Development of a Long-term Bridge Element Performance Model Using Elman Neural Networks

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ABSTRACT

A reliable deterioration model is essential in bridge asset management. Most deterioration modelling requires a large amount of well-distributed condition rating data along with all bridge ages in order to calculate the probability of condition rating depreciations. This means that the model can only function properly when a full-set of data is available. To overcome this shortcoming, an improved Artificial Intelligence (AI)-based model is presented herein to effectively predict long-term deterioration of bridge elements. The model has four major components: (1) categorising bridge element condition ratings; (2) using the Neural Network-based Backward Prediction Model (BPM) to generate unavailable historical condition ratings for applicable bridge elements; (3) training by an Elman Neural Network (ENN) for identifying historical deterioration patterns; and (4) using the ENN to predict long-term performance. The model has been tested using bridge inspection records which demonstrate satisfactory results. This study mainly focuses on the establishment of a new methodology to address the research problems identified. A series of case studies, hence, need to follow to ensure the method is appropriately developed and validated.

CE Database subject heading: Bridges; Deterioration; Long-term performance predictions; Neural Network.

Author keywords: Bridge deterioration; Element level analysis; Artificial Intelligence (AI); Backward Prediction Model (BPM); Elman Neural Network (ENN).

1 INTRODUCTION

The efficient use of maintenance funds and of budgeting for the well-being of bridges requires an effective bridge asset management technology and its application. A Bridge Management System (BMS) is nowadays essential and helps determine the complexity of decision-making for bridge maintenance, repair and rehabilitation (MR&R) strategies for bridge authorities. The most well-known commercial version of BMS software was developed in the early 1990s and has become a common tool for many bridge agencies worldwide. However in current asset management practice, there still remain some fundamental shortcomings associated with the health status of bridge elements for long-term planning of asset management strategies. A bridge element or element type refers to a group of similar structural members (e.g. beams, columns, or support bearings etc) of a bridge. Reliable long-term forecasting of bridge element performance is crucial and can be used as input information for various key functions in a BMS, i.e. cost-related and MR&R priority etc. However, the reliability of currently available long-term performance modeling is still doubtful thus requiring further development. However there exist some underlying problems with respect to the development of a deterioration model. They are elaborated below:

(1) Insufficient historical condition ratings: The deterioration rate is calculated based on historical condition ratings obtained from routine bridge inspections, i.e. the structural element-level bridge inspections. Commercial BMS software has only been used for less than 20 years and even those bridge agencies which implemented BMSs from an early stage, have only approximately 7 to 9 inspection records per structure. Although most bridge authorities have previously conducted inspections, these past inspection records are incompatible with what are required by a typical BMS as input. Such incompatibility is one of the causes for the deficiency of the current BMS outcomes. Because of limited bridge condition rating records, it is very difficult to use typical stochastic-based deterioration models to accurately predict future condition ratings. This limitation has been recognised and has not yet been adequately addressed (Agrawal et al. 2006; DeStefano and Grivas 1998; Madanat et al. 1997; Morcous et al. 2000).

(2) Overall Condition Rating (OCR) methods: The OCR methods are used in most existing bridge management technologies. The condition rating information is collected via a quantitative bridge inspection procedure; it is then converted into OCR in a subjective manner. The conditions of bridge elements collected using the element-level bridge inspection process, are expressed quantitatively via the conventional "grading" system, i.e. the health index or the four condition states (CSs 1 to 4). The overall condition of one or more element types of a bridge is calculated with the aid of a weighted average condition state (CS) numbering system. Thus the OCR is incapable of capturing the condition status of individual structural members (i.e. individual beams, piers etc), be it at CS1 (i.e. condition as new or "excellent"), CS2 ("fair"), CS3 ("poor") and CS4 ("very poor"). This is a key drawback because bridge collapse may occur as a result of the failure of single member(s). In view of this, each of the four CSs for individual members needs to be evaluated in order to reduce the risks of total bridge failure. A further drawback with this stepwise "grading" system is that there are only four CSs with graduation of 1/4 or 25%. Such a step is too large to be used effectively in deterioration modeling. For example, for a CS2 rating, the numerical weighting is 62.5% which is the average of 75 and 50%, whereas in reality the condition of the member can be anywhere between "as new" and "defective". This indeterminacy seriously increases the degree of uncertainty with time in predicting long-term bridge element performance. Note also that it is too expensive to change the current inspection method, which has been used for many years and already produced massive amounts of historical condition rating records. Any change to the current inspection method will be cost ineffective and will also create data-incompatibility issues.

Despite the abovementioned limitations, substantial research has been conducted to develop a reliable bridge deterioration model. Among many existing research outcomes, stochastic bridge deterioration modeling is one of the most prominent techniques. It can be classified into two types, namely state- and time-based. Some limitations in state-based modeling are: (1) initial condition ratings are independent of the historical condition ratings (a stationary process which is memory-less) and transition probabilities are constant (DeStefano and Grivas 1998); (2) lack of knowledge of the hidden nature of deterioration (Madanat et al. 1995); (3) failure to account for maintenance issues; (4) only handles an ideal condition rating data distribution (Mishalani and Madanat 2002). On the other hand, time-based modeling overcomes many of the disadvantages of state-based modeling: (1) it considers the time spent in an initial condition state (DeStefano and Grivas 1998) - meaning that it overcomes the limitations of the stationary process; and (2) it provides more reliable long-term prediction than the state-based model if the condition rating data is available over a long period of time (Mauch and Madanat 2001). However, the decision of which type of modeling is more appropriate for deterioration prediction is also highly dependent on the nature of the available condition ratings with time (bridge ages) (Mishalani and Madanat 2002). In other words, the stochastic approaches cannot guarantee workable modelling and/or reliable long-term prediction for various situations of condition rating input. Consequently, such fundamental problems as modeling input requirements still remain which need to be overcome.

To address the abovementioned problems, an Artificial Intelligence (AI)-based Backward Prediction Model (BPM) has been developed (Lee et al. 2008) to generate unavailable bridge condition ratings. The BPM also provides unknown historical bridge deterioration patterns to assist in predicting reliable long-term bridge deteriorations. In addition, an AI-based bridge deterioration modelling incorporating both BPM and Time-Delay Neural Network (TDNN) has also been proposed (Lee et al. 2008; Son et al. 2010) to improve the accuracy of long-term prediction. Despite such advancement of the deterioration modelling technique, for some cases of given type of element condition ratings from a single bridge, uncertainty has been observed in long-term prediction due to frequent maintenance (reactive MR&R strategy). As a result, less meaningful deterioration trends, i.e. irregular noise patters, were identified in the TDNN training for long-term prediction.

Therefore this study aims to develop an improved AI-based methodology to provide enhanced long-term prediction outcomes for reliable element level analysis. The development constitutes the following new components: adding a categorisation process and replacing the TDNN by an Elman Neural Network (ENN). Categorisation is the process of sorting and grouping in accordance with structural location, climatic zone, construction era, element type and material type. This categorisation process is added before performing the ANN process in order to observe common condition depreciation patterns from given condition data. This will in turn provide reliable neural network training outcomes.

2 STRUCTURE OF THE PROPOSED DETERIORATION MODEL

As previously indicated, the model has four main components: (1) Categorisation; (2) Generating missing historical condition records by BPM for eligible structural elements; (3) training by Elman Neural Network (ENN) for identifying historical deterioration patterns of a given type of structural elements; and (4) Performing long-term prediction. The structure of the model is depicted in Figure 1.

Figure 1. Flowchart for the Proposed AI-based Deterioration Model

A timeframe of the proposed AI-based deterioration model is presented in Figure 2. Detailed in the figure are indications of the time periods: year of construction completion (t_0); available condition ratings (t_p ~ t_{pn}); BPM inputs (t_0, t_p ~ t_{pn}); BPM outputs (t_1 ~ $t_{p\text{-}1}$); BPM and ENN validation using BPM outputs (t_1 ~ t_{p-1}); and ENN long-term prediction (t_{f1} ~ t_{fn}) using available and BPM-generated condition ratings (t_0 ~ t_{pn}).

Figure 2. Timeframe of the Proposed AI-based Model

2.1 Categorisation

Categorisation is the first step in the model when new condition data are received. In this study, available inspection records can be classified by bridge location, climatic condition, construction era, element type and material type. However it can be further classified based on information available from the bridge agencies. The aim of this classification is to group bridge elements of similar deterioration causes, for an enhanced identification of deterioration patterns within the grouped elements. It should be noted that the reason for inclusion of bridge construction era is due to the dissimilarity of bridge deterioration rates at different bridge ages. The different deterioration rates are also caused by the qualities of construction materials and methods, which have continuously improved in the last few decades as compared to the earlier constructed bridges. Therefore for bridges of different ages, their condition depreciation patterns could be different. In order to obtain more reliable prediction outcomes, the construction era classification follows an adopted zoning technique, which has been used in the development of pavement performance (Butt et al. 1987). In this study, is the grouping is done in 20 year segments, i.e. group 1 (2001-current year), group 2 (1981-2000), group 3 (1961-1980), and group 4 (prior to 1960). The outcomes of categorisation provide more common reference with respect to condition depreciation within the grouped elements. This in turn will assist the Elman training session.

2.2 Backward Prediction Model (BPM)

The BPM methodology in conjunction with the Elman Neural Networks (ENNs) technique is employed in this study. In the previously developed AI-model (Lee et al. 2008), missing condition ratings can be generated by the BPM to minimise the problem of insufficient historical condition rating data. This is done because: (1) it is difficult to obtain individual historic maintenance records for older bridges for the BPM to effectively generate the missing condition data; and (2) historical condition depreciation patterns will be obtained from a group of a given type of elements – whereas in the previous AI-model, it was obtained from a single element of a bridge. Accordingly, the BPM is only applicable for the following cases in this study: (1) when maintenance, repair and rehabilitation (MR&R) activity is performed at a known time; (2) no MR&R is performed after the construction year; and (3) if condition ratings at the year of construction can be confidently assumed by a bridge asset engineer.

In the case when the BPM is applicable, the missing historical condition ratings are generated (backward prediction) by the following mechanism as illustrated in Figure 3. An Artificial Neural Network (ANN) technique establishes the correlation between the existing condition rating datasets (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 hence the deterioration rate. The correlations are then applied to generate the historical trends using the non-bridge factors from year t_0 to t_p (Lee et al. 2008). The missing historical condition ratings for years $t_1 \sim t_{p-1}$ can then be generated. Each year of the BPM outcome, i.e. generated condition ratings, includes 66 data outputs which results from the combined number of learning rates (*lr*: 0.0-0.5) and momentum coefficients (*mc*: 0.0-1.0) in the neural network configurations. The number 66 also corresponds to the total quantity of a given bridge element. A forward comparison method is utilised in the BPM methodology to validate the BPM results. It produces forward prediction for years $t_p \sim t_{pn}$ using the BPM outcomes (years $t_1 \sim t_{p-1}$). The results of the forward predictions are then compared with the actual BMS condition ratings ($t_p \sim t_{pn}$). Once validated, the BPM-generated condition data is ready for training by the Elman Neural Network.

Figure 3. Mechanism of BPM (Lee et al. 2008)

It is also necessary to conduct time rescaling to generate historic condition paths by OCR over bridge ages. It is for a given type of bridge element from a bridge network. The original condition path of each bridge element is distributed across the years (year of inspection) as shown in Figure 4 (a) and, as a result, it is difficult to find their common deterioration patterns. On the other hand, the distribution of condition data over bridge ages is able to provide an effortless observation for network deterioration patterns as demonstrated in Figure 4 (b).

Figure 4. Time Rescaling: (a) OCR over inspection years; and (b) OCR over bridge ages.

2.3 Elman Neural Network (ENN) Training and Long-Term Bridge Performance (LTBP) Prediction

The Elman Neural Network (ENN) has been used in various fields for time related domains and is one of the well-known recurrent neural networks (Elman, 1990). Recurrent neural networks have a feedback architecture and can be distinguished from feed-forward neural networks. A typical ENN has three layers: input, middle (hidden) and output layers. A generalised structure of the ENN for the proposed study is depicted in Figure 5.

Figure 5: Structure of the ENN used in the Proposed Model

A hidden layer with delayed feedback in an ENN is composed of two layers, i.e. recurrent and linear layers. ENN feedback is used to construct memory within the local feedback loop. In Figure 5, the so-called context nodes are copied from the corresponding hidden nodes and are used to store memories from previous output values of the hidden layer neurons. Thus the network can maintain preceding events, allowing it to better perform sequence-prediction. In the proposed model, a condition rating at time (*t*) resulted from the last condition rating at time (*t*-1) is looped back as an input to the neural network at time (*t*). The local feedback loop provides a precedent with respect to the proceeding input condition rating. This ENN function is useful in providing superior learning outcomes for such temporal, spatial and chaotic input values (Elman, 1990). Thus, an ENN is effective for sequential prediction using such non-linearly characterised bridge deterioration patterns obtained from irregularly distributed condition data over time.

The proposed ENN provides only one-step ahead prediction at a time (one cycle). The result of the first one-step-ahead prediction is added onto the original ENN input (t_0 ~ t_{pn}). This indicates that the number of inputs to the ENN increases in the second cycle of the one-step-ahead prediction. Iterations of the above-described process are required until prediction up to year t_{fn} is completed.

Once network performance is predicted by the ENN, the probability of transition from one state to another over multiple discrete time intervals is required to be calculated based on the performance curve (Bogdanoff 1978; Jiang 1990). This is also referred to as the condition rating transition from one CS*i*, to another CS*j*, during a one unit year period, which is denoted by $p_{i,j}$. Based on the typical state-based stochastic modelling, the CS vector for any time t, $Q(t)$, can be obtained by multiplication of the initial CS vector $Q(0)$ and the transition probability matrix P to the power of t, which can be presented as follows:

$$Q(t) = Q(0) \times P^t \tag{1}$$

Hence, the transition probability matrix P can be defined as:

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

where $q(i)$ = 1-$p(i)$, $p(i)$ corresponds to $p_{i,i}$ and $q(i)$ corresponds to $p_{i,i+1}$. In Eqn. (2), $p(1)$ represents the probability of bridge elements remaining in the CS1, and $q(1)$ denotes the probability of bridge elements transferring to the next CS. Hence, the corresponding probability $p(4)$ is assumed to be 1. Let R be a vector of condition ratings, R = [100, 70, 50, 20], and R^T be the transpose of R, then the estimated condition ratings at age t provide the following:

$$E(t) = Q(t) \times R^T \tag{3}$$

In this study, the transition probability is obtained by minimising the difference between the condition ratings $A(t)$ from the predicted network performance curve by the ENN and the estimated condition ratings $E(t)$. This non-linear objective function can be described as:

$$Min \sum_{t=1}^{N} \left| A(t) - E(t) \right| \text{ subject to } 0 \le P(i) \le 1, i = 1,2,3....,U. \tag{4}$$

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

3 MODEL DEMONSTRATION

This section demonstrates the proposed model using a group of bridge element condition ratings provided by the Queensland Department of Transport and Main Roads (QTMR). The chosen bridge element is the concrete slab defined as 20C – obtained from 61 inspection records of 25 sample bridges. The construction era of these 25 bridges is between 1980-2000. All bridge elements have been inspected at a maximum of 3 with an average inspection records of 2.44 per element. The condition ratings of all the 25 slab elements are displayed in Figure 6.

Figure 6. Condition paths of the concrete slab element (20C) from 25 sample bridges

After categorising the available inspection records, an Overall Condition Ratings (OCR) is calculated for a given sample of condition ratings. The condition ratings are collected by Level 2 routine inspections to quantify the severity and extent of defect bridge elements. A four-CS scale is used in order of 1 to 4 (excellent to very poor), and in this study this scale represents the bridge condition ratings from 100% to 20% in a descending order. The OCR can be calculated based on the pre-defined element condition rating scale with the average weights of each Condition State (CS), as shown in Figure 7. The calculation of OCR is presented below:

$$\mathrm{OCR} = \frac{q_1 w_1 + q_2 w_2 + q_3 w_3 + q_4 w_4}{q_1 + q_2 + q_3 + q_4} \tag{5}$$

where, q_1, q_2, q_3 and q_4 are the element quantities in CSs 1, 2, 3 and 4, respectively, and w_1, w_2, w_3 and w_4 are the corresponding weightings of each CS (Thompson and Shepard 2000).

It should be noted that the sample bridge information is randomly selected from a regional network within a large bridge network. The results presented in this paper thus do not intend to reflect the official view of the bridge authority from which the condition ratings are obtained.

Figure 7. Condition rating scale and average weights of each Condition State (CS).

After OCR calculation, the process requires that the eligibility of the BPM to generate missing condition ratings is validated. Amongst the given samples, 12 bridges (Bridge# XX47XX, XX48XX, XX76XX, XX77XX, XX78XX, XX80XX, XX81XX, XX92XX, XX131XX, XX144XX, XX145XX, XX23897XX) are found to be eligible for applying the BPM. Also collected to be used in the BPM are the non-bridge factors of the corresponding years 1980-2000 (as the construction era), which are presented in Figure 8. The non-bridge factors are the historic climatic conditions (humidity, minimum and maximum temperature, maximum differences of temperature and rainfall) obtained from the local weather stations.

Figure 8. Non-bridge factors used in the BPM: (a) humidity; (b) temperatures; and (c) rainfall.

The specifications for the inputs, outputs and functions of the BPM are detailed in Table 1. The input layer accepts condition ratings (t_0 and $t_p \sim t_{pn}$) and their corresponding years' non-bridge factors. Note that the notations for time (t) can be referred to Figure 2. The inputs used in the BPM are trained using the feed-forward back propagation algorithm.

Table 1. Components of the BPM

For Bridge#XX80XX as an example, BPM requires the existing condition ratings (years 2000, 2003 and 2009, i.e. 3 of inspection records) together with the assumed condition rating at year of construction completion (CS1-Excellent at 1994) to generate missing condition ratings. The corresponding years' non-bridge factors are also required by the BPM to establish the relationship with the available condition data, and subsequently the BPM is able to generate missing condition rating data (1995-1999) using the non-bridge factors of years $t_1 \sim t_{p-1}$. An identical process can be applied to the other bridge elements in order to generate their missing condition data. The generated condition data are added to the existing condition rating data sets, as shown in Figure 9, to provide more meaningful distribution of the condition data over time. This in turn will provide more reliable and reasonable condition depreciation patterns for the given bridge element type.

Figure 9. The condition data distribution over time for the concrete slab element from 25 bridges

4 RESULTS OF LONG-TERM PREDICTION AND DISCUSSION

The existing and generated condition data sets are ready to be used as ENN input values to predict long-term network performance of a given bridge element type. The result of the first one-step-ahead prediction (i.e. t_{30}) is added on to the original ENN input (t_1 - t_{29}) for performing the prediction at time (t_{31}). In this study, iterations of this one-step-ahead prediction process are continued for 25 cycles without considering the maintenance effects. The outcomes of long-term network performance of the chosen element type 20C are presented in Figure 10 (a). The total number of long-term prediction by ENN is 10. Prior to the acceptance of these outcomes, the predicted condition ratings are required to undergo a filtering process for further improvement of long-term prediction quality. The filtering process follows a simple criterion, i.e. Condition Rating $_{(\text{year n-1})} \geq$ Condition Rating $_{(\text{year n})}$. In other words, the condition rating should not be improved if no MR&R, i.e. preservation, is undertaken. This is true because bridge deterioration may progress continuously, gradually and slowly (Mauch and Madanat 2001). In view of this, Long-term prediction (LTP) 2 as presented in Figure 10 (a) is removed from the long-term performance predictions. This is because the prediction result of LTP 2 at bridge age 54 (OCR=75.544) has increased by 0.054% as compared to that of the preceding year (i.e. age 53 with OCR=75.490).

Figure 10. Long-term network performance prediction for element type 20C – "Do Nothing" maintenance effect: (a) All prediction results from ENN; and (b) Selected long-term performance outcomes.

Upon completion of filtering, the selected long-term performance results are presented in Figure 10 (b). Long-term performance curves are required to be selected to calculate the transition probability at the network level to the element level. In this study, the worst case scenario, i.e. LTP 7, is selected. The selected long-term prediction by ENN together with the estimated value of condition ratings at each year, as presented in Figure 11, are used to calculate the transition probability at the element level.

Figure 11. Long-term network performance for element type 20C – "Do Nothing" maintenance effect

In order to predict the performance of individual bridge elements, the transition probability is calculated using Equations (1) - (4). Figure 12 presents the transition probabilities of each age group for element type 20C in a matrix form. The values in each group age represent the probability of the element quantities remained in the current condition state. For example, for bridge element type 20C with age group (20-25), 93.2% of the element quantities remain in CS1 during a one year interval.

Figure 12. Transition probability matrix for element type 20C

The advantage of this study in determining the transition probabilities lies in the use of the long-term network performance curves predicted by the ENN ($t_1 \sim t_{pn}$, $t_{f1} \sim t_{fn}$), whereas typical state-based stochastic modelling can only provide the transition probability for years ($t_1 \sim t_{pn}$). Thus, the typical approach usually assumes a probability in-between $t_{f1} \sim t_{fn}$, which is the same as the probabilities of last age group within $t_1 \sim t_{pn}$ (Butt et al. 1987). This assumption inevitably ignores the nonlinear behaviour of the bridge deterioration process. This indeed is a common shortcoming of the existing state-based stochastic deterioration modelling.

It is worthwhile mentioning that the accuracy of the transition probability depends on the closeness of $A(t)$ and $E(t)$. The Chi-square goodness of fit test can often be used to validate the accuracy of the transition probability. The Chi-square method is given below:

$$\chi^2 = \sum_{i=1}^{k} \frac{(E_i - A_i)^2}{E_i} \tag{6}$$

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 state-based stochastic modeling, A_i = value of condition rating in year i predicted by network performance curve, and k = number of prediction years. Upon establishment of the transition probability matrices and an initial state vector defined from the given condition ratings for each bridge element, the bridge condition ratings can be predicted by using Equations (1) and (3).

Table 2 presents the degrees of freedom, the critical χ^2 values at the significance level α = 0.05 and those obtained from the long-term performance curve using the ENN. The comparisons show that the estimated χ^2 values for bridge element 20C are much smaller than those at the significance level α = 0.05. This suggests that the generated transition probabilities are acceptable for predicting long-term bridge performance.

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

Once the transition probabilities are confirmed, the long-term bridge element prediction can be simply performed using Equations (1) and (3). The outcome of Equation (1) indicates the percentage of element quantities, whereas the outcome of Equation (3) represents the OCR values. As illustrated in Figure 13, bridge element 20C-Bridge #XX94XX is chosen as an example to demonstrate long-term bridge element performance prediction. The figure presents the future condition ratings of the bridge element by element quantities and OCRs. The long-term prediction is based on the latest inspection record as an initial condition state vector, by which the element condition ratings for the future 25 years are predicted. It is evidenced in the figure that the predicted condition ratings gradually decrease as the bridge age increases. This suggests that the transition probabilities correctly reflect the network bridge deterioration pattern.

Figure 13. Example of long-term performance for bridge element type 20C (Bridge#XX131XX) – "Do Nothing" maintenance effect

5 CONCLUSION

The previously developed AI-based bridge deterioration modelling technique incorporating the Backward Prediction Model (BPM) has been refined to improve accuracy of long-term prediction of individual bridge elements. This AI-based model has incorporated a Time-Delay Neural Network (TDNN), which has a strong ability to detect patterns from dynamic data. Nevertheless, in some cases, it provides irregular noise pattern(s) or illogical pattern(s) leading to poor training results. This has been found to be impractical from the perspective of bridge asset management practice and there are a number of issues associated with this approach. These issues are: (1) it is difficult to acquire a confident level of condition ratings at the year of construction completion (t_0) and at the year after maintenance work completion (in between t_1 ~ t_{p-1}); and (2) there is change in condition states in some of the available condition data (t_p ~ t_{pn}). In order to address the above-mentioned issues, this study presents a new and enhanced AI-based methodology aiming to improve the reliability of long-term prediction outcomes. The enhancement is reflected by a categorisation process in conjunction with an Elman Neural Network (ENN) technique in the deterioration prediction model. The new model helps to minimise the deficiency of historic condition transitions in individual elements and to provide meaningful condition depreciation patterns for time-series prediction of a given type of network bridge elements.

A series of case studies will be carried out in the next stage of study to further confirm the methodology presented in dealing with various situations with respect to the condition rating data availability and their various distributions. Further work should also consider the maintenance effects in predicting long-term bridge element performance. Nevertheless, the outcome of the present study is useful to bridge authorities, which may experience difficulties in using the existing deterioration modelling techniques.

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ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
BMS	Bridge Management System
BPM	Backward Prediction Model
CS	Condition State
ENN	Elman Neural Network
LTBP	Long-term Bridge Performance
MR&R	Maintenance, Repair & Rehabilitation
OCR	Overall Condition Rating
TDNN	Time-Delay Neural Network

Table 1. Components of the BPM

Training Algorithm	Back Propagation Algorithm
Transfer Function	Log-sigmoid Function
Inputs	Climates (5 factors), Condition ratings (4 sets): assumed condition rating (t_0) and available condition ratings (t_p~t_{pn}).
Total number of input neurons	6@each year
Hidden layers	2
Output	Bridge condition ratings (t_1 ~ $t_{p\text{-}1}$)
Total number of output neurons	1@each year
Scale of learning rate (*lr*)	0.0 – 0.5 in 0.1 steps (5 cases)
Scale of Momentum coefficient (*mc*)	0.0 – 1.0 in 0.1 steps (11 cases)
Total number of cases generated	66 (combination of lr and mc)@each year

Table 2. Comparison of the χ^2 values at significance level α = 0.05

Bridge Element	Element name	Construction era	Degrees of freedom	$\chi^2_{critical}$ (α=0.05)	χ^2 from Elman method
20C	Deck slab	1980-2000	48	65.17	0.016

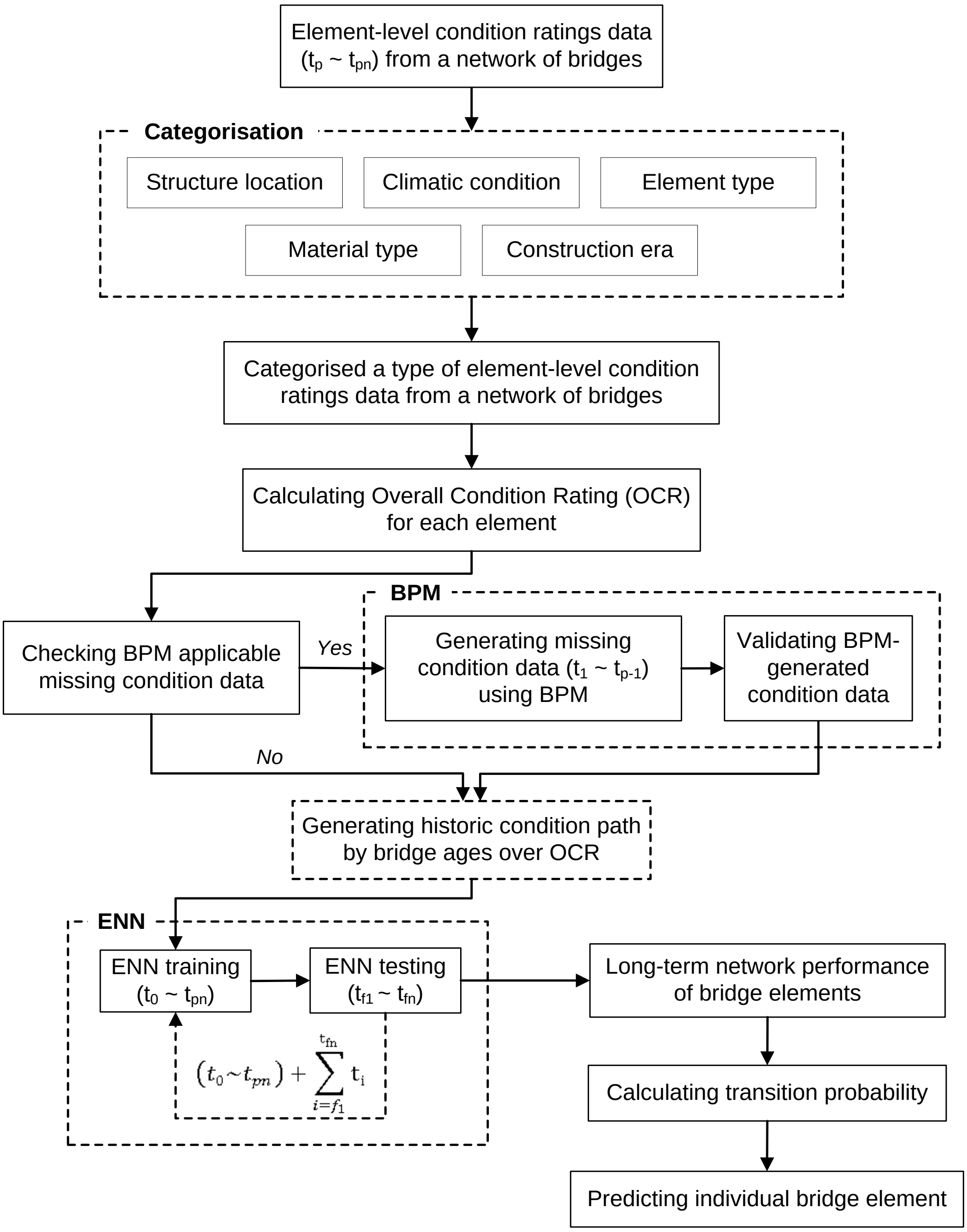


Figure 1. Flowchart for the Proposed AI-based Deterioration Model

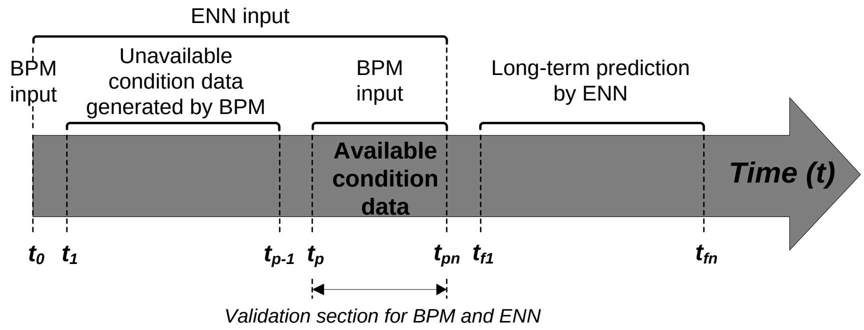


Figure 2. Timeframe of the Proposed AI-based Model

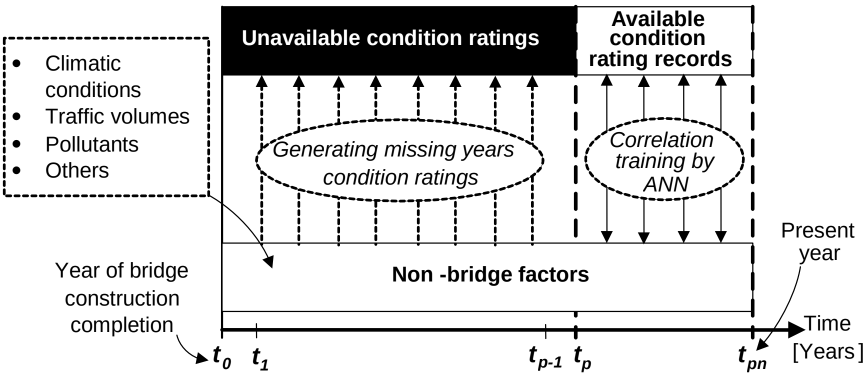
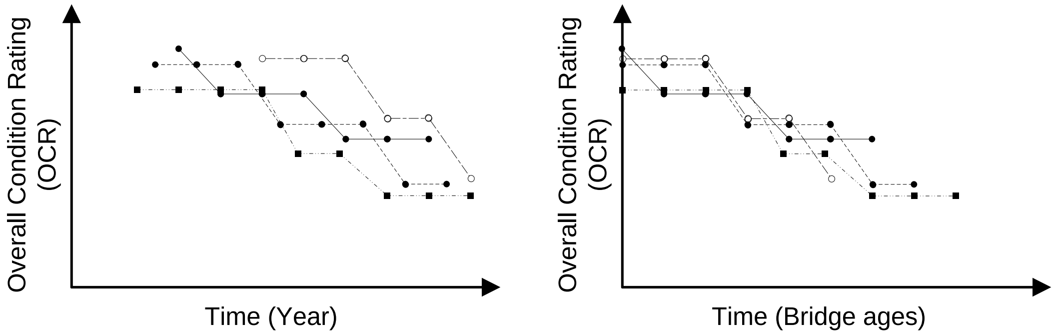


Figure 3. Mechanism of BPM (Lee et al. 2008)



(a) (b)

Figure 4. Time Rescaling: (a) OCR over inspection years; and (b) OCR over bridge ages.

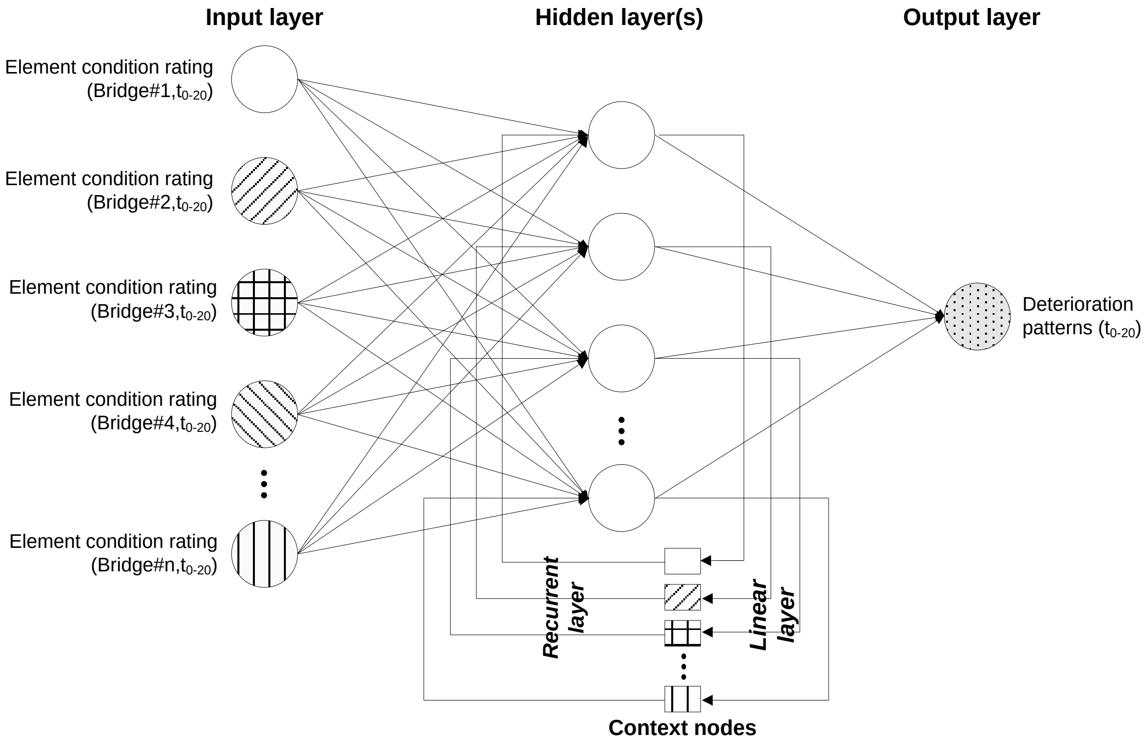


Figure 5. Structure of the ENN used in the Proposed Model

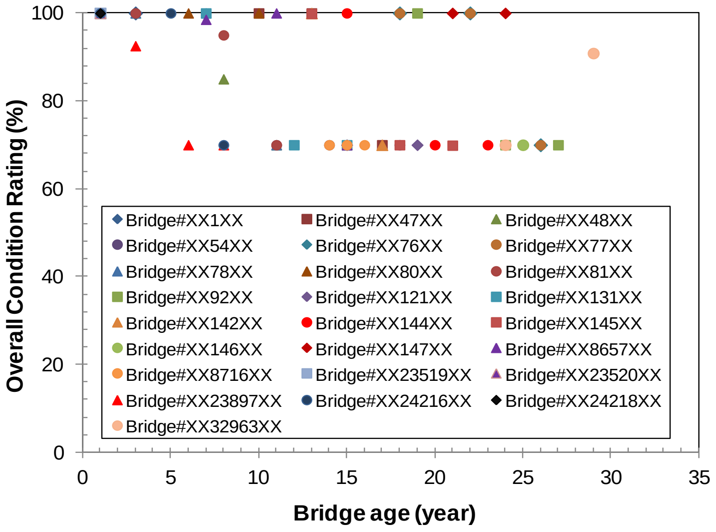


Figure 6. Condition paths of the concrete slab element (20C) from 25 sample bridges

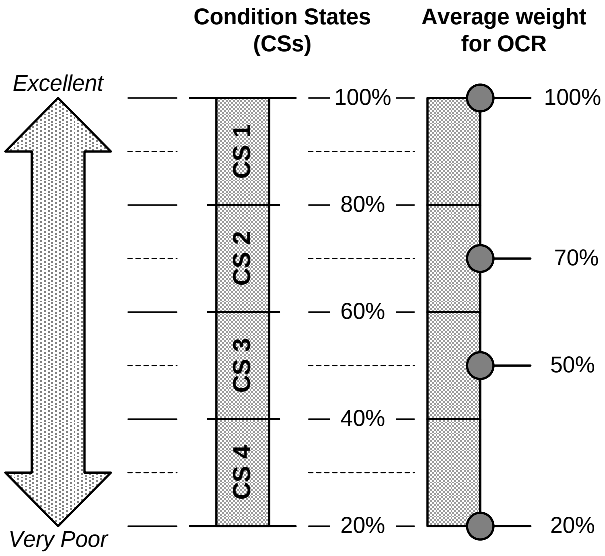


Figure 7. Condition rating scale and average weights of each Condition State (CS).

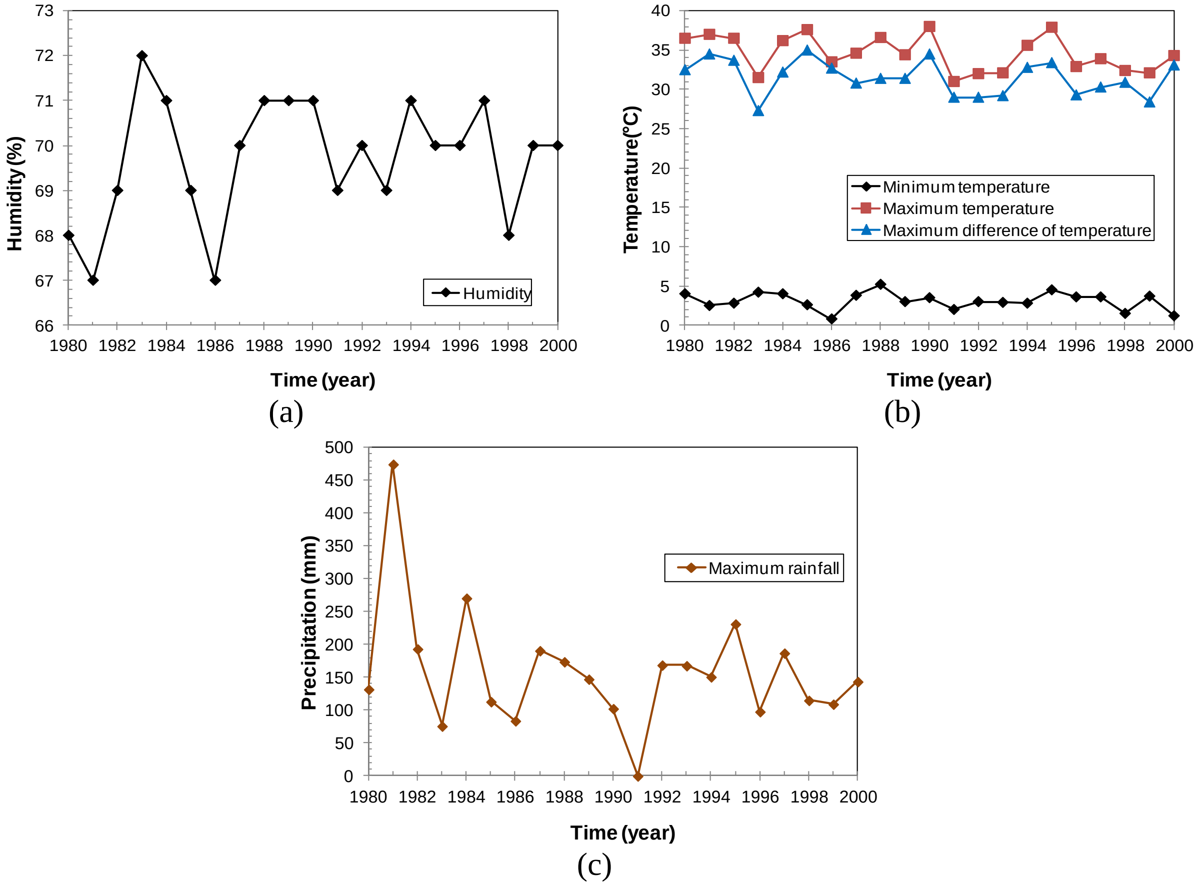


Figure 8. Non-bridge factors used in the BPM: (a) humidity; (b) temperatures; and (c) rainfall.

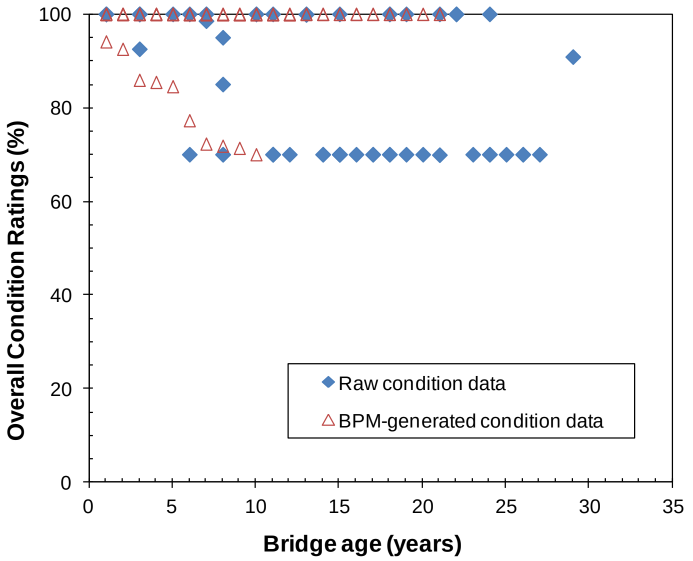
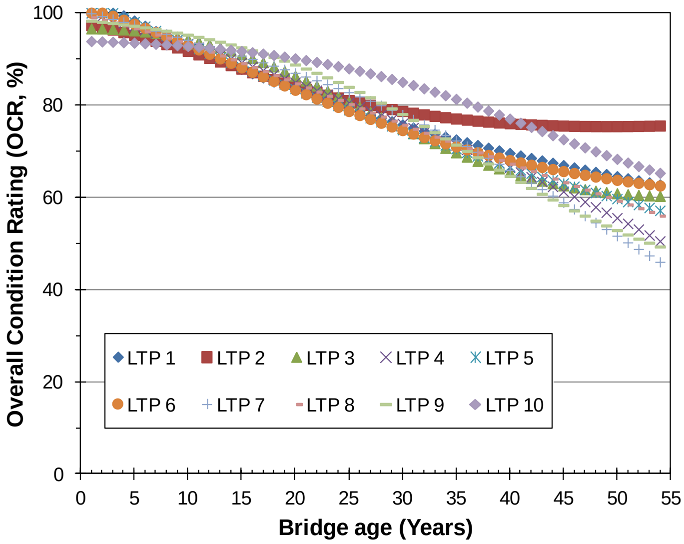
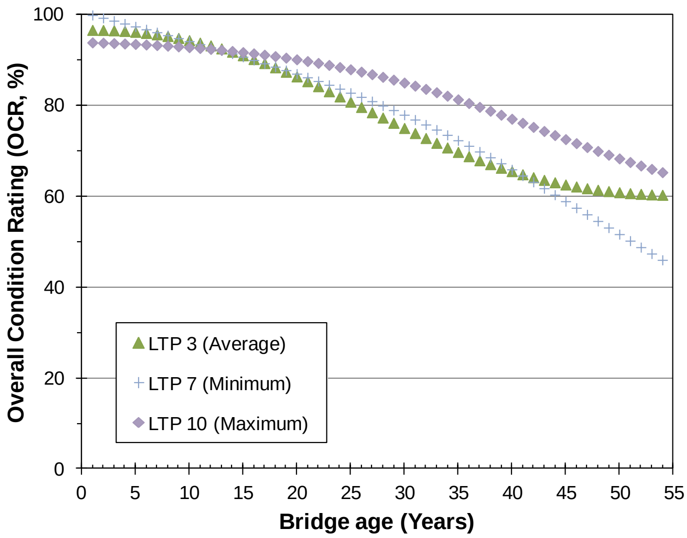


Figure 9. The condition data distribution over time for the concrete slab element from 25 bridges



(a)



(b)

Figure 10. Long-term network performance prediction for element type 20C – "Do Nothing" maintenance effect: (a) All prediction results from ENN; and (b) Selected long-term performance outcomes.

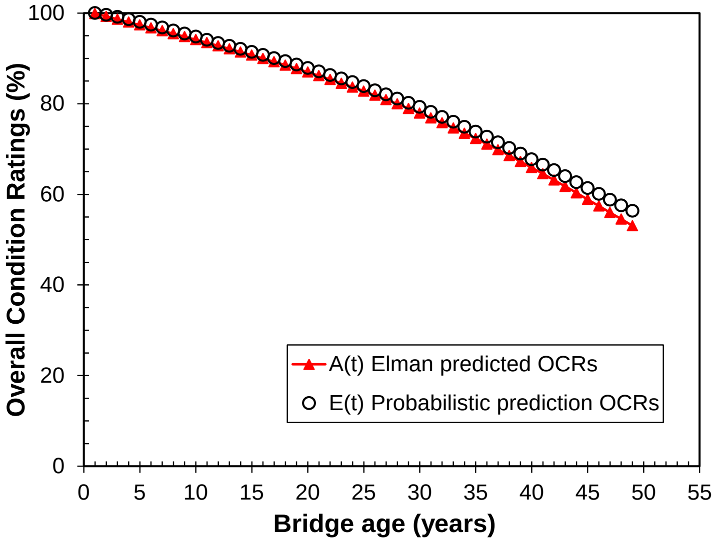


Figure 11. Long-term network performance for element type 20C – "Do Nothing" maintenance effect

Transition matrix for bridge age group (1-7)

	1	**2**	**3**	**4**
1	0.987	0.013	0	0
2	0	0.697	0.303	0
3	0	0	0.856	0.144
4	0	0	0	1.000

Transition matrix for bridge age group (8-13)

	1	**2**	**3**	**4**
1	0.979	0.021	0	0
2	0	0.925	0.075	0
3	0	0	0.993	0.007
4	0	0	0	1.000

Transition matrix for bridge age group (14-19)

	1	**2**	**3**	**4**
1	0.987	0.013	0	0
2	0	0.915	0.085	0
3	0	0	0.923	0.077
4	0	0	0	1.000

Transition matrix for bridge age group (20-25)

	1	**2**	**3**	**4**
1	0.983	0.017	0	0
2	0	0.915	0.085	0
3	0	0	0.937	0.063
4	0	0	0	1.000

Transition matrix for bridge age group (26-31)

	1	**2**	**3**	**4**
1	0.978	0.022	0	0
2	0	0.908	0.092	0
3	0	0	0.939	0.061
4	0	0	0	1.000

Transition matrix for bridge age group (32-37)

	1	**2**	**3**	**4**
1	0.970	0.030	0	0
2	0	0.900	0.100	0
3	0	0	0.938	0.062
4	0	0	0	1.000

Transition matrix for bridge age group (38-43)

	1	**2**	**3**	**4**
1	0.962	0.038	0	0
2	0	0.896	0.104	0
3	0	0	0.929	0.071
4	0	0	0	1.000

Transition matrix for bridge age group (44-49)

	1	**2**	**3**	**4**
1	0.954	0.046	0	0
2	0	0.885	0.115	0
3	0	0	0.926	0.074
4	0	0	0	1.000

Figure 12. Transition probability matrix for element type 20C

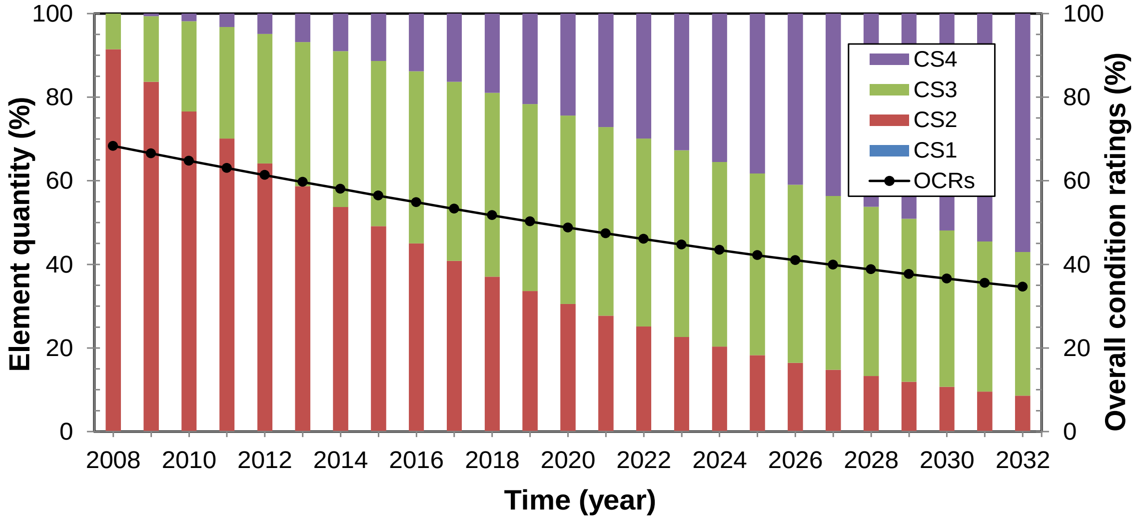


Figure 13. Example of long-term performance for bridge element type 20C (Bridge#XX131XX) – "Do Nothing" maintenance effect