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Development of an Integrated Method for Probabilistic Bridge Deterioration Modelling

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Abstract: Probabilistic deterioration models such as state-based and time-based models are only capable of predicting future bridge condition ratings when a sufficient amount of condition data and reasonable data distribution are available. However, such are usually difficult to acquire from limited bridge inspection records. As a result, these probabilistic models cannot guarantee reliable long-term prediction for each of the bridge elements concerned. To minimise this shortcoming, this paper proposes an advanced integrated method to construct workable transition probabilities for predicting long-term bridge performance. A selection process within this method automatically chooses a suitable prediction procedure for a given situation in terms of available inspection data. The Backward Prediction Model (BPM) is also incorporated to effectively predict the bridge performance when sufficient inspection data is unavailable. Four different situations in regard to the available inspection data are predefined in this study to demonstrate the capabilities of the proposed integrated method. The outcomes show that the method can help develop an effective prediction model for various situations in terms of the quantity and distribution of available condition rating data. **CE Database subject headings:** Bridges; Deterioration; Performance; Predictions.

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Introduction

Bridge Management Systems (BMSs) as a Decision Support System (DSS) have been continuously developed since the early 1990's to effectively manage large bridge networks. A BMS assists bridge asset engineers to make correct decisions for planning Maintenance, Repair and Rehabilitation (MR&R) activities. The MR&R decision-making is highly dependent on the current (measured) and future (predicted) infrastructure facility conditions (Madanat et al. 1997). A deterioration model is one of the most essential components in a BMS to predict future bridge performance. A large number of historical bridge condition ratings are usually required for a deterioration model to achieve reliable prediction outcomes. However, the BMS-compatible routine inspection records are usually insufficient due to two reasons: (1) commercial BMS software has been used for less than 20 years and even those bridge agencies which implemented BMSs from an early stage, have only about 7 to 9 inspection records available for developing long-term performance modelling; (2) Previously conducted inspections are incompatible with what are required as input by a typical BMS. In view of all this, it is necessary and desirable to develop an advanced deterioration model for the reliable prediction of future bridge performance.

Generally, the natural bridge deterioration process is continuous and cumulative without any MR&R interruptions during the bridge's service life. The deterioration process is normally affected by explanatory variables, such as traffic volume, bridge age, bridge type, environment, bridge design and material properties (Mauch and Madanat 2001). However, the most explanatory variables are not usually captured by routine visual inspections. This is because the visual inspection method applies discrete condition ratings or states to represent defects of the bridge elements. These discrete condition ratings are normally used to develop probabilistic deterioration models for bridge elements (Morocus et al. 2010). These probabilistic models can be classified into two categories, namely state-based and time-based.

The state-based models predict long-term bridge performance using transition probabilities obtained from the difference between the two condition states at a given discrete time interval. Markov chain models are the most common example of state-based models (Morcous and Akhnoukh 2006b). The key prerequisite for Markov chain models is to generate accurate and reliable transition probabilities for infrastructure facilities in order to predict future condition ratings. Several methods were proposed in the past to calculate transition probabilities, including the expected-value method (Jiang et al. 1988), Poisson regression (Madanat and Ibrahim 1995a), and ordered profit model (Madanat et al. 1995b, 1997). However, all these approaches suffer such limitations as stationary transition probability, state independence assumption (a stationary process), ignorance of the hidden nature of the deterioration and failure to account for maintenance issues (Madanat et al. 1995b; DeStefano and Grivas 1998). Furthermore, a pre-filtering process is usually required by these models to achieve typical bridge deterioration patterns. An example of using the pre-filtering process can be found in the work of Agrawal et al. (2010).

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The time-based models employ a probability density function of time, referring to the state duration time required for each bridge element to deteriorate from an initial condition state to its next lower state. Time-based models are also called duration models; they were developed to estimate infrastructure deterioration. For example, DeStefano and Grivas (1998) presented a time-based deterioration model for bridge decks in which the Kaplan and Meier (K-M) method was used to estimate the non-parametric distribution functions of the duration time. Prozzi and Madanat (2000) applied parametric models to estimate time-to-failure in the pavement deterioration process. Mauch and Madanat (2001) used semi-parametric hazard rate modelling to develop duration models for a bridge deck. A common critical shortcoming exists in time-based models in that they require frequent inspection of condition ratings over a long observation period within the bridge service life. In view of the above, the decision on the appropriateness of a given modelling type for deterioration prediction is largely dependent on the nature of the available condition data (Mauch and Madanat 2001). In other words, the stand-alone model such as the state-based or time-based model cannot guarantee workable long-term prediction outcomes for various situations in terms of available condition data.

In order to minimise the above-mentioned shortcomings, this paper presents an advanced integrated Markov-based method incorporating both state-based and time-based models, which is more effective as compared to the stand-alone model (i.e. state-based or time-based model). This is because a selection process is embedded in the integrated method to automatically select a suitable prediction approach (either state-based or time-based) for a given situation of available condition

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data. This is however not an option for the stand-alone model. The state-based model used in this study incorporates the expected-value method which has been proven in the published literature as the most common method in state-of-the-art BMSs in estimating the transition probability (Madanat et al. 1995b). On the other hand, for the time-based model, the K-M method is applied to estimate the non-parametric probability distribution function of transition time. This is because the explanatory variables are not available in routine bridge inspections for a BMS (DeStefano and Grivas 1998).

In the present study, a previously published Backward Prediction Model (BPM) will also be used to generate the missing historical data for insufficient data scenarios (Lee et al. 2008). To verify the performance of the proposed integrated method, four different types of available condition data distributions are cross-validated within the given sample bridge condition data. A detailed validation procedure and results are presented in the section on “Results and discussion” hereunder. The advantages of the integrated method in minimising the shortcomings associated with insufficient data and unrealistic data distribution are discussed in some detail.

An integrated method for bridge deterioration modelling

The major components and procedures of the integrated method are summarised in Figure 1. The figure includes categorisation of bridge element inspection records and calculation of element Overall Condition Ratings (OCRs), a selection process, and the prediction procedures of the state-based and time-based models.

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Element-level inspection records

Element-level bridge inspection or a Level-2 inspection record is essential as input for deterioration modelling in a BMS. It is based on visual inspections by which the conditions of a bridge structure or elements can be assessed and rated. The inspected condition ratings are used to assess the effectiveness of past maintenance treatments and identify current maintenance needs, thereby modelling and forecasting future changes in condition and estimating future budget requirements (Queensland Department of Main Road 2004).

The element-level inspection places the bridge elements into various Condition States (CSs) to quantify the severity and extent of damage of the elements. A five-CS scale is used for Level-2 inspection in Queensland, Australia. It is a common practice that the conditions of bridge elements are expressed quantitatively via the conventional stepwise "grading" system. As shown in Figure 2, the health index of the four condition states (CSs) includes CS1 (i.e. condition as new or "good"), CS2 ("fair"), CS3 ("poor") or the perilous CS4 ("very poor"). These four condition states represent the bridge condition ratings from 100% to 20%. Note that each CS has a 20% range. In this study, to calculate the OCRs of each bridge element, the corresponding weighting factors for CS1, CS2, CS3 and CS4 are assumed to be 100%, 70%, 50% and 20%, respectively. It should be noted that CS5 is used to rate the condition of the whole structure and the present study focuses on bridge elements only. The four CSs are defined as follows: CS1 is free from defects with little or no deterioration; CS2 is free from defects affecting the structural performance, whereas showing a minor deterioration such as minor spalls or cracking; CS3 shows advancing deterioration and

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affects the serviceability of the bridge; CS4 shows advancing deterioration and affects overall performance and structural integrity which requires immediate intervention (Queensland Department of Main Road 2004).

The categorisation of bridge inspection records is carried out according to the classification of structural deterioration obtained from the Queensland Department of Transport and Main Roads (QTMR), Australia. This research only deals with classifications in relation to bridge location, element type and material type. The bridge location is classified based on traffic volume; the element type refers to the component type such as deck unit, girder/beam and slab; the material type includes concrete (cast-in-situ and pre-cast), steel, timber and others. Note that construction era is also considered as one categorisation. This is to encompass the fact that the quality of construction materials and construction processes have continuously improved over the past several decades. In order to obtain more reliable prediction outcomes, the construction era classification is considered herein and is grouped in a period of 20 years: group 1 (2001-the current year), group 2 (1981-2000), group 3 (1961-1980), and group 4 (prior to 1960). After categorising the available inspection records, the following method is used to calculate the OCRs. Or,

$$\text{OCR} = \frac{q_1 w_1 + q_2 w_2 + q_3 w_3 + q_4 w_4}{q_1 + q_2 + q_3 + q_4} \tag{1}$$

where q_1, q_2, q_3 and q_4 are element quantities in Condition States (CSs) 1, 2, 3 and 4, respectively, and w_1, w_2, w_3 and w_4 are weighting factors for each condition state (Thompson and Shepard 2000).

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Model selection process

The decision-making in regard to which model is more appropriate for deterioration prediction is highly dependent on the nature of the available condition data (Mauch and Madanat 2001). A time-based model in the selection process is considered as a priority because it considers the time spent in an initial condition state (a non-stationary process), which has found to be more realistic according to a number of published outcomes (Madanat et al. 1995b; Ravirala and Grivas 1995; DeStefano and Grivas 1998). However, in the case where a "no-condition-change" event is identified, i.e. less than two sequential changes in condition states in the available condition data, the state-based model is applied as an alternative. Moreover, the Backward Prediction Model (BPM), as detailed in the section hereunder on "The BPM process", can be used to generate missing condition rating data when the historical condition data is insufficient to calculate reliable transition probabilities. The BPM-generated missing condition data together with the available data can enhance the quality of historical condition depreciation patterns, which in turn satisfies the requirements for running the selected model.

As detailed in Figure 1, the selection process primarily checks whether or not the given type of element condition data from a network bridge satisfies the requirements of at least two sequential changes in condition states. If the requirements are satisfied, the given condition data can be used directly by the time-based model. If not, the first step is to check whether the given data meets the requirements of using the BPM or otherwise. To execute the BPM, the given inspection data have to satisfy the following two constraints: (1) bridge elements in the given dataset have to be less than

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20 years old and without MR&R; (2) the given data for each bridge element should have at least two inspection records not in CS1. After applying the BPM, the BPM-generated condition ratings in conjunction with the available data can satisfy the requirements of running the time-based model. If the given data fails the conditions of applying the BPM, then the state-based model is used. The criteria for running the state-based model are: (1) it requires at least 2 sets of inspection records for each type of element; (2) the deterioration pattern in the form of best fit curve is generated using a 3rd-order polynomial regression method. The gradient of such a curve represents the change in condition ratings. A positive gradient implies an increased condition rating which is unrealistic when no MR&R work is performed. If the gradient is negative, then the state-based model is able to estimate the transition probabilities, and in turn predict long-term bridge element performance. If the curve gradient is positive, the first trial is to apply the BPM, because the BPM-generated missing historical condition ratings can enhance the trend of condition depreciation. If the gradient is still positive after the first trial of the BPM, then other types of regression functions, such as exponential, linear and logarithmic should be used to generate the average OCRs for the available inspection data as the last option. Finally, the state-based model is able to estimate the transition probabilities using the average OCRs obtained from the other types of regression functions, and thereby making it capable of predicting long-term bridge element performance.

The BPM process

The model selection process may require the BPM to generate missing historical condition ratings when inspection records are insufficient. The BPM-generated historical data in conjunction with the

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available inspection data can increase the number of sequential changes in condition states thereby leading to a more meaningful bridge depreciation pattern. The BPM process is depicted in Figure 3 (Lee et al. 2008).

The BPM consists of two stages in generating the missing historical condition ratings. In Stage 1, an ANN technique is used to establish a correlation between the existing condition rating datasets (year t_p-t_{pn}) and the corresponding years' non-bridge factors. The non-bridge factors, including climate and environmental condition changes, traffic volume increases and population growth, directly and indirectly influence the variation of the bridge conditions and thus the deterioration rate. The correlations established are then applied to generate the historical trends for year t_0 to t_p using the non-bridge factors from the same time period. The missing historical condition ratings for years t_1-$t_{p\text{-}1}$ can then be generated. Each year of the BPM-generated condition ratings include 66 data outputs resulting from the combined number of learning rates (*lr*: 0.0-0.5 at 0.1 increment) and momentum coefficients (*mc*: 0.0-1.0 at 0.1 increment) in the neural network configurations. The number 66 also corresponds to the total quantity of a given bridge element. In Stage 2, a forward comparison is conducted to validate the BPM results. A forward prediction is produced for years t_p-t_{pn} using the BPM outcomes (years t_1-$t_{p\text{-}1}$). The results of the forward predictions are then compared with the actual BMS condition ratings (for years t_p-t_{pn}). Upon satisfactory validation, the generated condition rating records are ready for use in a deterioration model (Lee et al. 2008). It should be noted that the BPM is only applicable when the following conditions are satisfied: (1) the Maintenance, Repair and Rehabilitation (MR&R) activity is performed at a known time; (2) no

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MR&R is conducted since the construction year; and (3) the condition rating at the year of construction is known. The reliability of the BPM has been proven in an earlier study (Lee et al. 2008).

Methodology of state-based model

The process of the state-based model as illustrated in Figure 1 is detailed herein. The Markov chain model, as a typical state-based model, is used in the proposed integrated deterioration method. A Markov chain is a special case of the Markov process. Its development can be considered as a series of transitions between certain condition states. When the probability of a future state in the process depends only on the present state but not the past states, the Markov chain becomes a stochastic process and is referred to as a first-order Markov process (Morcous 2006a). The property of the Markov chain can be expressed for a discrete parameter stochastic process (ξ_t) with a discrete state space as

$$P\{\xi_{t+1} = x_{t+1} | \xi_t = x_t, \xi_{t-1} = x_{t-1}, \ldots, \xi_1 = x_1, \xi_0 = x_0\} = P\{\xi_{t+1} = x_{t+1} | \xi_t = x_t\} \quad (2)$$

Here the symbol | means “the given condition”, P means the probability, and x_0, x_1, x_2, ……, x_t, and x_{t+1}, are states of ξ_0, ξ_1, ξ_2, ……, ξ_t, and ξ_{t+1}. The probability P is also referred to as the one-step transition probability. This is the conditional probability of the element being in state x_{t+1} at t+1 given that it was in state x_t at t (Devaraj 2009).

The Markov chain model forecasts the bridge condition ratings based on the concept of defining the states of bridge condition transitions from one to another during one transition period (Jiang

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1990). Without repair or rehabilitation, the bridge condition rating should decrease with time. Therefore, there is a probability of condition rating transition from one CS*i*, to another CS*j*, during a one unit year period, which is denoted by $p_{i,j}$. According to the Markov chain method, the CS vector for any time *t*, *Q*(*t*), can be obtained by multiplication of the initial CS vector *Q*(0) with the transition probability matrix *P* to the power of *t* (Jiang and Sinha 1989). Or

$$Q(t) = Q(0) \times P^t \tag{3}$$

The transition probability matrix *P* is defined as

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

where $q(i)$ = 1-$p(i)$, $p(i)$ corresponds to $p_{i,i}$ and $q(i)$ corresponds to $p_{i,i+1}$. In Equation (4), *p*(1) represents the probability of bridge elements remaining at CS1, and *q*(1) denotes the probability of bridge elements transferred to the next lower CS2, and so on. It should be noted that the lowest condition rating before a bridge is repaired is 20% (CS4). Hence, the corresponding probability *p*(4) is assumed to be 1. Let *R* be a vector of condition ratings, or *R* = [100, 70, 50, 20], and R^T be the transpose of *R*, then the estimated OCRs at age *t*, *E(t)* by the Markov chain method (Jiang and Sinha 1989) is,

$$E(t) = Q(t) \times R^T \tag{5}$$

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Since the deterioration rate of a bridge condition is dissimilar at different bridge ages, the transition process of bridge conditions is not homogeneous with respect to the bridge age (Jiang 1990). In order to meet the homogeneity requirements of the Markov chain model, a zoning technique is used to obtain the transition matrix. This approach was used previously for the development of pavement performance curves (Butt et al. 1987). With the zoning technique, the bridge age is divided into groups and within each age group the Markov chain model is assumed to be homogeneous. A six-year group for bridge age is found appropriate for the available bridge inspection database and for solving equations of unknown probabilities (Jiang 1990). A new bridge element (age 0) is given a condition rating of 100%. Thus, the initial state vector $Q(0)$ for a new element is [1, 0, 0, 0], where the 4-vector coefficients are the probabilities of having a condition rating of 100%, 70%, 50%, and 20%, respectively, at age 0. Equations (3) and (5) can be used for Age Group 1 (i.e., 1-6 yrs) using the initial state vector $Q(0)$. The initial state vector for Age Group 2, $Q(7)$ is taken in the same form as the last CS vector of Age Group 1, $Q(6)$. Following this procedure for all age groups, the condition ratings versus age relationship can be obtained for a particular element using the Markov chain method (Agrawal et al. 2010).

The transition probability is obtained by minimising the difference between the average OCRs $A(t)$ from the regression function and the estimated OCRs $E(t)$ by the Markov chain method. This is described in Equation (6) in the form of a non-linear programming objective function (Jiang and Sinha 1989). Or,

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$$Min\sum_{t=1}^{N}\left|A(t)-E(t)\right| \text{ subject to } 0 \le P(i) \le 1, i = 1,2,3....,U. \tag{6}$$

where N = the number of years in one age group; U = the number of unknown probabilities; $A(t)$ = the average of condition ratings at time t, estimated by the regression function.

The accuracy of the transition probability depends on the closeness of the average OCRs and the OCRs predicted by the Markov chain method. The Chi-square goodness of fit test is used to validate the accuracy of the transition probability. The calculation formula for the Chi-square distribution as suggested by Jiang and Sinha (1989) is given as

$$\chi^2 = \sum_{i=1}^{k}\frac{(E_i - A_i)^2}{E_i} \tag{7}$$

where χ^2 = a Chi-square distribution with k-1 degrees of freedom, E_i = value of the condition rating in year i predicted by the Markov chain method, A_i = value of condition rating in year i predicted by the regression, and k = number of prediction years. Upon establishing the transition probability matrices and the initial state vector defined from the inspection records, prediction of the bridge condition ratings can be undertaken using Equations (3) and (5).

Methodology of time-based model

Referring to Figure 1, the time-based models require sequential changes in condition ratings to define state transition events and the corresponding transition times. These sequential condition ratings include historical, current and future inspection records. They can be denoted as i, j, and k, respectively. The value of sequential condition rating j is transferred to a lower condition state $k = j$

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-1. This is defined as a state transition event. Each transition event can be denoted as TE (j, k) (DeStefano and Grivas 1998). For a given bridge element, the time spent for an element deteriorating from an original condition state to the next lower state in the condition rating scale is called the transition time. A set of available inspection data usually includes transition events and those without changes in condition states. The latter are called the censored events. A censored event can become a transition event after a specific time (right censored, or R-censored), before a specific time (left censored, or L-censored), or both (interval censored, I-censored) (Morcous et al. 2010).

Generally, inspection activities are performed periodically over an observation period. Therefore the accurate time of a transition event is unknown. In normal practice, the transition event is assumed to occur at the middle of the observation period if it is observed between two consecutive condition states (Morcous et al. 2010). The time-in-state includes the time spent for censored events and transition events. It can be calculated with the aid of two tables: Table 1 is only used for calculating the time-in-state for TE (1,2) when the construction or MR&R work is performed at a known time, and no MR&R is performed after that time; Table 2 is used for estimating the remaining transition events, i.e. TE (2,3) and TE (3,4).

The time-based model estimates the transition probability from the cumulative probability of the transition event within the transition time. In the present study, the K-M method is employed to estimate the non-parametric reliability function with respect to the cumulative transition probabilities and the corresponding transition times and events (DeStefano and Grivas 1998). The

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reliability is defined as the probability of a bridge element maintaining its original condition state for a specific time period. The cumulative transition probability can be obtained by simply using one minus the reliability obtained from the K-M method. According to DeStefano and Grivas (1998), the equations for calculating the reliability of a bridge element and estimating the cumulative transition probability take the form

$$\hat{R}(t_x) = [(r_x - 1)/r_x] \times R_{x-1} \quad (8)$$

$$\mathrm{TP}(t_x) = 1 - \hat{R}(t_x) \quad (9)$$

where $\hat{R}(t_x)$= estimated reliability of a bridge element at time t_x (years); r_x = reversed rank order of all time values observed within the sample interval; TP(t_x) = cumulative transition probability for all x = 1, 2, 3,….yth sample observations in ascending time order; R_0 = 1 at t = 0.

A parametric distribution function that relates the cumulative transition probabilities and the corresponding transition times is produced by either a linear, logarithmic or exponential regression technique. The criteria used to select the best fit regression curve are the coefficient of determination R^2. If R^2 is close to 1 it indicates that the regression curve reflects the best relationship with the range of observed data. The parameters obtained from the regression function of transition time are used to calculate the transition probability for the specified transition events. Finally, the transition probability matrices can be established based on the transition probability.

As shown in Figure 1 under "Time-based model", more than three state transition events, i.e. TE≥3 are required to compute the transition probabilities. Note that in this study we have TE(1,2), TE(2,3) and TE(3,4). However, when the state transition events are less than 3, i.e. only TE (1,2) or

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TE (1,2) and TE (2,3), the Markov chain method needs to be employed to generate an individual transition probability matrix. In this process, the condition ratings generated from the time-based model are assumed as the average OCRs, $A(t)$. The estimated OCRs at age t, $E(t)$ can also be calculated using Equation (5). Subsequently, Equation (6) is used to derive the individual transition matrix for each bridge element. The predicted condition ratings using this individual transition matrix follow the dominant deterioration behaviour of the previous prediction from the time-based model. However there are some exceptional cases: (1) the bridge element condition rating decreases abruptly from one condition state to another during a very short time period; (2) only one element inspection record is available for a bridge; (3) available inspection records are all in the same condition state - in other words, there is no condition state change from the inspection records; (4) bridge elements have been rehabilitated by performing MR&R work. In these cases, an average transition probability must be employed to predict long-term performance of these bridge elements.

Benchmark examples

The reliability of deterioration models depends strongly on the quantity and distribution of the available condition data. When the condition data exhibit different characteristics, the stand-alone model has been proven to be difficult in predicting reliable and accurate long-term bridge element performance. The proposed integrated method, on the other hand, has the ability to predict bridge deterioration performance for most situations including insufficient inspection data and poor data distributions meaning that the condition ratings are disordered due to regular maintenance or

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inconsistent inspection processes. Four typical and different situations are selected from a bridge network as benchmark examples to demonstrate the advantages of the proposed integrated deterioration method. All bridge information is obtained from the QTMR in Queensland, Australia. Necessary information related to element types and names, construction era, total numbers of bridges and inspection records are presented in Table 3 for four different situations. These include: Situation 1 - suitable for the time-based model only; Situation 2 - suitable for time-based model incorporating BPM-generated missing historical data; Situation 3 - suitable for the state-based model only; Situation 4 - suitable for state-based model incorporating BPM-generated missing historical data. It should be noted that the sample bridge information is randomly selected from a regional network within a larger bridge network. The results presented in this paper do not intend to reflect the official view of the abovementioned bridge authority.

Procedural analysis using time-based deterioration model

The selection process indicates that Situation 1 in Table 3 satisfies the condition of using the time-based model to estimate the transition probability. This is because the selection process identifies that there are 15 available transition events TE (1,2) among the total 25 bridges from a network. On the other hand, Situation 2 in Table 3 is unable to be directly used by the time-based model as it only has one transition event. However, the selection process suggests that the BPM can be used to generate the missing historical condition ratings for bridges #1, #2 and #3. Consequently, the BPM-generated missing condition ratings together with the available data, provide a total of 4 transition events TE (1,2) to be used in the time-based model to determine the transition probability.

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The K-M method is used to generate the non-parametric values with regard to the cumulative transition probabilities corresponding to transition times and specific transition events, as outlined in the section on "Methodology of time-based model" hereinabove. A linear regression is used to calculate the uniform distribution function for element types 20C and 59C, as presented in Figures 4 and 5, respectively. The linear regression parameters are then used to generate the transition probability for transition event TE (1,2) for these two element types. Note that the generated transition probabilities can only be used to predict condition ratings from CS1 to CS2. For future and long-term prediction, the Markov chain method has to be used in this case to generate an individual transition probability for each element. Table 4 summarises the predicted OCRs using transition probabilities obtained from the time-based model for bridge element 20C-Bridge #4. The predicted OCRs are considered as the average condition ratings $A(t)$ to be used in Equation (6) to generate the individual transition probability.

Procedural analysis using state-based deterioration model

Situation 3 has 12 bridges with 36 inspection records. The selection process indicates that the time-based model is unable to generate the transition probability. This is because there are no sequential changes in the condition states. Moreover, all the 12 bridges are more than 20 years old. Therefore even the BPM is not helpful in this case. As such, the state-based model as an alternative should be used to generate the transition probability and predict the long-term bridge element performance for this element type. A 3rd-order polynomial regression function is used to estimate the relationship between the bridge element condition rating and age. Figure 6 shows the best fit regression curve

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and the associated parameters. It can be seen that the regression performance curve gradually decreases as the bridge age increases. This means that the parameters obtained from the regression equation correctly reflects the average trend of bridge degradation. Therefore, these parameters are able to be used to calculate the average condition rating $A(t)$ at bridge age t, thereby enabling the transition probabilities to be estimated using the state-based model. The last situation, Situation 4, has 4 bridges with 8 inspection records. The selection process indicates that it requires the BPM to generate the missing historical condition records to provide a more meaningful bridge depreciation pattern. Amongst the 4 bridges, the selection process suggests that only one bridge #5 satisfies the condition of using the BPM. Figure 7 shows that the available inspection records in conjunction with the BPM-generated missing historical records can provide a more reasonable bridge element deterioration pattern. Finally, the transition probabilities are estimated using the state-based model.

Results and discussion

Transition probabilities

The purpose of the present study is to develop an integrated method based on Markov-based probabilistic deterioration modelling. Four typical bridge situations with varying condition rating data quantity and distributions are selected as benchmark examples to demonstrate the capability of the integrated method. Detailed results of the four typical situations are presented in this section. Figure 8 presents the individual transition probability matrices for bridge elements 20C-Bridge #4

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and 59C-Bridge #6. These transition probability matrices are obtained using the time-based model incorporating the Markov chain method.

Table 5 presents the transition probabilities of each age group for element types 20C (Situation 3) and 4C (Situation 4). The transition probabilities are obtained from the state-based model. The values in each age group represent the probability of the element quantities remaining in the current condition state. For example, for bridge element type 20C with age group (20-26), 94% of the element quantities remain in CS1 during a one year interval.

The Chi-square distribution is used herein to validate the generated transition probabilities from both the state-based and time-based models. The Chi-square distribution require the condition ratings of predicted $E(t)$ and average $A(t)$. Figure 9 compares the OCRs $A(t)$ obtained from the time-based model and the predicted $E(t)$ from the Markov chain method for bridge elements 20C-Bridge #4 and 59C-Bridge #6. Figure 10 shows the comparisons between the 3rd-order regression function and the Markov chain method in generating the OCRs $A(t)$ and $E(t)$, respectively, for element types 20C and 4C. All comparisons show that the predicted OCRs $E(t)$ from the Markov chain method are close to the OCRs $A(t)$ obtained from the time-based model and the 3rd-order polynomial regression functions.

Table 6 summarises the degrees of freedom, critical χ^2 values at significance level $\alpha = 0.05$ and those obtained from the integrated prediction method. The comparisons show that the estimated χ^2 values for bridge elements 20C-Bridge #4 and 59C-Bridge #6, and element types 20C and 4C are

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much smaller than those at significance level α = 0.05. This means that the generated transition probabilities are well acceptable to predict the future condition ratings.

Validation

Once the transition probabilities are confirmed, future prediction can simply be performed using Equations (3)-(5). A cross-validation method is employed herein to measure the accuracy and reliability of the predicted condition ratings by comparison with the existing condition ratings. Figure 8 presents the transition probability matrices for 20C-Bridge #4 (Situation 1) and 59C-Bridge #6 (Situation 2) which are generated based on the available conditions ratings of Years 1999 and 2004 (i.e. two inspection records) using the time-based model. To validate the predicted outcomes of 20C-Bridge #4 (Situation 1), the condition rating of 100% at Year 1999 are used as initial input together with the transition probabilities from Year 1999 to 2004, as presented in Figure 8. Equations (3) and (5) are then used to estimate the condition rating for year 2007, which are subsequently compared to the existing one at the same "future" year. Note that only one available condition rating (Year 2007) can be used for comparison. The condition rating factors at Year 2007 are calculated as: R = [100, 70, 50, 20]; Q (1999) = [1, 0, 0, 0]; Q (2007) = Q (1999) × P^8 = [0.005, 0.893, 0.102, 0], which leads to the predicted condition rating as E (2007) = Q (2007) × R^{T} = 68%. Note that the prediction of 68% (CS2) is very close to the actual condition rating (70%, CS2) and both are in the same condition state.

An identical process is also performed for 59C-Bridge #6 (Situation 2). The predicted condition rating at Year 2007 is 60% (CS2) which makes a 10% difference from the actual value for the same

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year, i.e. 70% (CS2). Despite such a discrepancy, both condition ratings still remain in the same condition state or CS2. For both situations, the prediction results clearly demonstrate that the performance of the time-based model is satisfactory.

In order to validate Situation 3 for the state-based model with the given sample condition rating data, 31 inspection records from 11 bridges are used to generate the transition probabilities. Five inspection records from the remaining Bridge #7 are used to validate the accuracy and reliability of the predicted condition ratings. The prediction process is also identical to that for Situations 1 and 2. The predicted condition ratings of 20C-Bridge #7 are compared with the actual values as shown in Table 7.

A similar validation procedure used for Situation 3 is adopted for Situation 4 except that the latter also incorporates the BPM-generated historical condition ratings. The transition probabilities are generated using five inspection records from three bridges together with nine BPM-generated historical condition ratings. Three inspection records from the remaining one bridge (bridge #5) are used to validate the accuracy and reliability of the predicted condition ratings. A comparison with the actual condition ratings is also given in Table 7.

As indicated in Table 7, the actual condition ratings for bridge element 20C-Bridge #7 are 70% (CS2) from 2004 to 2008 excluding 2007. The predicted condition ratings for 2004 and 2005 remain the same as the actual ones, i.e. 70% (CS2) and those for 2006 and 2008 are slightly smaller (i.e. 69% and 68%) but still remain in the same condition state or CS2. For bridge element 4C-Bridge #5, the predicted condition ratings for 2003 and 2007 are 82% (CS1) and 71% (CS2)

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respectively and their corresponding actual condition ratings are 85% (CS1) and 70% (CS2). These validation outcomes in terms of both condition ratings and condition states (CSs) are considered satisfactory. This further confirms the satisfactory performance of the state-based model.

A summary of the model validation is given herein. If the predicted and the actual condition ratings are in the same Condition State (CS), the prediction is considered accurate and the modelling, satisfactory. However, it should be noted that the element-level inspection OCR is defined using four condition states each having a 20% range. This means that the discrepancy between the predicted and the actual condition ratings may be as large as 19%. Nevertheless, this is an acceptable and common practice in the prevailing condition-state "grading" system.

Long-term prediction and discussion

Once the accuracy and reliability of the prediction is validated, long-term bridge predictions can subsequently be conducted using the generated transition probabilities. The outcome of Equation (3) indicates the percentage of element quantities, whereas that of Equation (5) represents the OCR values. A typical bridge element 20C-Bridge #8 from Situation 3 is chosen as an example to demonstrate the prediction of long-term bridge element performance. This is presented in Figure 11. The figure illustrates the future condition ratings of each bridge element by element quantities and OCRs. The long-term prediction is based on the latest inspection record as an initial condition state vector from a given bridge element, by which the element condition ratings for the future 25 years are predicted. It is evident in the figure that the predicted condition ratings gradually decrease as the

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bridge age increases. This suggests that the transition probabilities correctly reflect the bridge deterioration pattern.

The benchmark examples demonstrate that the integrated bridge deterioration method can be applied to deal with various situations with respect to the condition rating data availability and distribution in long-term prediction of bridge element performance. The proposed method has shown to be more effective than the stand-alone probabilistic models. This is because it employs a selection process to automatically determine an appropriate deterioration model for a given situation. The advantages of the integrated method may be summarised as follows:

(1) The integrated method categorises the bridge elements by bridge location, construction era, element type and material type, by which similar elements are grouped together to identify common deterioration patterns at the network level of bridge elements. The main feature of categorisation is to group similar deterioration behaviour by sorting the available condition data for identical types of bridge elements.

(2) The element level analysis, i.e. the bottom-up approach, is used to calculate the OCRs of an element for the long-term prediction at project and network levels. Although time consuming, it is more effective than the top-down approach in that it reduces the failure risks. This is because a bridge usually collapses due to the lower condition rating of the elements being summarily ignored.

(3) The proposed integrated method applies a selection process to choose a suitable prediction approach from either the state-based or time-based model for a given situation of available condition data. If the time of bridge maintenance is known, the maintenance data can be used to

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generate transition probabilities by the time-based model, but not the state-based model. On the other hand, for some situations such as those with less than two sets of sequential change condition data, the time-based model is unable to generate the transition probability. For these situations, the state-based model can be used as an alternative. This advantage is demonstrated through Situations 3 and 4.

(4) The integrated method uses the BPM-generated missing historical condition ratings to establish workable transition probabilities when the inspection records are insufficiently available. This is demonstrated using Situations 2 and 4 hereinabove.

Conclusions

This paper proposes an integrated method using typical probabilistic bridge deterioration modelling techniques to provide alternative workable solutions for various situations in terms of available condition data. The proposed method in its implementation deploys and integrates the state-based and time-based models. Both these models are commonly used individually in major state-of-the-art BMSs. The time-based model utilises the Kaplan and Meier method to estimate the cumulative transition probability with respect to the transition times and the corresponding transition events. The expected-value method is used for the state-based model to generate the transition probability.

The application and reliability of the integrated method is demonstrated using four predefined and distinguishable situations with various quantities and distributions of available inspection records. The major advantages of the integrated method are: (1) when the time of bridge maintenance is known, the maintenance data can be used to generate transition probabilities by the time-based model. This is however not the case for the state-based model; (2) the state-based model, on the other hand, can be used as a workable alternative in situations where there are less than two sequential changes in the available condition data, and where the time-based model is unable to calculate the transition probability; (3) in situations where the historical condition-rating records are insufficient for a reliable prediction of future bridge performance, the integrated method can incorporate the BPM into the model selection process and generate the necessary but unavailable historical data.

Acknowledgements

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List of figures

Fig 1

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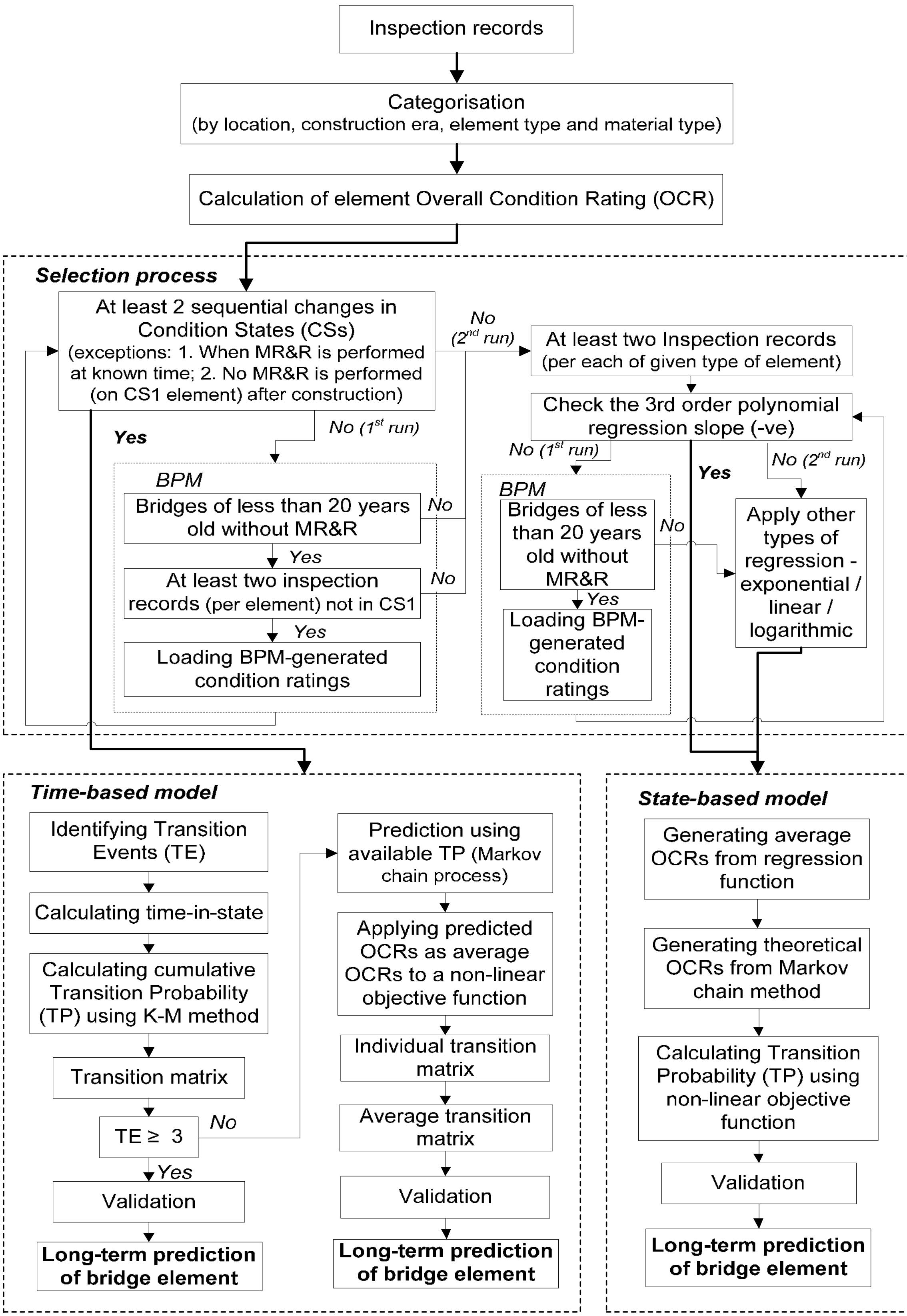

Fig 2

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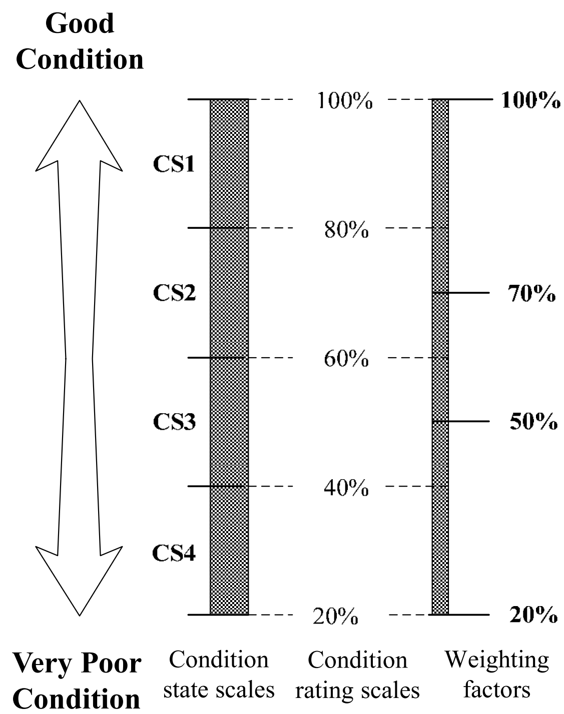

Fig 3

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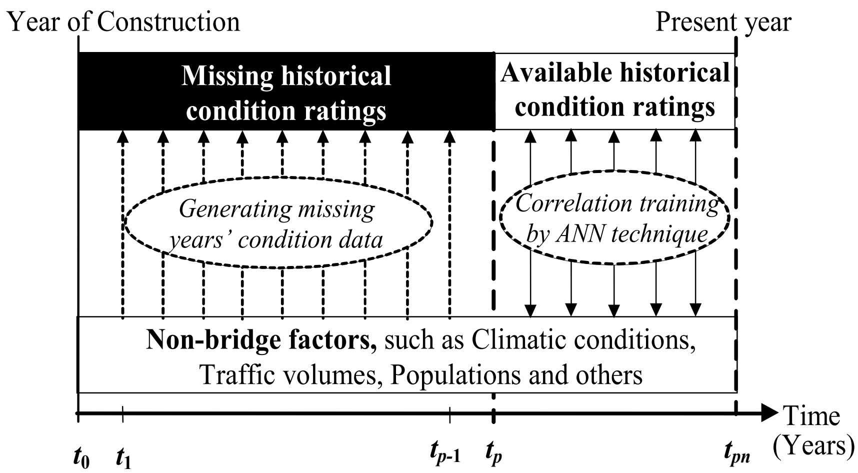

Fig 4

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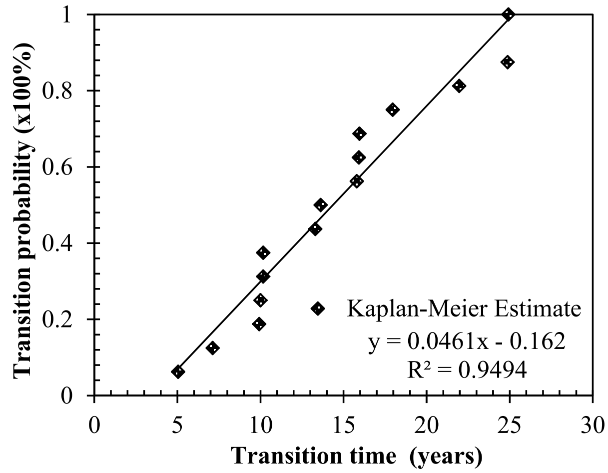

Fig 5

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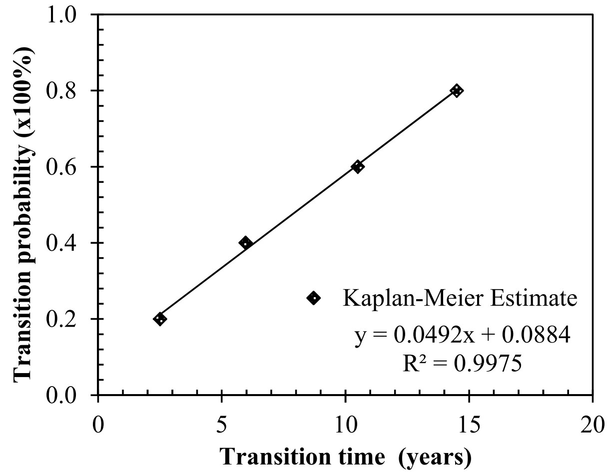

Fig 6

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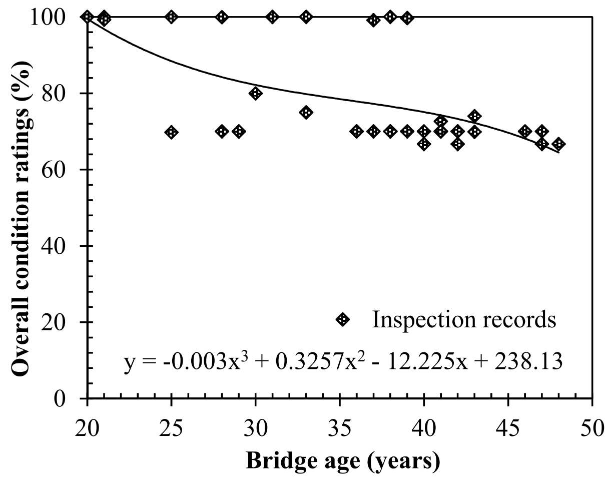

Fig 7

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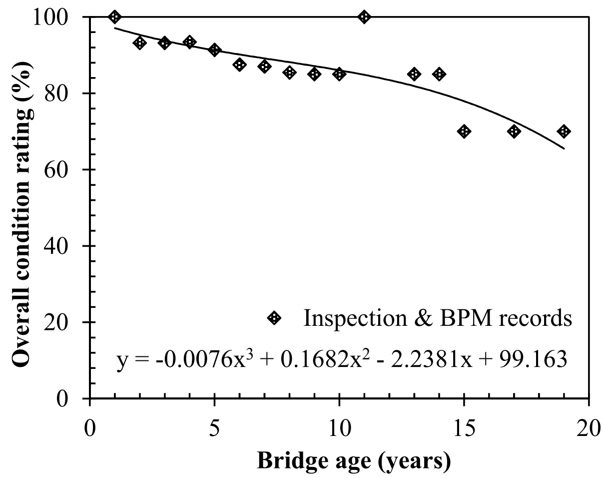

Fig 8

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	1	2	3	4
1	0.512	0.488	0	0
2	0	0.982	0.018	0
3	0	0	1.000	0
4	0	0	0	1.000

(a) 20C-Bridge #4 (Situation 1)

	1	2	3	4
1	0.795	0.205	0	0
2	0	0.546	0.454	0
3	0	0	1.000	0
4	0	0	0	1.000

(b) 59C-Bridge #6 (Situation 2)

Fig 9

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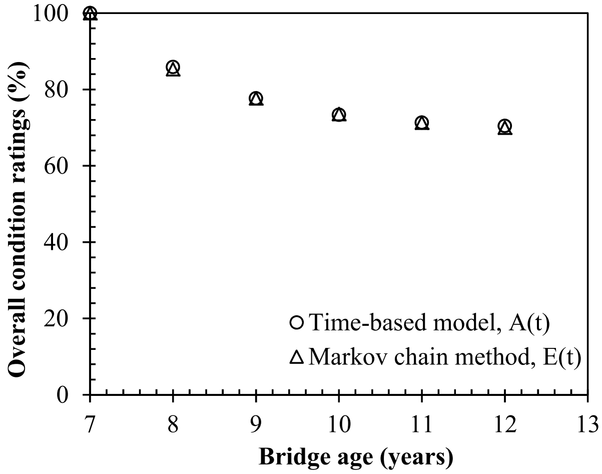
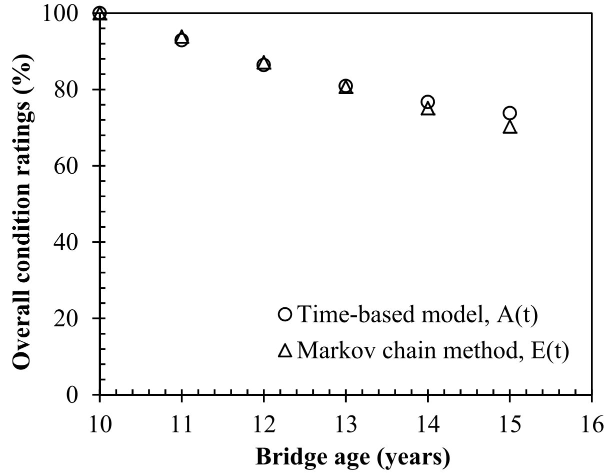


(a) 20C-Bridge #4 (Situation 1)



(b) 59C-Bridge #6 (Situation 2)

Fig 10

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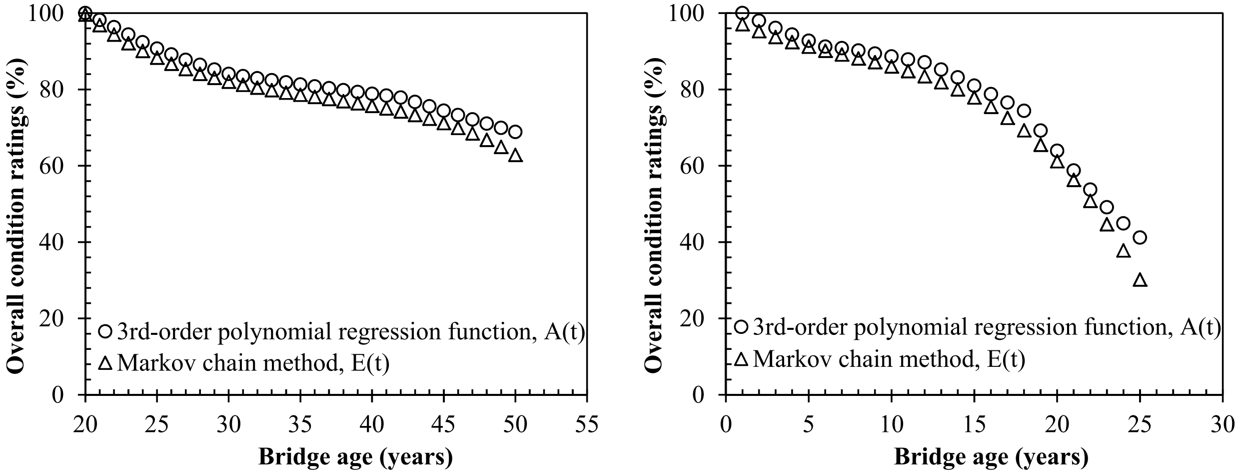

(a) Element type 20C (Situation 3)

(b) Element type 4C (Situation 4)

Fig 11

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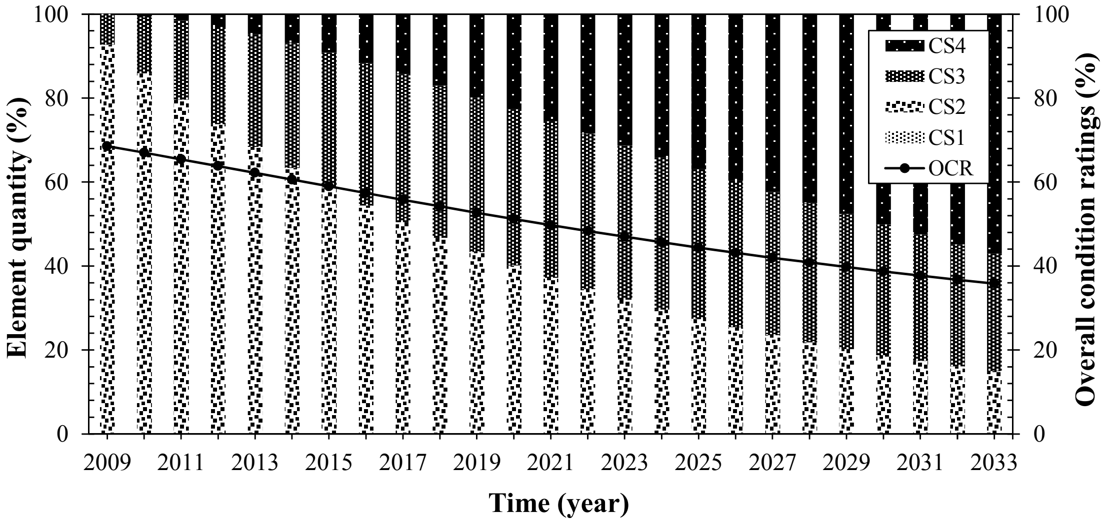

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Table 1. Time-in-state for TE(1,2) from CS1 to CS2

Condition state			Time-in-state	Data type
i	j	k	T_j	
Construction yr	CS1	CS2	$T_{ij} + T_{jk}/2$	Uncensored
Construction yr	CS1	CS1	$T_{ij} + T_{jk}$	R-censored

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Table 2. Time-in-state for TE(2,3) from CS2 to CS3 and TE(3,4) from CS3 to CS4

Condition state						**Time-in-state**	**Data type**
TE(2,3)			**TE(3,4)**				
i	j	k	i	j	k	T_j	
CS1	CS2	CS3	CS2	CS3	CS4	$T_{ij}/2+T_{jk}/2$	Uncensored
CS1	CS2	CS2	CS2	CS3	CS3	$T_{ij}/2+T_{jk}$	R-censored
CS2	CS2	CS3	CS3	CS3	CS4	$T_{ij}+T_{jk}/2$	L-censored
CS2	CS2	CS2	CS3	CS3	CS3	$T_{ij}+T_{jk}$	I-censored

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Table 3. Necessary information for four different data situations

Benchmark examples	Element type	Element name	Construction era	Total No. of bridges	Total No. of records	Type of model
Situation 1	20C	Deck slab	1981-2000	25	61	T
Situation 2	59C	Pile cap	1981-2000	7	15	T+B
Situation 3	20C	Deck slab	1961-1980	12	36	S
Situation 4	4C	Footways	1981-2000	4	8	S+B

Note: T: Time-based model; S: State-based model; B: BPM

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Table 4. Predicted OCRs using transition probabilities obtained from the time-based model (Bridge element 20C-Bridge #4)

	Initial input	**Predicted values using transition probability obtained from the time-based model**				
Year	1999	2000	2001	2002	2003	2004
Bridge age	13	14	15	16	17	18
OCRs (%)	100	86	78	73	71	70

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Table 5. Transition probabilities of each age group for element types 20C and 4C

Element type	Situation	Age group	1	2	3	4
20C	**3**	**(20-26)**	0.940	0.842	0.939	1.000
		(27-32)	0.930	1.000	1.000	1.000
		(33-38)	0.997	0.946	0.977	1.000
		(39-44)	0.998	0.966	0.951	1.000
		(45-50)	0.976	0.927	0.923	1.000
4C	**4**	**(1-7)**	0.933	1.000	1.000	1.000
		(8-13)	0.998	0.937	0.512	1.000
		(14-19)	0.956	0.838	0.672	1.000
		(20-25)	0.826	0.626	0.614	1.000

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Table 6. Comparison of the χ^2 values at significance level $\alpha = 0.05$

Element type	**Element name**	**Construction era**	**Degrees of freedom**	**χ^2 critical (α=0.05)**	**χ^2 from integrated prediction method**
20C-Bridge #4	Deck slab	1981-2000	5	11.07	0.01
59C-Bridge #6	Pile cap	1981-2000	5	11.07	0.22
20C	Deck slab	1961-1980	31	44.98	3.66
4C	Footways	1981-2000	24	36.41	6.84

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Table 7. Validation outcomes for Situations 3 and 4

Bridge element	**Input data**		**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
20C-Bridge #7	2002 with condition rating 70%	A:		70%	70%	69%		68%
		B:		70%	70%	70%		70%
4C-Bridge #5	2000 with condition rating 85%	A:	82%				71%	
		B:	85%				70%	

Note: A: Prediction results; B: Existing condition rating data