Development of a Road Bridge Deterioration Model in a Data Constrained Environment

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ABSTRACT

A stochastic time-based deterioration model for use with New Zealand bridges is presented, comprising two parts and being based on the condition management process that is used to assess the extent and severity of a defect or defects. The first part is an expert based severity deterioration model, which can be used to simulate the deterioration of timber, concrete, pre-tensioned and steel load bearing elements. The second part is the data derived extent model, which uses a novel approach, not previously used, to simulate the growth of defects with time. By creating these extent and severity models the general absence of deterioration models in the Australian and New Zealand region is addressed. Furthermore, the development of both the extent and severity model was achieved in a data constrained environment, which led to validation and development challenges. How these challenges were dealt with, and the novel methods that were used to solve them are also covered.

KEYWORDS

Bridge; deterioration; asset management; lifecycle; stochastic modelling

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INTRODUCTION

New Zealand bridges are designed to last for 100 years. Nevertheless, for older bridges constructed in the post-war period between 1940 and 1950 a bridge's design life was not explicitly considered (Rogers et al. 2013). To provide insight into how best to manage these post war bridges, and to ensure that road users continue to be provided with the expected level of service, bridge performance models are created (Lake and Seskis 2013). By creating performance models, such as condition and strength models, the bridge asset manager is able to assess the remaining life of the asset and to investigate the future rehabilitation budgets required to maintain the expected service levels (Bu et al. 2012). In a more general context the creation of models can also lead to new insights into the system being simulated, can challenge old modelling paradigms and assumptions, can be used to demonstrate trade-offs between competing objectives, can illuminate uncertainties, and can lead to new questions being asked (Epstein 2008).

Even though there are numerous benefits that can be derived from developing and using models, research shows that bridge deterioration models are not widely implemented in Australia and New Zealand (Lake and Seskis 2013). Similarly, Bush et al. (2012) also identified that bridge asset management decision-making in New Zealand was less developed than that used in pavement decision-making. Accordingly, a bridge deterioration model for use in improved bridge asset management decision-making is presented.

The development of the bridge deterioration model, which includes a severity model and an extent model, is detailed in the following sections. In these sections the impact of developing a deterioration model in a constrained data environment is first addressed. A general overview of the different deterioration model types, and the details of which model type was chosen is then provided. Following on, a description of the severity model and its development, and a description of the extent model and its development is detailed. Also described in these sections are the challenges of creating a bridge deterioration model in a data constrained environment, which arose as a result of New Zealand bridge managers only collecting extent and severity data between 2011 and 2015 (NZTA 2011; NZTA 2015). The final sections detail how the deterioration curves were validated, given the short history of condition data collection in New Zealand.

SETTING MODELLING EXPECTATIONS

Two data extremes exist when developing deterioration models. In the first most favourable extreme a data rich environment exists. Herein, a data rich environment is one that comprises sufficient condition data that comprehensively covers the different components of a bridge. Such a situation often exists when there is a long history of data collection. In the second extreme, limited data exists because of a limited history of data collection or because an organization is embarking on a new or altered data collection strategy. Consequently, the limited history leads to a data constrained environment because there is perceived to be insufficient data to create a condition model. In an organization with a long history of data collection predictive models can be developed and rigorously validated to ensure the future views they provide are accurate. In a data constrained environment the limited availability of data presents a challenge, but the paucity of data does not preclude the development of a deterioration model. Although predictive models are widely used, they are not the only developmental class of model. Three model development classes exist comprising generator, mediator and predictor (Heath et al. 2009). Generator models are used to generate hypotheses, mediator models are used to compare competing strategies and predictor models are used to gain insights into the future state of the modelled system or system's components, such as bridge or bridge components. As a result of the combined problem of a limited data history and the requirement to compare the effectiveness of different bridge management strategies, a mediator model was developed. Thus, the deterioration model has to provide sufficient insight to be able to comprehend the relative benefits of competing strategies, rather than an accurate future prediction. Accordingly, there has to exist sufficient confidence that each part of the model and the model's results provide a sufficient level of accuracy. The following sections detail how this was achieved.

MODELLING METHODOLOGY

A significant amount of research has been undertaken into the types of models that can be used to simulate bridge performance (Kotze et al. 2015; Lake and Seskis 2013). For this reason the types of models that can be applied are only briefly reviewed here, primarily with the aim of justifying the choice of model used herein.

Deterministic, stochastic and artificial intelligence are the three modelling approaches generally used to simulate bridge deterioration processes (Wang et al. 2012). Deterministic models are the simplest approach and include model types such as average time to failure, and linear and regression models (Kotze et al. 2015). Although simple to implement, deterministic models provide limited opportunity to investigate the effect that uncertainty has on asset management objectives. In deterministic models the limitation arises because the same output will always be derived from the same set of inputs. Consequently, two bridges with the same construction form and in the same environment will always degrade at the same rate. If a deterministic approach is applied to a network of bridges, then the condition distribution can be easily calculated, provided that no maintenance is undertaken. Given that the output from a condition model is often used to plan future maintenance interventions or is used in business case development

(Kotze et al. 2015), this type of determinable performance can infer a level of certainty not present in the real-world system. To address the inherent randomness found in a real-world system, stochastic models are used.

In a stochastic model the underlying assumption is that no two bridges, even with the same construction form and in the same environment, will deteriorate at the same rate. To take account of this variability a distribution function is used to describe the probability of a bridge of a given age being in a certain condition state. A stochastic approach can also be used to incorporate environmental influences and material characteristics into the deterioration model (Kotze et al. 2015). By acknowledging the uncertainty present within the asset management system, and by modelling this uncertainty, the full spectrum of decision options can be explored and more appropriate risk management strategies can be developed.

A number of feasible methods can be used to model stochasticity including Markov, Semi-Markov and Gamma deterioration processes (Agrawal et al. 2010; Golabi and Shepard 1997; Kuhn and Madanat 2005; Wang et al. 2012), with the most common method being the Markov Chain (Kotze et al. 2015). A Markov chain is a state-based model, as the annual likelihood of a bridge changing from one condition state to the next is simulated. In a Markov chain unless an outside intervention occurs there is no improvement in the condition state. Thus, a bridge remains in the final condition state, known as the absorbing state, until rehabilitation is undertaken.

Markov chain models are commonly used to model bridge deterioration, but as argued by Aboura et al. (2008), they do not accurately represent real-world deterioration processes. The inaccuracy in Markov models arises because the period between each condition state is non-homogenous and as such cannot be modelled using the uniform or geometric progressions assumed in Markov models. Deterioration in real world systems is non-homogeneous, because the time spent in each state, referred to as the sojourn time, decreases with worsening condition (Black et al. 2005). To account for the non-homogeneity of bridge deterioration processes a time based approach such as a Semi-Markov methodology is used (Black et al. 2005). Time-based models have the potential to provide a more realistic representation of real-world deterioration processes, when compared to state-based models (Thomas and Sobanjo 2013), because of their ability to model the changing rate of deterioration as a bridge ages.

Artificial intelligence is a third method which can be used to model deterioration. To apply this method a large dataset in combination with machine learning is used to derive a relationship between the dependent and independent variables (Kotze et al. 2015). Once the relationships have been defined, the model is then used to assess the long-term performance of the bridge asset (Lee et al. 2011). Given the limited availability of bridge condition data, an artificial intelligence approach was not used to develop the bridge deterioration model, leaving only deterministic and stochastic approaches as viable options. Considering that a stochastic model is preferable to a deterministic model and a time-based model is preferable to a state-based model, a time-based stochastic methodology was chosen.

THE TIME BASED MODEL

In a Markov chain the probability of transitioning to the following state is estimated. In accordance with Semi-Markov modelling assumptions the state that a bridge will deteriorate to is chosen first, then the sojourn time. In this deterioration model a third transition was also added to the severity and sojourn selection process to represent the growth of a defect with time. The time at which the deterioration will take place is a function of the bridge's existing severity state i and the probability P_{ij} of a transition from the existing state to a new state j occurring. The sojourn time H_{ij}, given that the bridge has transitioned from severity level i to severity level j is also derived stochastically. In the new deterioration model the growth of the defect D_{ij} occurs after the condition state and transition time has been selected. The value of D_{ij} is also derived stochatically. Figure 1 details the generalized form of the model.

In the generalized form of a Semi-Markov model there are clearly a number of potential deterioration paths, as illustrated in Figure 1. For example, a bridge with a severity level of 1 can potentially transition to severity level 2 (P_{12}) or to severity level 3 (P_{13}). To simplify the severity model the deterioration process can be assumed to move sequentially through all states (Noortwijk and Kallen 2014). By assuming a simplified deterioration process the generalized model is reduced to the central path comprising P_{12}, P_{23} and P_{34}. In the simplified Semi-Markov model the next state is known and so the probability of selecting State 2, if State 1 is the current state, is 1.0. Thus, the deterioration characteristic of a bridge is defined by the sojourn time H_{ij} and the size of the defect D_{ij}.

THE SOJOURN MODEL

The following section details the expert based methodology used to develop the sojourn model, which comprised the aggregation of expert opinion using a statistical method known as linear pool analysis. Linear pool analysis was used to develop a set of pert-beta distributions that define the sojourn times for each of the state-time transitions.

Prior to creating the model the number of deterioration states had to be defined. The number of states being influenced by the condition data collection standards that were employed by bridge management agencies. In New Zealand two severity rating systems were identified. The first was the four state system detailed in the Bridge Manual (NZTA 2014) and the second New Zealand system that was identified was based on a more recent five state system state that was used in the UK (UKHA 2007). An example of the five state data that was collected in New Zealand is detailed in Figure 2. For brevity only the super structure element is shown. The remaining elements comprise substructure, durability elements, safety elements, waterway elements, retaining elements and other elements.

As the reason for creating the bridge deterioration model was to understand how the performance of the road network changed with deteriorating strength, the four state system detailed in the bridge manual was used. Furthermore, by using the four state system the data collection process was simplified, as the bridge asset managers only had to define the transition times between good, fair, deteriorated and seriously deteriorated. Given the use of the four state system, the five state data that was collected and which was used in the validation process was converted so that it could be compared to the selected four state system. Based on a comparison of the four state system and the five state system, the first two states of the five state system were combined (Refer Table 1). The same modification was also used in the development of the extent model, as the extent data was also based on a five state system. As a result of combing the first two states the dwell time in severity state one is increased before the bridge transitions to severity state two. The combining of the two states was considered to be inconsequential, because bridges with such minor defects generally have no rehabilitation actions applied to them.

When the availability of data is limited, the development of a severity model can be addressed through the application of industry guidance or by employing pre-existing models from similar networks and updating these models over time. Alternatively, expert judgment can be used to generate the required data. Due to the difficulty of obtaining comprehensive historical data for similar networks and because of the limited availability of existing New Zealand bridge deterioration models, an expert based approach was chosen.

When developing an expert based model the size of the expert panel can vary from three to in excess of one hundred participants (Skulmoski et al. 2007), but expert panels typically range between six and ten participants (Goossens and Cooke 2005). In the study used to develop the deterioration model, sixteen New Zealand bridge asset managers were contacted and seven replied. Thus, the size of the expert panel was within the typical range highlighted in the literature.

To obtain the data required to model bridge deterioration a three part questionnaire was provided to each bridge manager. The first section of the questionnaire was used to obtain data on deterioration rates and the second part covered management details including the typical percentage of the asset in a given condition state, and the cost of repairing and strengthening bridges. The final part was open and provided space for additional comments, should those being surveyed wish to add any. In the first section, the bridge managers were asked how long they believed steel, in-situ concrete, pre-tensioned (pre-stressed and post-tensioned) and timber load bearing elements would take to transition from one severity state to the next. The aim of this question was to provide insight in to the differing lengths of time taken by each material type to transition between each of the four severity states. In the questionnaire no attempt was made to identify the effect that the different coastal, inland and volcanic environments would have on the rate of bridge deterioration. Environmental effects were omitted from the questionnaire because even though bridge engineers had an appreciation that the location of a bridge affected its service life, quantifying the general deterioration processes was found to be difficult enough. Given the aim of the model was to compare high level strategies, the omission of environmental effects was considered to be an appropriate simplification. The incorporation of environmental effects into a bridge model constitutes a future improvement, which can be developed should the required data become available. Adding the environmental effects is one way of transitioning to a predictor model.

To address the uncertainty in the sojourn times each bridge engineer was asked to provide an assessment of the most pessimistic, the expected and the most optimistic length of time each material would take to transition from one severity state to the next. Using these estimates a three point Beta-Pert Distribution (Davis 2008) was developed. The Beta-Pert distribution was chosen because of its use in modelling systems with minimal information and because of its use in modelling expert opinion. The following definition of a Beta distribution was used:

$$P(x) = \frac{1}{B(\alpha,\beta)} x^{\alpha-1}(1-x)^{\beta-1} \quad (1)$$

Where $P(x)$ is the probability of an event x occurring, B is the normalizing Beta function, α and β are shape factors, $\alpha, \beta > 0$ and $0 \le x \le 1$ (Abramowitz and Stegun 1972). The Beta function is itself a function of two Gamma Distributions, which are described by a factorial series. To derive the Beta distribution shape factors from the pessimistic (a), expected (m) and optimistic (b) time estimates provided by the bridge engineers, the following equations were used (Davis 2008):

$$\alpha = \left(\frac{2(b + 4m - 5a}{3(b - a)}\right)\left[1 + 4\left(\frac{(m - a)(b - m)}{(b - a)^2}\right)\right] \quad (2)$$

$$\beta = \left(\frac{2(5b - 4m - a}{3(b - a)}\right)\left[1 + 4\left(\frac{(m - a)(b - m)}{(b - a)^2}\right)\right] \quad (3)$$

Where α and β illustrated in Equations 2 and 3 are the shape functions used in Equation 1.

To simulate the bridge deterioration process a single distribution is required to model the transition between each severity state. Given that no two bridge engineers provided the same range of bridge sojourn times these results had to be aggregated. As detailed by Clemen and Winkler. (2007), the aggregation of expert data can be dichotomized into behavioral and mathematical approaches. The Delphi approach is one behavioral method that can be used, whereby each round of the process is used to elicit information from a group of experts or stakeholders. Over a number of rounds, usually between three and five, a common consensus between those involved is arrived at (Skulmoski et al. 2007). Delphi has been successfully employed in a number of studies, but its main weakness is that a mutually agreeable consensus may not be forthcoming, which was a foreseeable outcome given that those being surveyed would be attempting to rationalize their initial opinion based on limited information. Mathematical methods provide an alternative to Delphi and use recognized techniques such as Axiomatic and Bayesian methods to provide the desired single distribution. To combine the estimates provided by those being surveyed an axiomatic approach known as linear pool analysis was used. Linear pool analysis is expressed by the following equation (Clemen and Winkler. 2007):

$$p(\theta) = \sum_{i=1}^{n} w_i p_i(\theta) \qquad (4)$$

where n is the number of experts, $p_i(\theta)$ represents the probability distribution function used to model the reported sojourn times of expert i and w_i is the weighting applied to each expert's data, which sums to one. By providing the opportunity to adjust w_i the confidence in those being surveyed and their data can be adjusted. In this case all weightings were assumed to be equal, as all experts were assumed to provide an equally valid viewpoint.

To derive the sojourn distributions for each severity state a Monte-Carlo model was used. The process that was used is detailed in Figure 3. In the Monte-Carlo model, for each individual state transition the estimated length of the transition is drawn from each expert's distribution. Each individuals estimate is then combined to provide an overall estimate. To obtain the desired data the sojourn model was run 10000 times and the *0^{th}, 50^{th}* and *100^{th}* percentiles noted. The *0^{th}* percentile was used was considered to be the most pessimistic and the *100^{th}* percentile was used as it was considered the most optimistic.

The outcome of the linear pool analysis is detailed in Table 2. Using the data in Table 2 in combination with equations *(2)* and *(3)* the shape factors for the material specific Beta distribution *(1)* can be derived and inputted into a stochastic time model. To use the sojourn model, as a bridge transitions from one state to the next the length of time to the next state change is calculated. The length of time being drawn from the beta distribution.

If the sojourn time for a, m and b are summed for each severity state an overall lifetime estimate can be made for each material type (Refer Table 2). Using the lifetime summation methodology, pre-tensioned and in-situ concrete bridges have similar overall total life ranges, with in-situ concrete bridges surviving between 53.3 and 103.4 years and pre-tensioned bridges surviving between 53.7 and 98.3 years. The surprise was that steel bridges only survive without maintenance for between 42.2 and 75.9 years, which is a similar length of time to that identified for timber bridges, which survive between 30.6 and 68.4 years. While the assessment of bridge lives is not the focus of the paper, this initial result implies that concrete bridges perform better than steel bridges in the environmental conditions found in New Zealand. In reality other factors such as initial capital costs, cost and ease of maintenance, and the time taken to reach functional obsolescence all have to be taken into account in order to assess whether the lifecycle management costs of one material is lower than another. One reason for the comparable ages of steel and timber bridges, is that timber bridges present on the state highway network represent a set of older bridges that have happened to deteriorate at a much slower rate. Finally, based on the estimated life for each material type, there is an apparent shortfall between the expected design life and the estimated life. The reason for the difference is that the design life of a bridge does not necessarily infer a life without maintenance, but the time taken for a bridge to deteriorate to point where major maintenance is required (NZTA 2014). Accordingly, the estimated life for each material can be considered a time to major maintenance.

THE DEFECT EXTENT MODEL

In the pavement asset management sector roads are divided into treatment areas, which are based on the defined treatment length and the lane or pavement width. In cases where bridge renewals, component replacements such as joint replacements, or maintenance actions such as resurfacing or waterproofing are being undertaken this wholesale intervention approach can also be applied, as the whole component or component set is being replaced. Nevertheless, interventions such as concrete repairs or painting are often applied to localized areas. In a pavement management context this is similar to simulating the growth of potholes with time or other defects such as cracking. To account for this type of localized maintenance management, a method of estimating the growth of a defect is required, which requires knowledge how a defect's extent increases with time. The development of the growth model is covered below.

During the inspection process the inspector records not only the severity of the defect, but the extent of the defect as well. As highlighted previously, to align with the New Zealand Bridge Manual, the first two states of the five state extent and severity system were combined to create a four state system. The extent ranges that were used in the model are illustrated in Table 3. The ranges were adapted from those used by the UK Highways Agency (Bevc et al. 1999; UKHA 2007) and those used in the inspection policy trail that was undertaken in New Zealand (NZTA 2011).

To identify the proportion of the asset in a given extent state, bridge inspection records were drawn from the Opus Bridge Information System (Reynolds and Rooke 2009). Using these records the percentage of the asset in a given condition state was calculated. The percentages where then used as an input into a genetic algorithm, which was used to search for potential solutions for D_{ij}. In total 1628 bridges were included in the dataset, which equates to 37 % of the New Zealand bridge stock. To minimize the number of transition matrices and to provide a larger dataset, the data for all material types was aggregated. As more data becomes available individual material type distributions can be modelled. The dataset was used to calculate the general percentages of the asset found in a given extent state. Table 4 details the proportion of the bridge stock in a given extent range for each of the severity states. It is acknowledged that using the data directly without filtering out bridges that have received maintenance results in improvements being unaccounted for, but this methodology had to be used given the limited time period the data covered.

To define the defect growth D_{ij} a Markov Transition Matrix is required for each severity state. Thus, the probability of a defect growing is dependent on the severity state the bridge is in and the existing defect state. In the extent growth model a defect can potentially miss an intermediate state and so transition from extent state A to extent state C. To address this state skipping process and to identify potential solutions for the transition model, a three stage process was used. As an example, in Table 4 the row relating to severity level two constitutes the pre-transition distribution of the asset in each extent range, and the row relating to severity level three constitutes the distribution of the asset post-transition. Thus, the mapping between the pre- and post-transition states is defined by the extent growth model. Three potential solutions to the severity state 1 to severity state 2 transitions are depicted in Figure 4. In Figure 4, the arcs represent the proportion of asset moving between the defined extent states.

To identify potential solutions for the defect growth matrices D_{ij} the genetic algorithm BehaviorSearch (Stonedahl 2010) was used. BehaviorSearch was used because the deterioration model was originally written as part of a larger model already coded in Netlogo (Wilensky 1999) and BehaviorSearch was specifically written to work with Netlogo. BehaviorSearch comprises three main components including the variables in the Netlogo model controlled by the genetic-algorithm, the objective function and the genetic algorithm search engine. Behavior Search works by controlling the variables in the model until a minimum or maximum solution to the objective function is obtained. In the extent derivation model the variables comprised the percentage of the bridge stock transitioning from one extent state to the next. The objective function compared the modelled extent distribution of the asset with the required extent distribution, once the transition had occurred. Accordingly, the aim was to minimize the difference between the known and calculated post transition extent distributions.

The search method used to identify potential solutions for D_{ij} was inspired by the Bayesian search model developed by Welton and Ades (2005). In their model limited medical data was used to derive a rate of change matrix used in a continuous time Markov model. Once they had developed the rate of change matrix it was converted to a discrete time Markov matrix. Their methodology employed this conversion because they wanted to calculate how long a patient may take to transition to a more severe state, given that the patient had already spent a length of time in an existing state. To identify potential solutions for D_{ij} an adapted methodology was used. An adapted methodology was used, because the desired outcome for the extent model differed to that being sought by Welton and Ades (2005). In the defect extent only knowledge of how much the defect had grown was required, given that the bridge had already transitioned from one severity state to the next. Consequently, only a single discrete time Markov transition matrix was required, and this could be calculated directly without first calculating a rate of change matrix. To search for solutions to D_{ij} the objective function used by BehaviorSearch was based on a goodness of fit test, which further modified the method used by Welton and Ades (2005).

To simulate the pre-transition state a set of 1000 bridges was created and the extents distributed according to those detailed in Table 4. Given that there are three transitions (i.e. 1-2, 2-3 and 3-4), three matrices are required to fully model the growth of a defect.

Thus, the genetic algorithm must be run in order to simulate each severity state transition. The defect transition matrix for each of these state changes being defined by the following:

$$D_{ij} = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ - & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ - & - & \gamma_{33} & \gamma_{34} \\ - & - & - & \gamma_{44} \end{bmatrix} \tag{5}$$

where D_{ij} is the extent transition matrix detailing how a defect grows as a bridge transitions from severity state i to j. A '-' in the matrix indicates that the extent of a defect cannot improve without an external intervention. The value of γ_{kl} is the probability of transitioning from extent state k to extent state l as the bridge transitions from severity state i to j. In the matrix each row sums to one.

In the genetic algorithm the proportion of the asset in each extent state γ_{kl} was initially selected using a uniform distribution ranging between zero and one. Clearly, this method of selecting transition probabilities can result in cases where the rows of the matrix total to more than one. To address this problem each row was normalized, such that it summed to one. Once the matrix rows were normalized the defect extent for each bridge in the model was transitioned according to the selected probabilities. Once transitioned according to the identified values for γ_{kl} the percentage of bridges found in each defect extents state was noted. The percentages of bridges in each extent state was then compared to the actual distribution and the square of the difference calculated δ. The square of the difference was calculated as follows:

$$\delta = \sum_{i=1}^{n} (O - E)^2 \tag{6}$$

where O is the proportion of the bridges found in each extent state, E is distribution of bridges, as identified from the bridge inspection records, and n is the number of extent ranges. Thus, the aim of the genetic algorithm was to identify a set of solutions that minimized the difference between O and E. The algorithm is able to identify increasingly improved solutions by adjusting the percentage of the bridge stock that transitions from one defect extent state to the next. Using the identified approach clearly results in a number of potential solutions, but when linked with expert input the solution set can be reduced to a credible set. Thus, by using the identified search method the potential solution space does not have to be explored manually.

A set of solutions for D_{ij} is detailed in Equations 7, 8 and 9. To note, in Equation 7, rows 2, 3, and 4 all have γ_{kl} set to 1.00. The value of γ_{kl} was set to 1.00 , because all of the bridges in the 0-5% extent range where in good condition and so rows γ_{2l} and γ_{3l} were not used in this case. The modification to the matrix was carried out manually and was done to highlight that the model does not have to account for these transitions.

$$D_{12} = \begin{bmatrix} 0.90 & 0.10 & 0.00 & 0.00 \\ - & 1.00 & 0.00 & 0.00 \\ - & - & 1.00 & 0.00 \\ - & - & - & 1.00 \end{bmatrix} \tag{7}$$

$$D_{23} = \begin{bmatrix} 0.33 & 0.56 & 0.11 & 0.00 \\ - & 0.95 & 0.05 & 0.00 \\ - & - & 0.25 & 0.75 \\ - & - & - & 1.00 \end{bmatrix} \tag{8}$$

$$D_{34} = \begin{bmatrix} 0.66 & 0.03 & 0.23 & 0.08 \\ - & 0.32 & 0.37 & 0.31 \\ - & - & 0.12 & 0.88 \\ - & - & - & 1.00 \end{bmatrix} \tag{9}$$

MODEL VALIDATION

As highlighted by Landry et al. (1983) a model can be used either to predict the future or to better comprehend what an appropriate strategy might be. Similarly, Heath et al. (2009) also noted that models have a developmental cycle with them starting as generators used to test hypotheses, then becoming mediator models that are used to inform the decision making process, and finally developing into models that are used to predict the future state of the system. Each of these developmental stages requires a different approach to model validation and may include an assessment of whether the concepts and logic used in the model are appropriate, whether the data the model is based on is accurate and whether the model provides appropriately accurate outputs (Landry et al. 1983). Thus, if the purpose of a model is to predict the future, then recognized data and output validation techniques must be employed. In these situations part of the data is used for training the model and the remainder of the data is used to assess the models accuracy. In cases where limited data is available no training data exists and simply asking more experts what their opinion is will result in one collection of opinions being compared to another collection of opinions.

As only five years of severity data existed there was insufficient information that could be used to validate the severity model using recognized techniques. Nevertheless, even in a limited data environment there still has to be a level of confidence that the severity deterioration model will provide credible results. To undertake the validation of the mediator model the construction sequence of 889 bridges constructed over the last 70 years was recreated and the severity and extent states were noted. The modelled bridges comprised 262 concrete, 383 pre-tensioned concrete, 243 steel and 1 timber.

If the annualized level of rehabilitation, after 70 years, approximated to the low level of rehabilitation discussed by the planning agency (NZTA 2011), the results would be considered adequate to mediate between different bridge management strategies. A time period of 70 Years was selected, as it provided a useful planning horizon and also provided the model sufficient time for asset deterioration to occur, given the length of time taken for a bridge to require rehabilitation.

The process used to model the development and deterioration of the identified bridges is detailed in Figure 5. In Figure 5 the required bridges are first created and the state transition times and extent of defects are calculated. Each individual bridge is then aged and the time to the next transition updated. If a new decade is reached the creation of the next group of bridges is triggered and the sojourn times and extent of defects for these bridges is calculated. Each year the requirement to change severity states is assessed and for bridges that have reached their sojourn time limit the sojourn time for the next state transition is calculated. At the same time the defect extent size is also reassessed. The creation of new bridge group and the deterioration of the asset continues until the model reaches the defined 70-year duration, which equates to present day.

The model of the construction and deterioration process was run 10 times and the average number of bridges found in each condition state was noted. An average was taken because of the stochastic process used to select sojourn times and the extent of defects. The mean number of bridges found in each condition state at the end of the modelling process is presented in Table 5. The modelled results are also presented alongside the actual distribution of condition states, which were based on bridge inspection records. It was assumed that the difference between the modelled results and the expected results occurred because of the maintenance that was undertaken over the last 70 years. The rehabilitation required to closely approximate the actual distribution is thus the difference between the modelled and actual condition state distributions. Based on the assumption that bridges in condition states 2A to condition state 4D will require rehabilitation, 663 bridges were identified, which equates to 74.6 % of all bridges requiring rehabilitation after 70 years or 1.1 % of the bridge stock per year. Given that the low rate of rehabilitation that was identified is similar to the reported low rate of rehabilitation, both the severity and extent models are considered accurate enough to be used as mediator models.

CONCLUSIONS

It was identified that a limited numbers of bridges managers were using or were considering the use of bridge deterioration models in New Zealand. Nevertheless, such models are required to provide insight into how best to manage the risks surrounding ageing bridge stocks. To support the development of bridge deterioration models in New Zealand, a bridge model that can be used with the four main bridge materials was presented. The new deterioration model was based on the extent and severity methodology used for a short time in New Zealand. To develop this model a combination of expert input and data mined from the Opus bridge management system was used. In developing the model a number of developmental and verification challenges where encountered, which occurred as a result of the limited availability of data, but these challenges were met using a range of techniques, including a genetic algorithm to search for extent growth matrices. It is hoped that by presenting the novel verification methods and by showing that data does not have to be in great abundance to develop a condition model, a path has been created for those in the early stages of developing their own bridge deterioration models.

REFERENCES

Aboura, K., Samali, B., Crews, K., and Li, J. "Stochastic Processes for Modeling Bridge Deterioration." *Proc., 20th Australasian Conference on the Mechanics of Structures and Materials*, 533-538.

Abramowitz, M., and Stegun, I. A. (1972). *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables*, Dover, New York, United States.

Agrawal, A. K., Kawaguchi, A., and Chen, Z. (2010). "Deterioration Rates of Typical Bridge Elements in New York." *Journal of Bridge Engineering*, 15(4), 419-429.

Bevc, L., Mahut, B., and Grefstad, K. (1999). "Deliverable D2 Review of Current Practice for Assessment of Structural Condition and Classification of Defects, Bridge Management in Europe (BRIME)." Transportation Research Laboratory, Woking, United Kingdom.

Black, M., Brint, A. T., and Brailsford, J. R. (2005). "A Semi-Markov Approach for Modelling Asset Deterioration." *The Journal of the Operational Research Society*, 56(11), 1241-1249.

Bu, G. P., H., L. G., Guan, H., and Loo, Y. C. (2012). "An Integrated Method for Probabilistic Bridge Deterioration Modelling". Paper presented at the Australasian Structural Engineering Conference: The Past, Present and Future of Structural Engineering, Perth, Western Australia

Bush, S. J. W., Omenzetter, P., Henning, T., and McCarten, P. (2012). "Data Collection and Monitoring Strategies for Asset Management of New Zealand Road Bridges."Wellington, New Zealand, 1-160.

Clemen, R. T., and Winkler., R. L. (2007). "Aggregating Probability Distributions." *Advances in Decision Analysis: From Foundations to Applications*, E. Ward, F. M. Ralph, and D. von Winterfeldt, eds., Cambridge University Press, 154-176.

Davis, R. (2008). "Teaching Note—Teaching Project Simulation in Excel Using PERT-Beta Distributions." *INFORMS Transactions on Education*, 8(3), 139-148.

Epstein, J. M. (2008). "Why Model?" *Journal of Artificial Societies and Social Simulation*, 11(4), 12.

Golabi, K., and Shepard, R. (1997). "Pontis: A System for Maintenance Optimization and Improvement of US Bridge Networks." *Interfaces*, 27(1), 71-88.

Goossens, L. H. J., and Cooke, R. M. (2005). "Expert judgement-calibration and combination". Paper presented at the Workshop on expert judgment, Aix En Provence, France, 2005

Heath, B., Hill, R., and Ciarallo, F. (2009). "A Survey of Agent-Based Modeling Practices (January 1998 to July 2008)." *Journal of Artificial Societies and Social Simulation*, 12(4), 9.

Kotze, R., Ngo, H., and Seskis, J. (2015). "Improved Bridge Deterioraton Models, Predictive Tools and Costs." Austroads, Sydney, Australia, i-vi, 1-124.

Kuhn, K. D., and Madanat, S. M. (2005). "Model Uncertainty and the Management of a System of Infrastructure Facilities." *Transportation Research Part C: Emerging Technologies*, 13(5–6), 391-404.

Lake, N., and Seskis, J. (2013). "Bridge Management Using Performance Models." Austroads, Sydney, Australia, i-vii, 1-163.

Landry, M., Malouin, J.-L., and Oral, M. (1983). "Model Validation in Operations Research." *European Journal of Operational Research*, 14(3), 207-220.

Lee, J., Guan, H., Loo, Y.-C., Blumenstein, M., and Xin-ping, W. (2011). "Modelling Long-Term Bridge Deterioration at Structural Member Level Using Artificial Intelligence Techniques." *Applied Mechanics and Materials*, 99-100, 444-453.

Noortwijk, J. M., and Kallen, M.-J. (2014). "Stochastic Deterioration." *Wiley StatsRef: Statistics Reference Online*, John Wiley & Sons, Ltd, 1-8.

NZTA (2011). "Bridges and Other Signficant Highways Structures Inspection Policy."Wellington, New Zealand, 1-20.

NZTA (2011). "State Highway Asset Management Plan 2012-2015." New Zealand Transport Agency, Wellington, New Zealand, 1-106.

NZTA (2014). "Bridge Manual: SP/M/022 (Third Edition)." New Zealand Transport Agency, Wellington, New Zealand, i - F-27.

NZTA (2015). "Bridges and Other Signifcant Highways Structures Inspection Policy."Wellington, New Zealand, 1-27.

Reynolds, J., and Rooke, A. (2009). "A Basic Bridge Information System". Paper presented at the 7th Austroads Bridge Conference, Bridges of the Future, Auckland, New Zealand

Rogers, R. A., Al-Ani, M., and Ingham, J. M. (2013). "Assessing Pre-Tensioned Reinforcement Corrosion Within the New Zealand Concrete Bridge Stock." New Zealand Transport Agency, Wellington, New Zealand, 1-488.

Skulmoski, G., Hartman, F., and Krahn, J. (2007). "The Delphi Method for Graduate Research." *Journal of Information Technology Education: Research*, 6(1), 1-21.

Stonedahl, F. (2010). "BehaviorSearch [Computer Software]." <http://www.behaviorsearch.org/ >.

Thomas, O., and Sobanjo, J. (2013). "Comparison of Markov Chain and Semi-Markov Models for Crack Deterioration on Flexible Pavements." *Journal of Infrastructure Systems*, 19(2), 186-195.

UKHA (2007). "Inspection Manual for Highway Structures, Volume 1: Reference Manual." Highways Agency, ed., The Stationary Office, London, United Kingdom.

Wang, R., Ma, L., Yan, C., and Mathew, J. "Condition Deterioration Prediction of Bridge Elements Using Dynamic Bayesian Networks (DBNs)." 566-571.

Welton, N. J., and Ades, A. E. (2005). "Estimation of Markov Chain Transition Probabilities and Rates from Fully and Partially Observed Data: Uncertainty Propagation, Evidence Synthesis, and Model Calibration." *Medical Decision Making*, 25(6), 633-645.

Wilensky, U. (1999). "NetLogo." Center for Connected Learning and Computer-Based Modeling, Northwestern University Evanston, IL

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Table 1. The Severity Ratings Used in the Deterioration Model

Severity	States noted in the bridge manual	States noted in recent inspection standards
1	Good	As new, and early signs of defects
2	Fair	Moderate defects
3	Deteriorated	Severe Defects
4	Seriously deteriorated	Element failed

Table 2. The Sojourn Times for Concrete, Pre-tensioned, Steel and Timber Bridges

Material	State transition	Sojourn Time (Years)		
		a	m	b
In-situ concrete	1 - 2	28.65	39.25	50.01
	2 - 3	17.33	26.50	35.07
	3 - 4	7.34	11.45	18.29
	Life estimate	53.32	77.20	103.37
Pre-tensioned concrete	1 - 2	30.56	39.73	47.59
	2 - 3	15.88	27.01	34.37
	3 - 4	7.22	11.33	16.38
	Life estimate	53.66	78.07	98.34
Steel	1 - 2	22.89	31.60	41.91
	2 - 3	12.88	15.68	19.68
	3 - 4	6.41	9.97	14.30
	Life estimate	42.18	57.25	75.89
Timber	1 - 2	16.24	20.39	25.74
	2 - 3	9.38	20.04	28.46
	3 - 4	5.02	7.53	14.16
	Life estimate	30.64	47.96	68.36

Table 3. The Extent Ratings Used in the Deterioration Model

Extent	Description
A	Slight, not more than 5 % of the surface area/length/number
B	Moderate, 5 % - 20 % of the surface area/length/number
C	Wide, 20 % - 50 % of the surface area/length/number
D	Extensive, more than 50 % of the surface area/length/number

Table 4. The Percentage of Load Bearing Elements in a Given Extent Range

Severity	Defect Extent Range (State: %)			
	A: 0 - 5	**B: 5 – 20**	**C: 20 - 50**	**D: 50 – 100**
1	100.0			
2	93.4	3.5	3.1	
3	28.4	63.2	7.3	1.1
4	28.6	14.3	42.8	14.3

Table 5. Comparing the Modelled and Actual Condition Distributions after 70 years

Condition state	Modelled condition distribution	Actual condition distribution	Rehabilitation required
1A	833	185	
1B	9	0	
1C	2	0	
2A	8	597	589
2B	29	72	43
2C	3	0	
3A	0	13	13
3B	1	19	18
3C	2	3	1