be compared directly with the known data. This study uses NBI because it has longer periods of historical data, which make it possible to measure the BPM's prediction reliability. For the purpose of this study, only backward comparison was employed to verify the results generated by the BPM.

To carry out the backward comparison, only 5 sets of existing NBI data were used in this study as BPM training inputs and outputs (from 1996 in a 2-year increment to 2004). Additionally, assumed condition rating in 1966, when the bridge was built, was used (i.e. excellent condition state). As a result, historical condition ratings were generated from 1968 to 1994 in 2-year increments.

As mentioned in Sections 1 and 2, non-bridge factors affect the reliability of prediction for unknown condition ratings. Thus, it was necessary to refine non-bridge factors to achieve more reliable BPM outcome. This paper employed 6 key non-bridge factors, which were refined from the original 21 non-bridge factors used in the initial BPM development process [3, 4]. These refined factors, including passenger vehicle, truck, total number of vehicle, maximum temperature, local city population and state population growth, were deemed significant as they demonstrated high-quality trends with the existing NBI data in the BPM methodology. As a result, historical data using each of the 6 non-bridge factors were generated, as shown in Figure 2. In the figure note that, a total of 396 prediction results are obtained in each year for combined 6 non-bridge factors, which were derived from the combined number of learning rates (lr:0.0-0.5) and momentum coefficient (mc:0.0-1.0) in the neural network [3, 4]. Also in the figure, only the condition ratings of superstructure are presented for each factor, with respect to the NBI data.

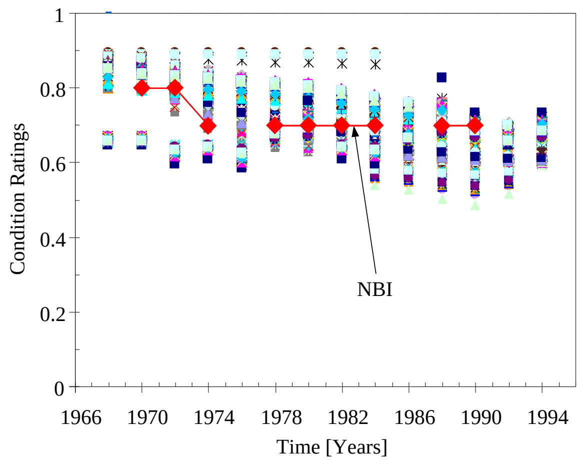
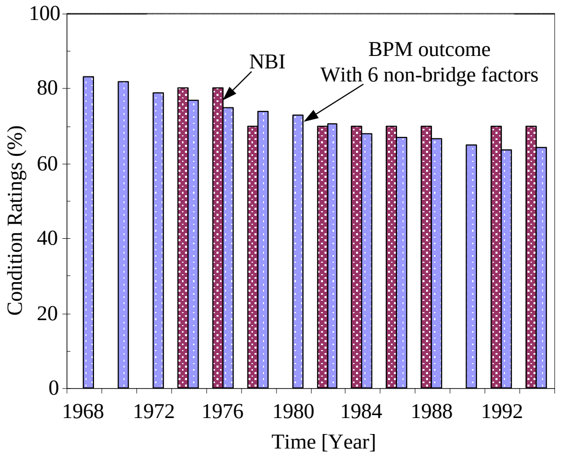


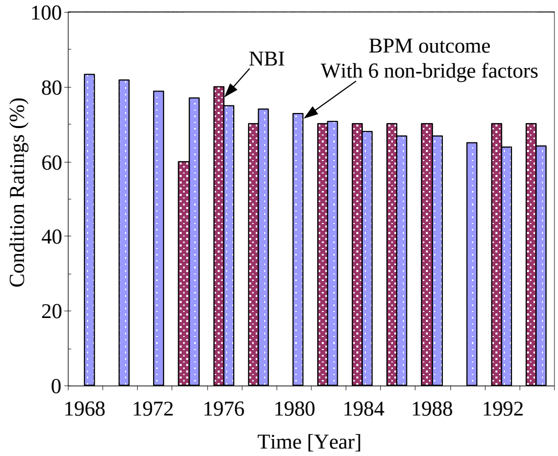
Fig. 2: Generated historical condition ratings (superstructure) for the combined 6 non-bridge factors

Figure 3 shows backward comparisons between the average refined BPM results (i.e. with respect to the 6 newly selected non-bridge factors) and the existing NBI data. The prediction error of each bridge element was calculated by averaging the differences between the BPM-generated condition ratings and the NBI. As shown in Figure 3, all of the prediction errors derived from the refined non-bridge factors (deck: 3.74%, superstructure: 5.26%, substructure: 5.78%) are less than those obtained from the original 21 non-bridge factors (deck: 6.68%, superstructure: 6.61%, substructure: 7.52%) [3, 4]. This improvement in the prediction accuracy can be attributable to the elimination of irrelevant non-bridge factors, which normally increase the noise level that existed in the original set of factors. Evidently, by using generated historical condition ratings from the BPM methodology, the prediction inaccuracy of the current deterioration modelling techniques could be reduced.

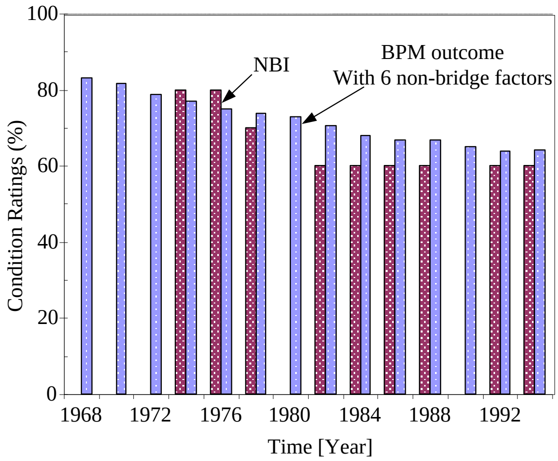
Notwithstanding this finding, it was still necessary to ascertain the efficiency of such generated historical data. To achieve this, the generated historical condition ratings were examined in relation to specific prediction techniques commonly used in the current deterioration models. This part of the study is presented in the following sections.



(a) deck



(b) superstructure



(c) substructure

Fig. 3 Comparison between BPM outcomes and actual NBI

4. Current bridge deterioration models

Numerous research on bridge deterioration models has been carried out to improve the dependability of BMS outcomes. However, it must be emphasised that the successful achievement analysis using such models relies heavily on the quality and sufficiency of data gathered [5]. Based on Morcous et al. [6], the currently available bridge deterioration models can be summarised as deterministic, stochastic and artificial intelligence. This paper focuses on the first two types of the models as they are prevalent in many BMSs currently in use worldwide. In general, a deterministic model predicts that a bridge will deteriorate with respect to a particular algorithm, whereas a stochastic model takes into account the fact that actual deterioration rate cannot be known and contains a probability that the bridge will deteriorate at a particular rate [7]. More details of these deterioration models are presented in Table 1.

Among the deterministic models, regression analysis is a method widely used in many bridge management systems [5]. As for the stochastic technique, Markovian model is considered as the most common one of this category [8]. However, the Markovian model is not suitable for the NBI data. This is due to the fact that NBI only considers condition ratings at the component level, while Markovian model requires element-level inspection data containing more detailed condition states.

Thus, only regression analyses were used in the current study to predict future bridge conditions based on generated historical data with the BPM methodology.

Table 1: Categories of Bridge-Deterioration Models

Categories	Methodology	Details
Deterministic	Straight-line	-
	Extrapolation	Stepwise regression
	Regression	Linear regression Nonlinear regression
	Curve-fitting	B-spline approximation Constrained least squares
Stochastic	Simulation	-
	Markovian	Percentage prediction Expected-value method Poisson distribution Negative-binomial model Ordered-probit model Random-effects model Latent Markov-decision process

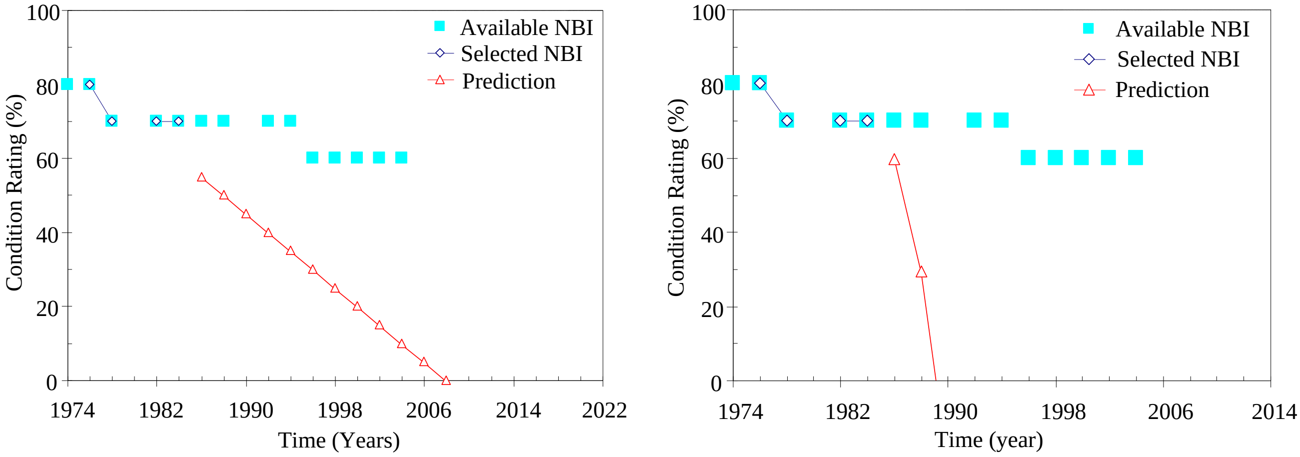
5. Comparison of deterioration models

As demonstrated in Section 3, the BPM results, applied to appropriate deterministic models to identify more historical data, can lead to improved prediction accuracy. In this section, the assessment of prediction accuracy obtained from both linear and non-linear regression analyses, using BPM results, is presented. In general, the important part of regression modelling is the determination of a functional form of the equation that could fit particular datasets (also referred to as a performance curve) [7]. In linear regression, this function is represented by a simple linear equation. In non-linear regression, this function is expressed as a polynomial form of second or more orders. Following Jiang and Sinha [9], this study only considered a third-order polynomial model to determine long-term depreciation of condition ratings. Equation 1 represents a performance curve of bridge element using a third-order polynomial.

$$Y_i(t) = \beta_0 + \beta_1 t_i + \beta_2 t_i^2 + \beta_3 t_i^3 + \alpha_i \qquad (1)$$

where, $Y_i(t)$ = condition rating of a bridge at age t; t_i = bridge age ; α_i = error term; β_0 = recorded condition rating of a new bridge.

The predictions from both linear and non-linear regressions were carried out using 4 available NBI datasets (1976, 1978, 1982 and 1984), as shown in Figure 4. The average prediction error of linear regression was obtained by averaging the differences between the condition ratings of the existing NBI data and the prediction data from 1986 to 2004, with the exception of 1990 due to the NBI data being unavailable. Similar method was employed to calculate the average prediction error of non-linear regression, except that this was carried out only for 1986 and 1988. This is mainly because only the prediction data in these two years are valid for comparison (see Figure 4(b)). As a result, the average prediction errors of linear regression and non-linear regression are 33.3% and 25.6%, respectively. It should, however, be noted that the prediction results generated by non-linear regression technique show unusual pattern of deterioration, as illustrated in Figure 4(b). This might be resulted from the very limited number of input data used in the prediction.

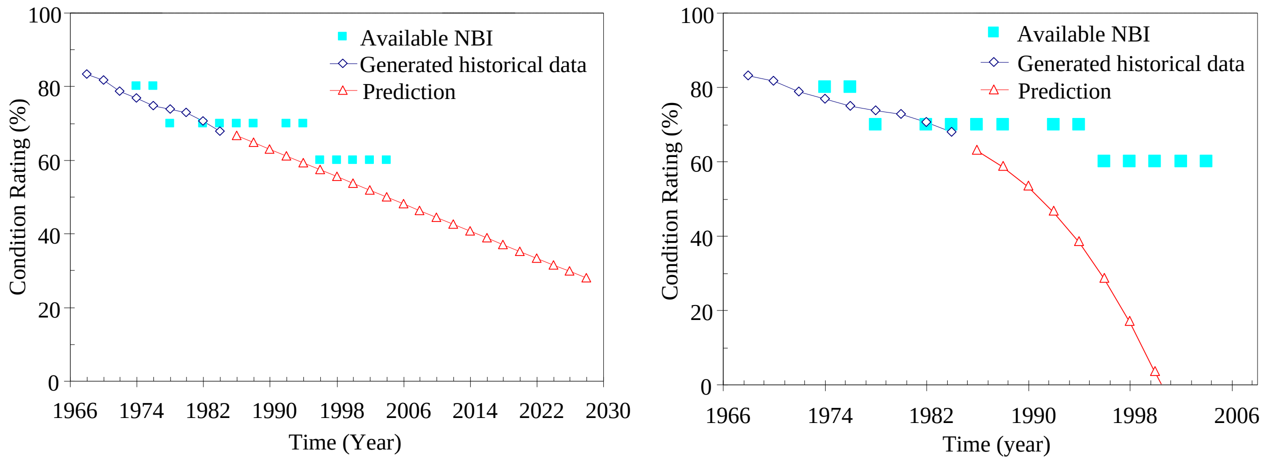


(a) Prediction results: linear regression (33.3% average prediction error)

(b) Prediction results: non-linear regression (25.6% average prediction error)

Fig. 4: Prediction results using 4 sets of historical condition ratings (1976, 1978, 1982 and 1984)

Figure 5 illustrates the prediction results based on 9 historical data records generated by the BPM using 6 non-bridge factors. In Section 3, BPM based historical condition ratings were generated as 66 combinations of learning rate and momentum coefficient. In order for these results to be used in the regression analysis, the 66 combinations in each of the year 1968 to 1984 were averaged to represent individual condition rating records. Following this, the existing NBI records and the BPM-based prediction results were compared to evaluate the prediction accuracy. Following the similar approach mentioned above, the average prediction errors between the generated condition ratings and the NBI records were calculated for both linear and non-linear regression models. This yielded the average prediction errors of 7.0% and 9.0%, respectively.

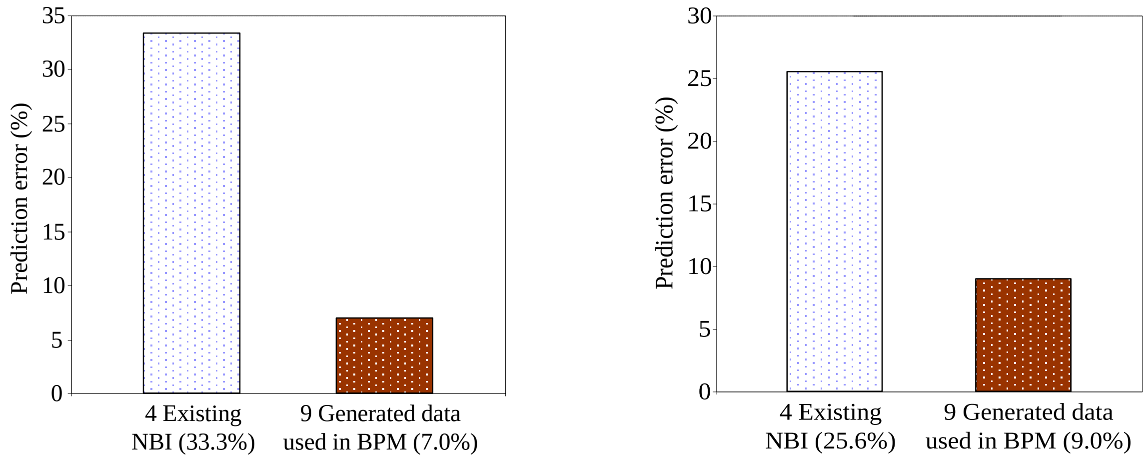


(b) Prediction results: linear regression (7.0% average prediction error)

(d) Prediction results: non-linear regression (9.0% average prediction error)

Fig. 5: Prediction results using 9 sets of BPM-generated historical data

Figure 6 compares the errors of the predictions using 4 existing NBI records and 9 BPM-based generated condition ratings, for both linear regression and non-linear regression techniques. It is evident in the figure 1 that, for both techniques, the prediction errors significantly decrease as more input data become available. In the case of linear regression, the average error of 33.3% from the prediction using 4 NBI records decreases to 7.0% when using 9 generated condition ratings. Similarly for the case of non-linear regression, the prediction error decreases from 25.6% to 9.0% when the number of input datasets increases.



(a) Prediction error: linear regression *(b) Prediction error: non-linear regression*

Fig. 6: Comparison of prediction errors using 4 NBI and 9 generated data in BPM

The above findings indicate that the amount of datasets is essential for numerical prediction methods to gain dependable prediction results. They also suggest that, in the deterministic models, the historical data generated by the BPM technique can contribute to the improvement of prediction accuracy. This reinforces the applicability of the BPM in generating missing historical condition ratings that are capable of providing a basis for more reliable predictions of future bridge conditions.

Notwithstanding the above findings, several limitations of the deterministic models are also worth noting. These are: (1) the models disregard the uncertainty due to the stochastic nature of bridge deteriorations [9]; (2) they predict the average condition of a bridge structure rather the current and historical condition ratings of individual elements; (3) they approximate bridge structure deterioration only for the case of "no maintenance" strategy because it is difficult to estimate the influence from various maintenance strategies [10]; (4) they ignore the interaction between the different bridge structure elements, for example, between the bridge deck and the deck joints [11]; and (5) they are difficult to be revised when new condition ratings are gained [6].

6. Discussion and Conclusion

The performance of BMSs for optimal MR&R strategy relies highly on bridge deterioration models, which in turn depends on the quality and sufficiency of data gathered. The lack of historical bridge condition ratings is a major problem encountered by the current deterioration modelling to achieve reliable prediction of future bridge conditions. To overcome this draw-back, the Backward Prediction Model (BPM) is introduced in this paper as a means to assist in generating unavailable historical condition data, which was achieved by correlating existing bridge condition dataset with non-bridge factors. By refining the 21 non-bridge factors used in the original BPM, this paper was able to extract 6 significant non-bridge factors that showed corresponding trends with existing bridge condition ratings. These refined factors included passenger vehicle, truck and total number of vehicles, highest temperature, local city population and state population growth.

The results of the BPM utilising these refined factors suggested an improved backward prediction accuracy. Prediction errors using the refined 6 non-bridge factors are less than those obtained from the original 21 non-bridge factors. As for deck, prediction error decreased from 6.68% to 3.74%, similarly, prediction error of superstructure and substructure decreased from 6.61% to 5.26% and from 7.52% to 5.78%, respectively. Subsequently, based on such refined factors, 9 historical condition records were generated and applied to the bridge deterioration models to predict future bridge conditions. To ensure that the quality of such generated data was sufficient, future prediction results using the generated data was compared with those obtained by using 4 existing NBI records. Under both linear and non-linear regression deterioration modelling scenarios, the average errors of the prediction results using 9 BPM-generated historical condition records were less than those using 4 NBI records. This indicated that the prediction errors became smaller as the amount of input data increases. Hence, using BPM to generate more historical condition data could contribute to improved prediction of future bridge conditions.

These findings, however, should be interpreted in light of the following main limitations of the deterministic deterioration models employed in this paper: (1) their prediction is based only on an average condition of a bridge structure with no regard to the variability of condition rating distributions in each year; and (2) they disregard the interaction between the different bridge structure elements. Further research is required to address such limitations and should aim to develop a more robust deterioration model that fully exploits the benefits of the BPM-generated historical condition records.

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