Forecasting Deterioration of Bridge Components from Visual Inspection Data

Md Saeed Hasan, Sujeeva Setunge, David W. Law, and Yew-Chin Koay

***Abstract*—In order to extract the optimal output in the form of good management decisions with least resources, a bridge management system or BMS in short, is an essential part for every road transport authority. In a BMS, decisions regarding frequency of maintenance, conducting repairs and rehabilitation are based on inspection data collected for the bridges by trained inspectors following a condition rating method developed by the authority. The road authorities are constantly trying to convert these condition monitoring data to a meaningful practical decision supporting tool. To address this need, a study has been conducted to forecast deterioration of reinforced concrete bridge elements using Markov process. The aim of the research work is to identify the future maintenance needs utilizing the visual inspection data. Visual inspection data has been sourced from Victoria, Australia and transition matrices have been derived using Bayesian optimisation techniques of Markov chain model to predict the future condition of bridge components. Clustering of data with respect to input parameters such as era of construction, exposure conditions, annual average daily traffic and percentage of heavy vehicles can provide an improved deterioration model for bridge Engineers. Deterioration trends for three major structural components are presented in this paper.**

***Index Terms*—Bridge deterioration, bridge management system, condition monitoring, markov chain.**

I. Introduction

Whole of life care of bridge network requires an understanding of deterioration. Bridges are the key structural elements in the transportation system. They are considered to be vital links in any roadway network. Complete or partial failure to maintain these links paralyses the overall performance of the roadway network and causes excessive public and private losses. Therefore, bridge networks need to be managed in a way that ensures their uninterrupted performance throughout their design life. Maintenance of highway bridges plays an important role to assure the desirable service and adequate reliability of highway networks provided to the community. Thus determining a reliable bridge maintenance and rehabilitation strategy is of great importance.

A primary goal of a Bridge Management System (BMS) is to assist bridge managers in determining the best bridge maintenance, repair and rehabilitation strategy with respect to current or future bridge conditions. With restricted funds, maximizing the effect of the investment on the improvement of serviceability and safety of the existing highway system is a major challenge for highway agencies. Transportation officials are continually dealing with intricate decisions involving whether to perform maintenance, rehabilitation, replacement, or a combination amid budgetary, political and other resource constraints. In addition, officials have to consider short-term and long-term solutions and their interrelationships to achieve overall cost-effective solutions. Therefore, it is imperative that a methodology be developed to aid bridge management officials especially at the project level in selecting the most appropriate bridge improvement alternatives. One essential requirement in this endeavour is service life estimates, which are required for life-cycle profiles, and in combination with cost estimates, to derive life-cycle costs.

Previously the BMS in most cases used to be based on a deterministic approach and the assessment of the reliability or the safety in general is based on subjective statements [1]. However, most recently researchers have tried to implement different techniques into BMS [2], [3]. Bridge management systems like PONTIS and BRIDGIT are stochastically based systems with rational assessment procedures [1]. These procedures set guidelines for data collection and reduce the subjective nature of data.

Min Liu, Dan M. [4] and Jung Baeg Son [5] fit regression prediction models based on Artificial Neural Network (ANN) techniques. However, the average prediction errors were up to 33.3%. Other authors [6]-[8] use Markov Chain techniques to model bridge deterioration. The Pontis bridge management system uses Markov chain modelling to represent bridge deterioration in its analysis routines [9].

Another technique to model the deterioration of facility structures comprises Artificial intelligence (AI) which exploits computer techniques that aim to automate intelligent behaviours. AI techniques encompass expert systems, artificial neural networks (ANN), genetic algorithm (GA), and case based reasoning (CBR) to optimise the prediction of future conditions obtained through a set of observations. Researchers are using ANN to determine expected deterioration of bridge structure from existing condition data with respect to age along with other input parameter [2], [10].

II. Significance of Research

This research project aimed to use stochastic methods to predict deterioration curves for different components of concrete bridges in Victoria, Australia. The specific objective of the research is to develop a model to predict future condition of the concrete bridge structures from the available condition monitoring data. An attempt has been

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made to predict the future condition of the bridge components using Bayesian methodology. The Bayes theorem has been applied in conjunction with Metropolis-Hasting Algorithm to optimise the Markov model. This methodology has been used for deriving Markov model for three different components of concrete bridges.

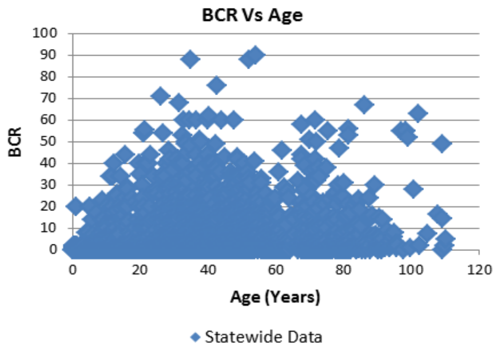

Fig. 1. Discrete relationship between age of the bridges and BCR when all records are considered.

The scope of the research is to enhance the decision making process using a Markov chain model for the use of road authorities from the available condition monitoring data which will significantly improve the reliability of the forecasts. It is very difficult to draw conclusive remark from the existing routine inspection data collected over a decade using simple techniques. From Fig. 1, it is clearly visible that drawing conclusive forecasting models is not possible using a deterministic method as there is no pattern. The coefficient of correlation is very poor for prediction purposes. Enhanced effort is required to understand and utilise this data.

Methodology

The data used in this study, provided by the road authorities of Victoria, Australia, were sourced from condition monitoring database collected over the period of 1995 to 2012. Analyses of three major structural elements, deck, abutment and girder are presented in this paper. Reviews of different methods of predicting deterioration were carried out to find the suitable technique for the available data sets. Firstly a deterministic approach were utilised to find any significant trend within the data set. After studying available literature, as a suitable means Markov method has been applied to this data set to predict the future condition of the bridge components using Bayesian approach where Metropolis Hasting algorithm were utilised.

III. Markov Decision Process

The Markov probability theory was created by Andrei A Markov (1907) who did significant research in probability and stochastic processes. Markov chain can be used to model the deterioration process which has been suggested by many researchers. The basic idea for modelling the deterioration process as a Markov chain process has been provided by Bogdanoff [11]. This process has been used to develop stochastic deterioration models for different infrastructure facilities. Markovian bridge deterioration models are based on the concept of defining states in terms of bridge condition ratings and obtaining the probabilities of a bridge condition changing from one state to another [12]. The Markov Chain is defined as a random process in which the probability that a certain future state will occur depends only on the present or immediately preceding state of the system, and not on the events leading up to its present state [13]. In other words, the analysis makes the assumption that given a present condition, the future is independent of the past. The result is a sequence of random events, but these events are related and similar to the original condition. Markov chains are proving effective in the engineering sciences as predicting algorithms for various infrastructures. Therefore, in this paper, the Markov model is used to predict the process of bridge deterioration as a discrete time condition state, where the condition of the bridge in the future is predicted using present conditions of the bridge while simultaneously being independent of its history.

Many researchers [14], [15] have suggested using Markov chain models in pavement management systems at earlier times. Jiang [12] has introduced Markov chain methodology to BMS in a similar fashion. A significant amount of research has been done in the application of the Markov chain theory in the infrastructure area. Micevski *et al.*, [16] successfully modelled the deterioration of storm water pipes using the Markov model utilizing the Metropolis-Hastings Algorithm (MHA), one of the Markov chain Monte Carlo methods for calibration. Baik [17] developed a Markov chain based deterioration model for wastewater systems, and its transition probabilities were computed by ordered probit model (OPM). In an integrated pavement management system application, pavement deterioration prediction was performed by applying a discrete-time Markov model [18]. Kleiner *et al.* [19] simulated the deterioration of infrastructure assets using a semi-Markov model, which is a non-stationary, time-dependent transition process.

A Markov process describes a system that can be in one of several states, and can pass from one state to another each time step according to fixed probabilities. To illustrate Markov process consider a system which is in state i, there is a fixed probability, pij, of it going into next state j with a single time step, and pij is called a transition probability.

One biggest challenge of using Markov model is its calibration. By the term calibration it is clearly understandable that it is the task of applying selective technique to estimate the model parameters or the transition probability. In this study Markov matrices have been calibrated with most optimised algorithm for attaining the most appropriate model for predicting the future condition rating of the bridges. The calibration technique using the Bayesian Markov chain Monte Carlo simulation was used to achieve the transition probability matrix from the existing condition monitoring data. The Metropolis-Hastings algorithm (MHA), a member of the MCMC simulation [20], was chosen to perform sampling from the posterior distribution.

IV. Data Processing

In this research paper condition monitoring data of precast deck/slab (8P), precast girder (2P) and cast-in-situ abutment (24C) were analysed. The maintenance history is not available for this data set although most of the bridges are experiencing regular routine maintenance. To overcome this problem in this analysis overall condition rating (OCR) of components were calculated and compared with the successive inspection record. The component which shows an improvement in the OCR has been removed from the calculation. Hence only the bridges that indicate a deterioration trend in their condition data were considered. The OCR value 1.0 indicates the bridge is in perfect condition which is also another indication of maintenance impact. To ensure the bridge is experiencing deterioration an attempt has been made to ignore the perfect condition bridges. Hence the data was filtered above a threshold value of OCR. Table I shows a typical sample raw data set.

TABLE I: SAMPLE DATA FOR PRECAST DECK/SLAB COMPONENT

Built Year	Inspection Date	Condition				AADT	CV
		1	2	3	4		
30/6/80	16/6/97	0	85	15	0	101	0.26
30/6/80	1/8/05	0	20	80	0	101	0.26
2/4/70	14/05/97	45	55	0	0	412	0.13
1/1/70	15/08/05	10	90	0	0	161	0.22
1/01/70	9/06/12	0	10	90	0	161	0.22

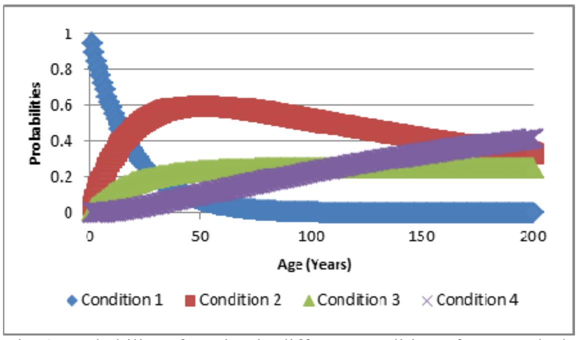

Fig. 2. Probability of staying in different condition of precast deck component (8P) for 200 years.

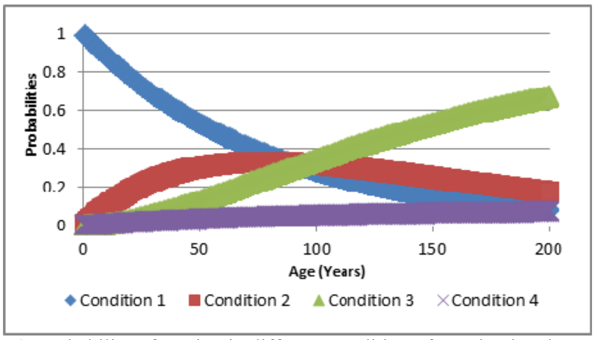

Fig. 3. Probability of staying in different condition of cast-in-situ abutment (24C) component for 200 years.

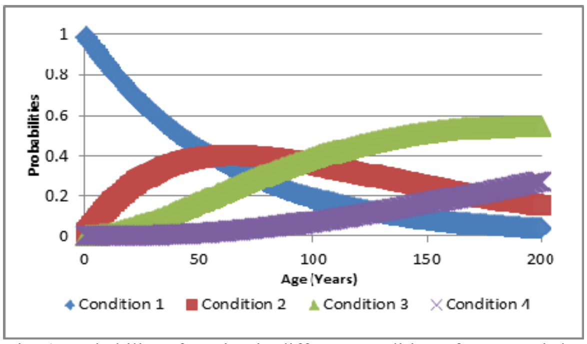

Fig. 4. Probability of staying in different condition of precast girder component (2P) for 200 years.

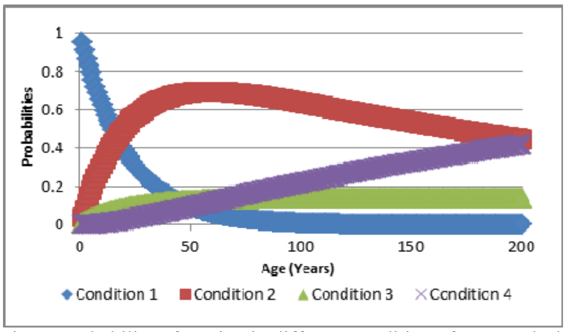

Fig. 5. Probability of staying in different condition of precast deck component for 200 years considering 1960-70 construction period.

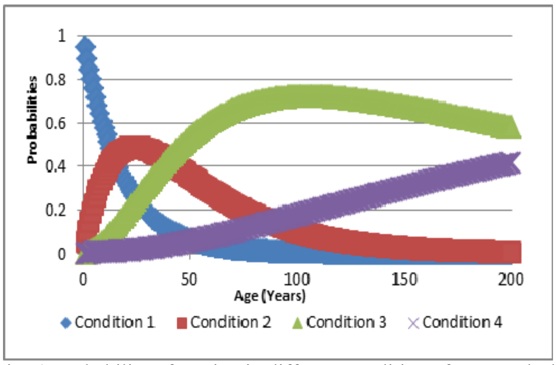

Fig. 6. Probability of staying in different condition of precast deck component for 200 years considering 1970-80 construction period.

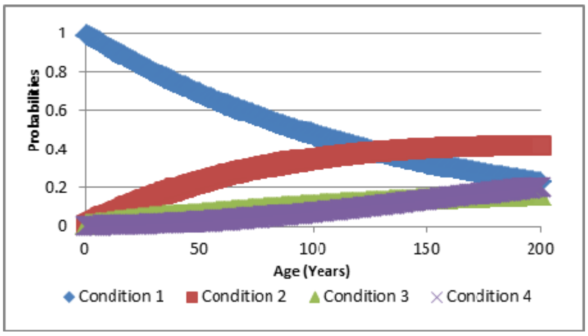

Fig. 7. Probability of staying in different condition of cast-in-situ Abutment component for 200 years considering 1950-60 construction period.

V. RESULTS AND DISCUSSIONS

Markov transition probability matrices have been used to estimate future probable condition for three different structural components, precast girder, precast deck/slab and cast-in-situ abutment using the complete state-wide data set. A two hundred year predictions are calculated which is represented graphically in Fig. 2, Fig. 3 and Fig. 4. Using these figures users can determine the probability of a structural component being in a given condition at a given age. A further clustering was applied on the data set using the construction period range, in this case 10 years, to identify any impacts of construction methods of bridges. Fig. 5 to Fig. 8 represents probability of different components to stay in four different conditions over a two hundred years span where only ten years interval data were considered.

Fig. 2 to Fig. 4 and the summary in Table II shows that deck/slab has a faster deterioration rate compared to abutment and girder which is expected in practice as deck/slab experiences the traffic loading directly.

Fig. 5 and Fig. 6 and summary in Table III presents transition probability of deck/slab constructed in two different time periods. The figure shows that bridge deck components built between 1960 to1970 have a slower deterioration trend compared to those built between 1970 to1980. However, Fig. 7 and Fig. 8 show that bridge abutment components built between 1950 and 1960 has similar deterioration trend with those built between 1960 and 1970. The data is affected by maintenance actions, which were not recorded with the raw data. However, improved condition rating over the period of time for successive inspection has been discarded from the model to overcome this issue. Moreover, a threshold value of OCR was considered to consolidate the maintenance impact. With collection and recording of maintenance data, road authorities would be able to refine these models with time.

TABLE II: SUMMARY OF COMPARISON OF CONDITION/AGE FOR FULL DATA SET

% of components in condition	Age	8P	24C	2P
1	20	34.39	77.71	71.58
	50	6.93	53.24	43.36
	100	0.48	28.35	18.80
2	20	46.83	18.06	24.67
	50	59.92	30.65	38.71
	100	52.02	32.12	35.65
3	20	16.37	2.73	3.65
	50	23.26	12.84	16.67
	100	24.96	34.24	38.62
4	20	2.39	1.50	0.09
	50	9.86	3.27	1.26
	100	22.52	5.29	6.93

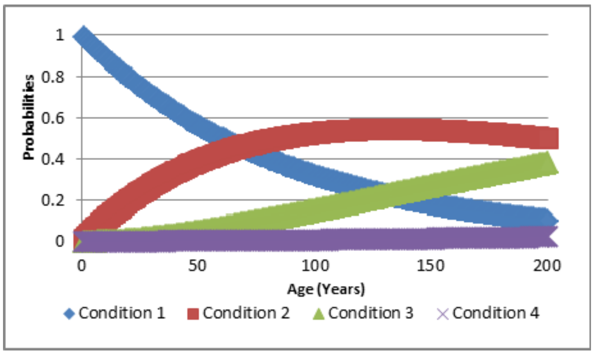

Fig. 8. Probability of staying in different condition of cast-in-situ abutment component for 200 years considering 1960-70 construction period.

TABLE III: COMPARISON OF EFFECT OF CONSTRUCTION ERA ON DETERIORATION 8P ELEMENTS

% of component in condition	Age	1960-1970	1970-1980
1	20	39.04	32.81
	50	9.52	6.17
	100	0.91	0.38
2	20	50.47	48.25
	50	68.97	35.51
	100	63.83	10.23
3	20	8.39	17.85
	50	12.45	53.01
	100	13.63	72.07
4	20	2.10	1.09
	50	9.06	5.32
	100	21.63	17.32

VI. CONCLUSION

The core element of a BMS is the database containing physical condition data obtained through regular inspection and maintenance activities over a significant amount of time. The reliability of a BMS is greatly dependent on the quality and accuracy of the bridge inventory and physical condition data obtained through field inspections [21].

The work presented here demonstrates that a stochastic method such as Markov chain can be used to forecast deterioration of bridge elements with time. Clustering of data with respect to input parameters such as era of construction, exposure conditions, annual average daily traffic and percentage of heavy vehicles can provide an improved deterioration model for bridge Engineers. However, linking maintenance actions to inspection data is extremely important to provide a reliable estimate of the deterioration.

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