PREDICTION OF BRIDGE DETERIORATION USING GIS-BASED MARKOV TRANSITION MATRIX

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***ABSTRACT*:** This manuscript proposes a bridge deterioration prediction method using a Markov chain model, whose transition probabilities are expressed as a function of environmental conditions. These conditions are obtained from a Geographic Information System (GIS) bridge database developed in Ehime University (E-GISDB). In addition, this paper validates the proposed method using the inspection results of bridges in City J in Ehime prefecture, Japan. The method enables different deterioration predictions to be made for different bridges, which is not possible with conventional methods. As a result, it is shown that predictions obtained by the proposed method are much more accurate than those obtained by conventional methods, especially for RC bridges near the coast, which experience the most severe degradation of all bridges due to the salt breeze.

KEYWORDS: deterioration prediction, Markov chain model, GIS

1. INTRODUCTION

The deterioration of bridges due to aging is a serious problem. For example, roughly half the bridges in Japan will be 50 years old or more within 15 years (Fujino & Abe 2002). In order to prevent future catastrophes involving bridges, maintenance, repair, and replacement (MR&R) action is required. This will maximize the effect of spending and reduce or minimize the deterioration rate. If underestimation of the deterioration of a bridge occurs, it is very likely that the best opportunity to use an MR&R strategy will be lost and bridge damage will accelerate, which will shorten the service life of the bridge. Meanwhile, overestimation of the deterioration would result in an unnecessary expenditure on maintenance (Huang and Rao, 2010).

Therefore, many statistical deterioration prediction models have been developed. (Li et al. 1996, Estes and Frangopol 2001, Frangopol et al. 2004, Mariza et al. 2009, Lounis & Vanier, 2010). These models predict the future health condition of bridges from the current and past health conditions obtained from visual inspection.

The health condition is often rated from A to E in Japan, where A represents a perfect or near perfect condition, and E represents the poorest condition (hereafter health rating). A linear or polynomial regression curve obtained from the current and past health condition is generally used to predict the future health condition in practice (e.g. Miyamoto et. al. 2001, Wirahadikusumah et al. 2001, Adams & Kang 2009). However, this model has suffered from the difficulty that some of the inspection results have been quite different from the predicted damage condition.

One of the reasons behind this is that

environmental conditions which affect bridge deterioration phenomena are not adequately considered in the prediction model. For example, these conditions are roughly divided into only a few categories including “coastal area” and “mountain area”, but these are not enough. To consider these conditions more quantitatively and realistically, we have developed a prediction model which considers the environmental conditions as quantitative parameters obtained from a GIS bridge database developed in the structural engineering laboratory at Ehime University (hereafter E-GISBD).

We have employed the Markov chain model to predict the future health condition of bridges. The Markov chain model is widely studied these days because it is considered to be accurate (e.g. Madanat & Ibrahim 1995, Morcous 2006, Amador-Jiménez & Mrawira 2009, Kobayashi et al. 2010). The model has the characteristic that a change in the proportions of each health rating can be considered. The key to modeling the condition deterioration process is to develop appropriate transition probabilities from one condition state to another. The probabilities are generally expressed in a matrix form, called the transition probability matrix. Though the Markov chain model is useful, there has been little effort to include the effect of environmental conditions in the model. Therefore, this paper addresses this issue.

In this research, inspection results and other related information on bridges in City J, which is one of the municipalities in Ehime prefecture in Japan, are used for the analysis. The case study of City J shows that the proposed model is more reasonable than the conventional models, particularly if the future health condition of RC bridges near the coast is predicted. This means that the proposed model is effective for bridges where the effect of environmental conditions is significant.

2. GIS BRIDGE DATABASE (E-GISBD)

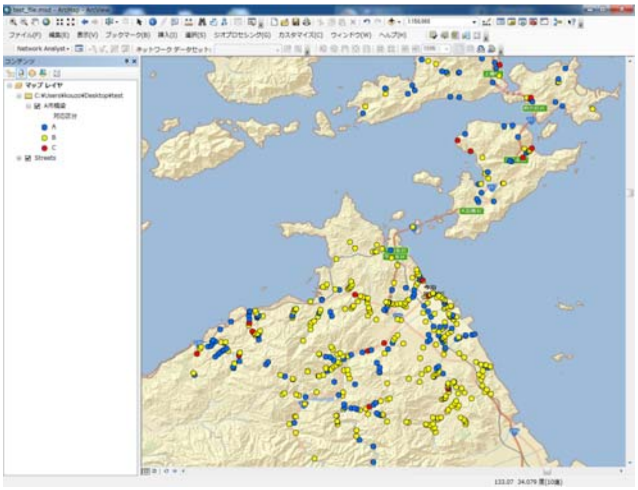
2.1 Overview of E-GISBD

The E-GISBD is being developed on the ArcGIS Desktop and ArcGIS Server platforms (Ormsby et. al. 2004). The database includes information on bridges including bridge dimensions, inspection results, photos of damaged members, and traffic volume. Geographical information is also provided on all the bridges in the database, such as the distance from coast and altitude. Typical screenshots of the E-GISDB are shown in Fig. 1, where bridges with different health condition ratings are shown on a map (Fig. 1(a)) and all the related data can be investigated by selecting the bridge (Fig. 1(b)) and using the options available from the ArcGIS Desktop and Server.

The E-GISBD has been developed with the aim of efficient management of municipal infrastructure systems including bridges, by integrating asset and geographical data. Data integration is defined by the Federal Highway Administration (FHWA) as the process of combining or linking two or more data sets from different sources to facilitate data sharing, promote effective data gathering and analysis, and support overall information management activities in an organization (FHWA 2001). Integrating these data into a consistent form is recognized as a critical step towards successful asset management (Halfawy and Figueroa 2006).

The FHWA report also identifies a number of benefits for data integration: integrated analysis, consistency and clarity, completeness, reduced duplication, faster processing and turnaround time, lower data acquisition and storage costs, informed and defensible decisions, and integrated decision making (Halfawy and Figueroa 2006). This paper particularly focuses on the integrated analysis, where

E-GISDB provides geographical information for the future deterioration prediction.



(a) Map of bridges with different health conditions

(b) Information about bridge

Fig. 1. Typical screenshot of the E-GISBD

2.2 Bridge inspection results stored in E-GISBD

The inspection results obtained in City J were used for analysis in this research. Bridge members inspected in City J are shown in Table 1. Each member had several items to be inspected. For example, cracks, reinforced steel bar exposure, and water leaks were checked for RC beams.

In addition to the health rating, the percentage of the members with the worst health rating is also recorded, e.g. “Cracks on the deck concrete: C, 50%”. This means that the worst part of the deck concrete is rated as C, which covers 50% of the area of the deck, while there is no information on the other 50%. Therefore, it is assumed in this research that an undetermined percentage is equally distributed in the other possible health ratings. For example, in the case of “C, 50%”, the health ratings of A and B are 25%. Note that the percentages of D and E are 0% in this example because it is recorded that C is the worst health rating. Hereinafter, the percentage of health ratings at discrete time step t is expressed as $\{p_t\}$, which is a five-dimensional vector, as follows:

$$\{p_t\} = \{p_A, p_B, p_C, p_D, p_E\} \tag{1}$$

Table 1. Bridge members inspected in City J

Members	Inspection item
Road surface	Pavement
	Joint
	Wheel guard/Guardrail
	Drainage
Superstructure	Girder
	Deck
	Interfilling
Support	Corrosion, Failure, etc.
Substructure	Abutment
	Bridge restrainer system
	Pier, Column, Footing

2.3 Environmental conditions of bridges

The E-GISBD associates the bridge inspection data with the environmental conditions. This research considers the environmental conditions of distance from the coast, and altitude. Because a salt breeze affects the speed of corrosion of reinforced steel bars and girders, the distance from the coast is an important factor when predicting future deterioration.

On the other hand, altitude is also an important factor because the effect of a salt breeze decreases as altitude increases.

The E-GISBD has information on the altitude and distance from the coast of arbitrary locations, provided by the Geographical Survey Institute. For example, Fig. 2 shows the contours of altitude in City J. Inspection results of bridges with environmental conditions are used for the analysis in a later chapter.

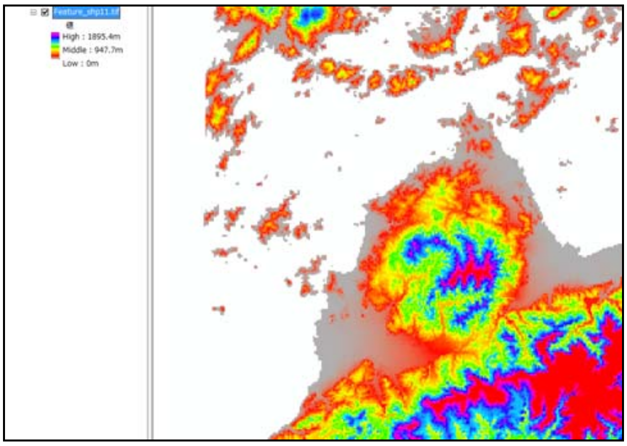


Fig. 2. Contours of altitude in City J

3. DETERIORATION PREDICTION

3.1 Markov Chain model

The Markov chain model is widely accepted for predicting future conditions. It works by defining discrete condition states and accumulating the probability of transition from one condition state to another over discrete time intervals. The probability of transition is generally expressed by the transition probability matrix [P]. Using the transition probability matrix, the condition at time t can be developed from that at time t-1 as follows:

$$\{p_t\} = \{p_{t-1}\}[P] \tag{2}$$

The following Eq. (3) shows a typical transition probability matrix of order (5×5) when MR&R work is not conducted.

$$[P] = \begin{bmatrix} P_{AA} & P_{AB} & 0 & 0 & 0 \\ 0 & P_{BB} & P_{BC} & 0 & 0 \\ 0 & 0 & P_{CC} & P_{CD} & 0 \\ 0 & 0 & 0 & P_{DD} & P_{DE} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$
$$= \begin{bmatrix} 1-P_{AB} & P_{AB} & 0 & 0 & 0 \\ 0 & 1-P_{BC} & P_{BC} & 0 & 0 \\ 0 & 0 & 1-P_{CD} & P_{CD} & 0 \\ 0 & 0 & 0 & 1-P_{DE} & P_{DE} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

P_{ij} in the matrix means the probability that the health rating will change from the current state i to state j after one discrete time interval of the transition process. All the elements of the matrix are 0 except for the on-diagonal elements and the elements above them. This formulation is based on the assumption that is generally made in the literature that a bridge element can change by at most one health rating in a year, and would never recover without any MR&R work.

To predict multiple time intervals, Eq. (2) can be developed as in the following Eq. (4).

$$\begin{aligned} \{p_t\} &= \{p_{t-1}\}[P] \\ &= \{p_k\}[P]^{t-k} \\ &= \{p_0\}[P]^t \end{aligned} \tag{4}$$

where k is the arbitrary discrete time, and $\{p_0\}$ is the initial health condition vector of the bridge, which is expressed as $\{p_0\}$ = {1,0,0,0,0} because no failure will exist at the beginning of the bridge's life.

It is essential to decide the transition probabilities in Eq. (3) to predict the future condition using Eq. (4). This research develops the transition probabilities as a function of environmental conditions by multiple regression analysis so that the effect of the environmental conditions on the deterioration of any bridges in the E-GISBD is derived. The following sections show how to conduct a multiple regression analysis.

3.2 Derivation of transition probabilities from inspection results

It is assumed that we have conducted the inspection at the discrete time $t = T$, and obtained the health condition vector as $\{p_T\}^R=\{p_A^R, p_B^R, p_C^R, p_D^R, p_E^R\}$, where superscript R indicates that the vector is the health condition of a real bridge obtained from an inspection. At the same time, we can calculate the health condition $\{p_T\}$ from $\{p_0\}$ and $[P]$ as:

$$\{p_T\}^C = \{p_0\}[P]^T \tag{5}$$

where superscript C indicates that the vector is the health condition predicted by the calculation. There are four unknowns (P_{AB}, P_{BC}, P_{CD}, and P_{DE}) in Eq. (5). To determine these unknowns, several researchers have proposed various methods. However, previous studies have limitations, such as requiring more than two sets of inspection results from one bridge; however it is not easy for local municipalities to archive these. Therefore, we have developed a method that requires only one inspection result from one bridge, as shown below. One possible way to determine unknowns P_{AB} to P_{DE} is to solve $\{p_T\}^C=\{p_T\}^R$ which takes the form of simultaneous equations in which the number of equations is five. However, because the number of equations is different from that of unknowns (=4), an exact solution cannot be obtained. This study derives the approximate solution by the least-square method, as shown below.

$$S = \sum_{i=A,B,\dots E} \left(p_i^R - p_i^C\right)^2 \tag{6}$$

P_{AB} to P_{DE} are determined to minimize S.

In the minimization process, the Nelder-Mead method, which is one of the most widely used methods for nonlinear unconstrained optimization, is employed. The method requires only function evaluations, not derivatives (Nelder & Mead 1965, Press et al. 2002).

3.3 Multiple regression analysis

This section develops a function to derive the transition probabilities from the environmental conditions by multiple regression analysis. This research considers the distance from coast d_c and altitude h as the environmental conditions. First of all, bridges in City J are divided into five groups by structure type and by distance from the coast. Table 2 shows details of the groups.

Table 2. Detailed information of the bridge groups

Group	Structure type	Distance from coast
a	RC bridges	<1000m
b	RC bridges	≧1000m
c	PC bridges	<1000m
d	PC bridges	≧1000m
e	Entire bridges	

Next, for each group, multiple regression analysis to investigate the relation between the transition probability and environmental conditions is computed as follows:

$$\begin{aligned} &P_{ij} = C_{1ijk} + C_{2ijk}h + C_{3ijk}d_c \\ &where \\ &ij = AB, BC, CD, DE \\ &k = a, b, c, d, e \end{aligned} \tag{7}$$

where k is the index of the group, P_{ij} is the transition probability changed from health condition i to health condition j, C_{1ijk} to C_{3ijk} are coefficients to derive P_{ij} in group k, and C_{1ijk} to C_{3ijk} are derived from the multiple regression analysis. After these coefficients are determined, transition probabilities can be easily obtained by substituting the altitude and distance from the coast into Eq. (7). The derived transition probabilities are considered to reflect environmental conditions, and more accurate future deterioration prediction is expected by using them.

4. CASE STUDY OF CITY J

The bridge inspection data offered by City J is used to show the effectiveness of the method developed here. There are 18 items to be inspected per bridge, and the weighted average of these is derived to evaluate the health condition of a bridge as in the following Eq. (8).

$$p_{ib} = \sum_{h=1}^{18} g_h p_{ih} \quad (i = A, B, C, D, E) \tag{8}$$

where p_{ih} and p_{ib} are respectively the percentage of health rating i of inspection item h and the entire bridge, and g_h is the weighting factor of inspection item h. This study uses g_h values as used in City J, which are determined based on (Sato et. al. 2010).

From the health rating of the entire bridge p_{ib} and bridge age t, the transition probabilities are derived using the least-square method shown in Eq. (6). Then, by the multiple regression analysis, the coefficients C_{1ijk} to C_{3ijk} in Eq. (7) are derived for each bridge group in Table 2. For example, Table 3 shows the coefficients of group 3. Next, the transition probabilities of the target bridge to be inspected are derived by substituting the altitude and distance from the coast obtained from the E-GISBD into Eq. (7). Finally, the future health condition is predicted from Eq. (4).

Table 3. Coefficients of group 3 ($\because k$=3)

ij	C_{1ijk}	C_{2ijk}	C_{3ijk}
AB	5.9×10^{-3}	-2.9×10^{-4}	4.1×10^{-6}
BC	6.3×10^{-2}	-3.4×10^{-3}	1.2×10^{-4}
CD	3.4×10^{-2}	-1.4×10^{-3}	3.3×10^{-5}
DE	5.3×10^{-3}	-8.3×10^{-4}	9.6×10^{-5}

Fig. 3 shows a comparison between the bridge health index (BHI) of inspection and the prediction results of bridges A, B, and C belonging to group a. The BHI is derived from the following equation.

$$\mathrm{BHI} = 1\times p_A + 0.75\times p_B + 0.5\times p_C + 0.25\times p_D + 0\times p_E \tag{9}$$

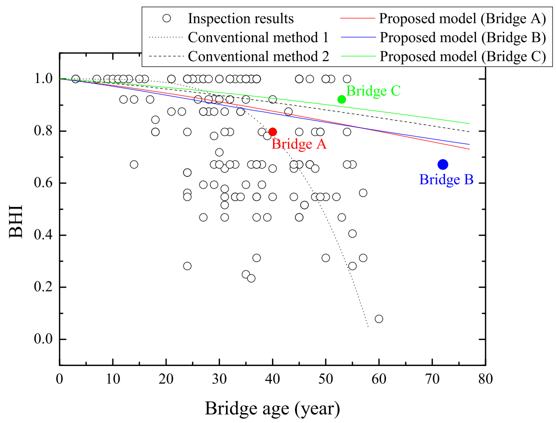


Fig. 3. Comparison between proposed and conventional methods

These figures have inspection results of other bridges in group a expressed as white circles. In addition, the results of the following two conventional prediction methods are shown for comparison.

1. Results from the 4^{th} order regression curve derived from the inspection results of all bridges in group a.

2. Results from the Markov chain model without considering the environmental conditions.
3.

As seen in Fig. 3, an important characteristic of the present method is that different prediction curves can be developed for different bridges, which is not possible with conventional methods. This characteristic improves the accuracy of prediction because the proposed model considers the environmental conditions thoroughly. For example, the present method shows better prediction than the conventional methods for bridges B and C. In contrast, conventional method 1 shows the best prediction for bridge A. This is because the inspection result of bridge A is incidentally very close to the 4th order regression curve. However, it can be judged that the present method is better overall by comparing the R^2 value, which is the determination coefficient defined as the goodness of fit of the model (Krus 2010).

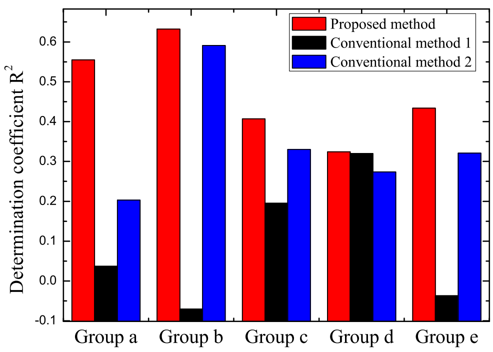


Fig. 4. Determination coefficient R^2 of the proposed and conventional methods

Fig. 4 shows the R^2 values of the proposed method and conventional methods for every group shown in Table 2. It can be seen from the figure that the accuracy of conventional method 1 is not very good. Especially for group *b* and *e*, the R^2 value is less than 0, which means that just using the simple average value of BHI without considering aging deterioration is better. Conventional method 2 is better than conventional method 1; however the proposed method is much better. Specifically, the proposed method shows superiority over conventional method 2 when group *a* (RC bridges near the coast) is analyzed. A possible reason is that the bridges in group *a* are the most sensitive to the salt breeze; therefore the present method, which considers environmental conditions thoroughly, gives much better results for the group.

5. CONCLUSION

This paper proposes a novel bridge deterioration prediction method using the Markov Chain model, whose transition probabilities are derived from environmental conditions. These conditions are obtained from the E-GISBD, which is the GIS bridge database system developed in Ehime University.

This paper demonstrates the validity of the proposed model using the inspection results of bridges in City J. It is shown that the proposed model is more reasonable than conventional models. Specifically, the effectiveness of the present method is indicated for RC bridges near the coast, in which damage, including corrosion due to the salt breeze, is the most serious.

In future work, it is suggested to consider not only the altitude and distance from coast in the prediction model, but also other conditions, including traffic volume and structural dimensions. It is expected that this will lead to more accurate predictions. We have already started this work and the details of our research will be reported in our next paper.

REFERENCES (11pt, bold, capital)

Adams, T.M. and Kang, M.M.K., 2009. *Sensitivity Analysis of Bridge Health Index to Element Failure Costs and Conditions*. Midwest Regional University Transportation Center, Report MRUTC 08-07.

Amador–Jiménez, L.E. and Mrawira, D., Roads performance modeling and management system from two condition data points: Case study of Costa Rica. *Journal of Transportation Engineering* 135(12), pp.999-1007, 2009.

Estes, A.C., and Frangopol, D.M., Bridge lifetime system reliability under multiple limit states. *ASCE Journal of Bridge Engineering* 6(6), pp.523–528, 2001.

FHWA. 2001. *Data Integration Primer*, Federal Highway Administration, URL: http://www.fhwa.dot.gov/asset/dataintegration/if10019/if10019.pdf, Washington, D.C. (last date accessed: 22 March 2012)

Frangopol, D.M., Kallen, M.J. and Noortwijk, J.M., Probabilistic models for life-cycle performance of deteriorating structures: review and future directions. *Progress in Structural Engineering and Materials* 6(4), pp.197-212, 2004.

Fujino, Y. and Abe, M., Structural Health Monitoring in Civil infrastructures and Research on SHM of Bridges at the University of Tokyo. In Fabio Casciati (ed.), *Proc. of the Third World Conference on Structural Control*, Somma Lombardo, Itary, 1, pp.125-140, 2002.

Halfawy, M. and Figueroa, R., Developing enterprise GIS-based data repositories for municipal infrastructure asset management, *Proceedings of Joint International Conference on Computing and Decision Making in Civil and Building Engineering*, Montreal, Canada., 2006.

Huang, X. and Rao, H., Intelligent health monitoring system for bridges, *Proceedings of 3rd ISDE Digital Earth Summit*, Nessebar, Bulgaria, 2010.

Kobayashi, K., Kaito, K., and Lethanh, N., Deterioration Forecasting Model with Multistage Weibull Hazard Functions, *Journal of infrastructure systems* 16(4), pp.282-291, 2010.

Krus, D. 2010. *Structure of Statistics: Multivariate Data Analysis*, CreateSpace, 62p.

Li, N., Xie, W.C. and Haas, R. Reliability-based processing of Markov chains for modeling pavement network deterioration. *Transportation Research Record* 1524, pp.203-213, 1996.

Lounis, Z. and Vanier, D.J., Optimization of bridge maintenance management using Markovian models. *Developments in Short and Medium Span Bridge Engineering '98* 2, pp.1045-1053, 2010.

Madanat, S. and Ibrahim, W.H.W., Poisson regression models of infrastructure transition probabilities. *Journal of Transportation Engineering* 121(3), pp.267-272, 1995.

Mariza, P., Matthew G.K. and Zongzhi, L., Nonparametric Binary Recursive Partitioning for Deterioration Prediction of Infrastructure Elements. *Advances in Civil Engineering* 2009: doi:10.1155/2009/809767, 2009.

Miyamoto, A., Kawamura, K. and Nakamura, H., Development of a bridge management system for existing bridges. *Advances in engineering software* 32, pp.821-833, 2001.

Morcous, G., Performance prediction of bridge deck systems using Markov chains. *Journal of Performance of Constructed Facilities* 20(2), pp.146-155, 2006.

Nelder, J.A. and Mead, R., A simplex method for function minimization. *The computer journal* 7(4), pp.308-313, 1965.

Ormsby, T., Napoleon, E. and Burke, R., 2004. *Getting to Know ArcGIS Desktop: The Basics of ArcView, ArcEditor, and ArcInfo Updated for ArcGIS 9*, Esri Press, Redlands, CA.

Press, W.H., Teukolsky, S.A.,Vetterling, W.T. and Flannery, B.P., 2002. *Numerical recipe in C++*. Cambridge University Press, New York.

Sato, H., Hagiwara, K., and Futagawa, H., 2010. *Research report on development of bridge management system*, Ministry of Construction Public Works Res. Inst. (in Japanese)

Wirahadikusumah, R., Abraham, D. and Iseley, T., Challenging issues in modeling deterioration of combined sewers. *Journal of infrastructure systems* 7(2), pp.77-84, 2001.