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IMPROVING RELIABILITY OF BRIDGE DETERIORATION MODEL USING GENERATED MISSING CONDITION RATINGS

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ABSTRACT: Bridges are vital components of any road network which demand crucial and timely decision-making for Maintenance, Repair and Rehabilitation (MR&R) activities. Bridge Management Systems (BMSs) as a decision support system (DSS), have been developed since the early 1990's to assist in the management of a large bridge network. Historical condition ratings obtained from biennial bridge inspections are major resources for predicting future bridge deteriorations via BMSs. Available historical condition ratings in most bridge agencies, however, are very limited, and thus posing a major barrier for obtaining reliable future structural performances. To alleviate this problem, the verified Backward Prediction Model (BPM) technique has been developed to help generate missing historical condition ratings. This is achieved through establishing the correlation between known condition ratings and such non-bridge factors as climate and environmental conditions, traffic volumes and population growth. Such correlations can then be used to obtain the bridge condition ratings of the missing years. With the help of these generated datasets, the currently available bridge deterioration model can be utilized to more reliably forecast future bridge conditions. In this paper, the prediction accuracy based on 4 and 9 BPM-generated historical condition ratings as input data are compared, using deterministic and stochastic bridge deterioration models. The comparison outcomes indicate that the prediction error decreases as more historical condition ratings obtained. This implies that the BPM can be utilised to generate unavailable historical data, which is crucial for bridge deterioration models to achieve more accurate prediction results. Nevertheless, there are considerable limitations in the existing bridge deterioration models. Thus, further research is essential to improve the prediction accuracy of bridge deterioration models.

Keywords: Feasibility Maintenance, Repair and Rehabilitation (MR&R); Bridge Management System (BMS); Bridge condition ratings; Backward Prediction Model (BPM); Non-bridge factors

INTRODUCTION

It has been widely accepted that critical decision-making for Maintenance, Repair and Rehabilitation (MR&R) activities is required to ensure optimum levels of safety and serviceability of a bridge [1]. Many Bridge Management Systems (BMSs), as a Decision Support System (DSS), have been developed during the past decades to effectively manage a large bridge network. A BMS generally assists significant future MR&R strategies, which are based on a reliable bridge deterioration model. The prediction accuracy of deterioration ratings is therefore highly crucial for an effective BMS [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 impractical 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 only around 8 to 9 biennial inspection records; (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].

Two steps of research have been developed by the authors in an attempt to improve long-term predictions of the BMS. The first step (currently underway) involves generating a robust set of missing historical bridge condition ratings, which indicates the trend of structural condition depreciations, 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]. 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 reliable 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 then be 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.

BACKWARD PREDICTION MODEL

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 help generate the current condition ratings [3].

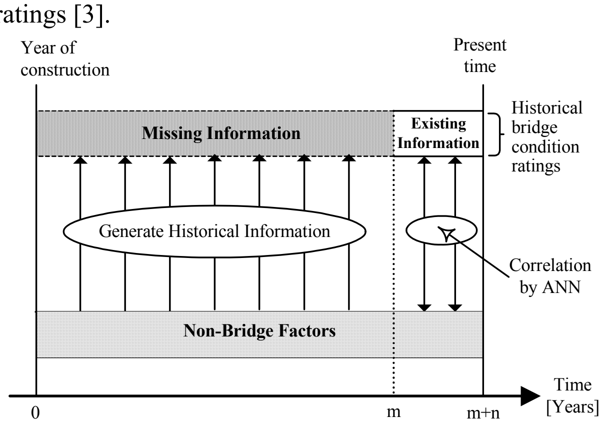


Fig. 1:Mechanism of BPM [3]

The core 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].

BPM FOR BMS CONDITION RATINGS

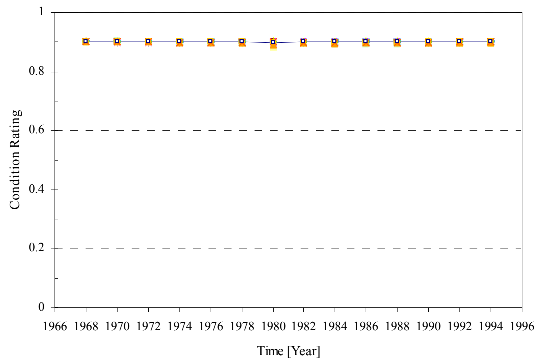
The results obtained from the BPM were validated by using both backward and forward comparison techniques. The former compares the BPM outcomes with the known historical data to assess the prediction accuracy.; whereas the latter uses the BPM outcomes as input data to predict present year's bridge condition ratings, which are then compared directly with the actual data in such year.

To carry out the backward comparison, only 5 sets of existing BMS condition ratings were used in this study as BPM training inputs and outputs (from 1996 in 2-year increment to 2004). As a result, historical condition ratings were generated from years 1968 to 1994 in 2-year increments. As mentioned in the previous sections, non-bridge factor affects 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 non-bridge factors, which were refined from the original 21 non-bridge factors used in the initial BPM development process [3]. These refined factors, including passenger vehicle, truck and total number of vehicles, highest temperature, local city population and state population growth, were deemed significant as they demonstrated high-quality trends with the existing BMS condition ratings. As a result, historical data using each of the 6 non-bridge factors were generated. As shown in Figure 2, note that in the figure, there are 66 prediction results in each year, being 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. The details of raw data for BMS inputs are shown in Table 1.

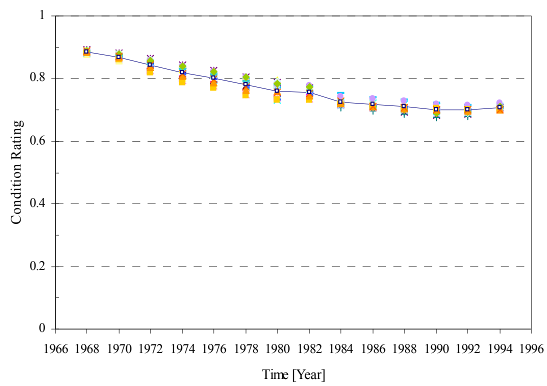
Table 1. Raw data of actual condition ratings (Element #234 on Bridge #0301xxxx1)

Year of inspection	Total Qty.(%)	CS1 (%)	CS2 (%)	CS3 (%)	CS4 (%)	CS5 (%)
1996	100	80	14	6	0	0
1998	100	80	14	6	0	0
2000	100	80	14	6	0	0
2002	100	80	19	1	0	0
2004	100	80	19	1	0	0

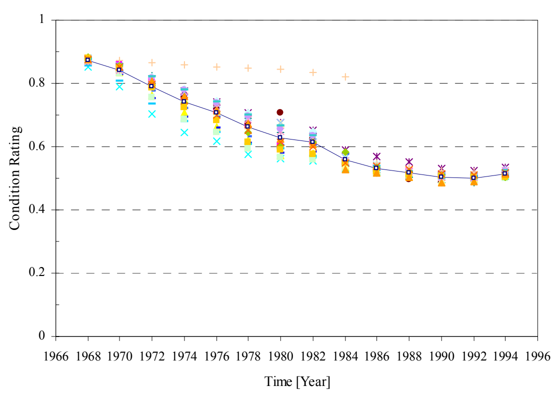
The average quantity of each CS (Condition State) on element #234 (Reinforced Concrete Pier Cap) between 1996 and 2004 is about 80%, 16.2% and 3.8% of the total element in CS1, CS2 and CS3, respectively. The BPM generates historical condition ratings from 1968 to 1994 in three different proportions of the condition state as shown Figure 2. Figure 2(c) shows that historical condition ratings in 3.8% of the total elements have historically fluctuated more than the other CSs. In other words, MR&R activities on these numbers of elements were previously performed. In addition, the format of the final results has to be modified to conform to the type of element level inspection. The BPM outcomes cannot be used directly as BMS inputs. Hence, the BPM results are required to go through a simple post-calibration process.



(a) About 80% of the total quantity



(b) About 16.2% of the total quantity



(c) About 3.8% of the total quantity

Fig. 2: BPM results (Element #234, Bridge #0312xxx1)

To validate the results of the BPM using the forward comparison technique, the generated backward-prediction results (1968-1994) were used as input datasets in this test to generate the condition ratings for the present years (1996-2004). The BPM-generated condition ratings were then directly compared with the existing condition rating datasets. The prediction error was calculated by averaging the differences between the BPM-generated condition ratings and the actual BMS condition ratings. Table 2 shows the final results from the BPM and their prediction errors. The yearly average prediction errors are less than ±10% which is acceptable. Therefore, the generated historical condition ratings (1966-1994) by the BPM can reasonably be used as historical BMS input data.

Table 2. Prediction errors of the proposed BPM using forward comparisons (Bridge #0312xxx1)

		Total (%)	CS1 (%)	CS2 (%)	CS3 (%)	CS4 (%)	CS5 (%)
1996	*A*	100.0	86.0	12.0	2.0	0.0	0.0
	B	100.0	80.0	14.3	5.7	0.0	0.0
	C		6.0	2.3	3.7	0.0	0.0
	D		2.4%				
1998	*A*	100.0	86.0	12.0	2.0	0.0	0.0
	B	100.0	80.0	14.3	5.7	0.0%	0.0
	C		6.0	2.3	3.7	0.0	0.0
	D		2.4%				
2000	*A*	100.0	86.0	12.0	2.0	0.0	0.0
	B	100.0	80.0	14.3	5.7	0.0	0.0
	C		6.0	2.3	3.7	0.0	0.0%
	D		2.4%				
2002	*A*	100.0	86.0	12.0	2.0	0.0	0.0
	B	100.0	80.0	19.1	0.9	0.0	0.0
	C		6.0	7.1	1.1	0.0	0.0
	D		4.7%				
2004	*A*	100.0	86.0	12.0	2.0	0.0	0.0
	B	100.0	80.0	19.1	0.9	0.0	0.0
	C		6.0	7.1	1.1	0.0	0.0
	D		4.7%				

A-results of forward prediction; B-actual condition ratings; C-difference between A and B; and D- average of difference

BRIDGE DETERIORATION MODELS

Many research studies on bridge deterioration models have been carried out to improve the reliability of BMS outcome. Nonetheless, it has been emphasized that the successful achievement of the analysis using these models remains highly dependent on the quality and sufficiency of data gathered [4].

According to Morcous et al. [5], current bridge deterioration models can be categorized as deterministic, stochastic and artificial intelligence. In this paper, only the first two modelling techniques are considered as they are most common in many current BMSs. Generally, a deterministic model predicts that a bridge will deteriorate with regard to a particular algorithm, while a stochastic model considers that actual deterioration rate is unknown and contains a probability that the bridge will deteriorate at a particular rate [6].

Among the deterministic models, regression analysis is a methodology widely used in many BMSs [4], whereas Markovian-based model is considered as the most common method among the stochastic techniques [7]. Therefore, these two models were used in the current study to predict future bridge conditions based on the BPM-generated historical data.

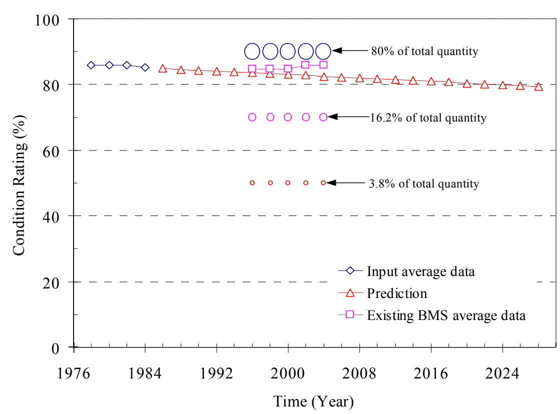
5. COMPARISON OF MODELS

As described in Section 3, the BPM outcomes can lead to improved prediction accurateness. In this section, the evaluation of prediction accuracy obtained from both linear and non-linear regression analyses, as well as Markovian based model are presented. Generally, the determination of a functional form of the equation that could fit particular datasets (also referred to as a performance curve) is considered as crucial part of regression modeling [6]. As for linear regression, this function is expressed by a simple linear equation; whereas in non-linear regression, this function is characterized as a polynomial form of second or more orders. In this study, following Jiang and Sinha [8], only a third-order polynomial model was used to determine long-term deterioration of bridge condition ratings. Equation 1 presents a performance curve of bridge element using a third-order polynomial.

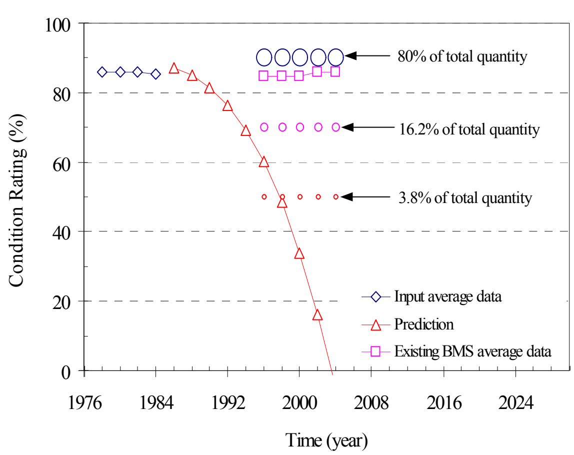
$$C(t) = \beta_0 + \beta_1 t_i + \beta_2 t_i^2 + \beta_3 t_i^3 + \alpha_i \quad (1)$$

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

The predictions from both linear and non-linear regressions were carried out using 4 available BMS datasets (from 1978 to 1984), as shown in Figure 3.



(a) Linear regression: 3.5% average errors

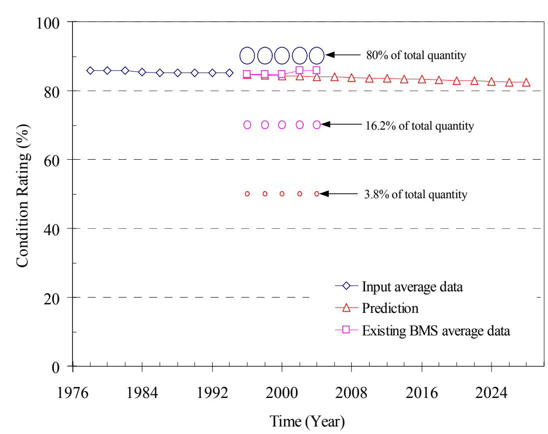


(b).Non-linear regression:74.4% average errors

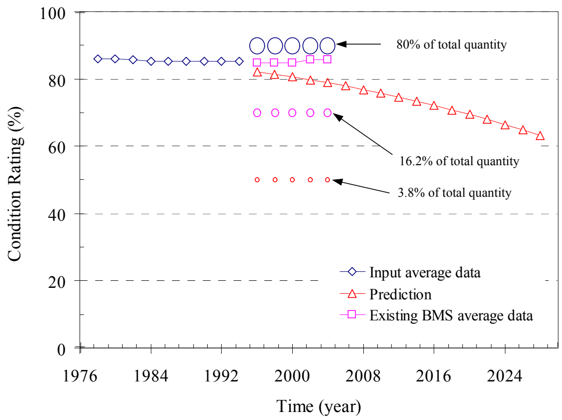
Fig. 3: Prediction results using 4 sets of historical condition ratings (from 1978 to 1984)

The average prediction error of linear regression was obtained by averaging the differences between the condition ratings of the existing BMS condition ratings and the prediction data from 1996 to 2004. Similar method was employed to calculate the average prediction error of non-linear regression. As a result, the average prediction errors of linear regression and non-linear regression are 3.5% and 74.4%, 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 3(b). This might be resulted from the very limited number of input data used in the prediction.

As illustrated in Figure 4, 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 1994 were averaged to represent individual condition rating records. Following this, the existing BMS condition ratings 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 BMS condition ratings were calculated for both linear and non-linear regression models. This yielded the average prediction errors of 1.5% and 4.7%, respectively.



(a) Linear regression: 1.5% average prediction errors



(b) Non-linear regression:4.7% average prediction errors
Fig. 4: Prediction results using 9 sets of BPM-generated historical data

As described in Figure 5, the prediction results of the Markovian-based model based on 4 historical data records generated by the BPM using 6 non-bridge factors. Theoretically, the Markovian-based model predicts bridge condition ratings using the probabilities of bridge conditions transition. These probabilities are characterized in a matrix type, namely, the transition probability matrix. If the current state of bridge conditions or the initial state is known, condition from one rating to another can be forecasted throughout multiplication of original state vector and the transition matrix [8].

To estimate the transition probabilities, the subsequent nonlinear programming objective function was formulated [8]:

$$\min \sum_{t=1}^{N} \left| A(t) - E(t,P) \right| \tag{2}$$

subject to

$0 \le p(i) \le 1 \qquad i = 1,2,\ldots,U$

where

N = 6, the number of years in one age group;
U = 6, the number of unknown probabilities;
P = a vector of length I equal to [$p(1)$, $p(2)$, …, p(I)];
A(t) = the average of condition ratings at time t, estimated by regression function; and
$E(t,P)$ = estimated value of condition rating by Markov chain at time t.

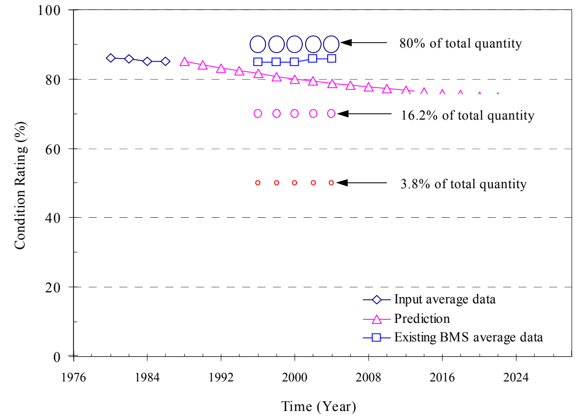


Fig. 5: Prediction results using 4 BPM-generated historical data in Markovian-based model

As illustrated in Table 3, it compares the errors of the predictions using 4 existing BMS condition ratings and 9 BPM-based generated condition ratings, for linear regression, non-linear regression and Markovian-based models. According to the table, it is evident that, for all modelling techniques, the prediction errors decrease as more input data become available. In the case of linear regression, the average error of 3.5% from the prediction using 4 BMS condition ratings decreases to 1.5% when using 9 generated condition ratings. Similarly for the case of non-linear regression, the prediction error decreases from 74.4% to 4.7% when the number of input datasets increases. As for Markovian-based model, only limited data can be used as input data for prediction on that account, in this paper, just 4 data are used as input data. The average prediction errors of Markovian-based model using 4 BMS condition ratings are 7.0%.

Table 3: Comparison of prediction error using 4 and 9 generated data in BPM

Prediction techniques	Number of input data	Difference between prediction and existing BMS condition ratings
Linear regression	*A*	3.5%
	B	1.5%
Non-linear regression	*A*	74.4%
	B	4.7%
Markovian-based model	*A*	7.0%
	B	*NA*

A: 4 generated data used in BPM; B: 9 generated data used 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 both deterministic and stochastic 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 above models are also worth noting. As for the deterministic models, these are: (1) the models disregard the uncertainty due to the stochastic nature of bridge deteriorations [8]; (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 [9]; (4) they ignore the interaction between the different bridge structure elements, for example, between the bridge deck and the deck joints [10]; and (5) they are difficult to be revised when new condition ratings are gained [5].

In case of the Markovian-based models, although they can address two problems in deterministic models by capturing the uncertainty of the deterioration process and accounting for the current facility condition in predicting the future one, they still suffer from the following limitations: (1) Markovian-based models currently implemented in advanced BMS use the first-order Markovian Decision Process that assumes state independence for simplicity [11], which means that the future facility condition depends only on the current facility condition and not on the facility condition history, which is unrealistic [12]; (2) transition probabilities assume that the condition of a facility can either stay the same or decline, thus avoiding the difficulty of estimating transition probabilities for facilities where treatment actions are performed [13]; (4) Markovian-based models cannot efficiently consider the interactive effects between the deterioration mechanisms of different bridge components [10]; and (5) transition probabilities require updates when new data are obtained as bridges are inspected, maintained, or rehabilitated, which is a time-consuming tack [5].

6. DISCUSSION AND CONCLUSION

The performance of BMSs for optimal MR&R strategy relies chiefly 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 drawback, 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 using 6 refined non-bridge factors, including passenger vehicle, truck and total number of vehicles, highest temperature, local city population and state population growth, 14 historical condition rating records (from 1968 to 1994) 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 5 existing BMS condition ratings. 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 BPM-generated 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) th ey disregard the interaction between the different brid ge structure elements. As for the Markovian-based model, prediction using 4 BPM-generated historical condition records is compatible with prediction of regression deterioration model using 9 BPM-generated records. However, prediction of Markovian-based model only depends on the current facility condition without facility condition history, which means unrealistic. Moreover, Markovian-based model cannot consider the proportion of each condition states in prediction. This means that it can ignore critical risk of bridge structure. Thus, further research is essential to deal with such li mitations and should aim to improve a more robust deterioration model that fully makes use of the benefits of the BPM-generated historical condition records.

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