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OPTIMISATION OF ASSET MANAGEMENT METHODOLOGY FOR A SMALL BRIDGE NETWORK

Jaeho Lee[1] and Kamalarasa Sanmugarasa[2]

[1] Research Fellow, Griffith School of Engineering, Gold Coast campus, Griffith University, Australia
[2] Managing Director, Asset-Smart Engineering Services P/L, Gold Coast, Australia
Correspond to j.lee@griffith.edu.au

ABSTRACT: A robust asset management methodology is essential for effective decision-making of maintenance, repair and rehabilitation of a bridge network. It can be achieved by a computer-based bridge management system (BMS). Successful BMS development requires a reliable bridge deterioration model, which is the most crucial component in a BMS, and an optimal management philosophy. The maintenance optimization methodology proposed in this paper is developed for a small bridge network with limited structural condition rating records. . The methodology is organized in three major components: (1) bridge health index (BHI); (2) maintenance and budget optimization; and (3) reliable Artificial Intelligence (AI) based bridge deterioration model. The outcomes of the paper will help to identify BMS implementation problems and to provide appropriate solutions for managing small bridge networks.

Keywords: Bridge Asset Management, Small Bridge Network, Bridge Management System (BMS), Deterioration, Artificial Intelligence (AI), Artificial Neural Network (ANN)

1. INTRODUCTION

The efficient use of maintenance funds for managing bridge networks requires an effective bridge asset management technology and its application. A Bridge Management System (BMS) helps determine the complexity of decision-making for proper bridge maintenance, repair and rehabilitation (MR&R) strategies within the allocated funds. The first commercial version of BMS software was developed in the early 1990s and has become a common tool for effective bridge management to the extended life cycle of bridge networks. With or without BMS software, bridge MR&R must be performed by any bridge authority at the right time, because most infrastructure facilities were planned, designed, constructed, operated and modified or rehabilitated under uncertain and risky conditions [1].

Most bridge agencies have begun the transition to BMS-based thinking through performance-based management and strategic planning for their local and state bridge management. However, inconsistencies between BMS inputs and bridge agencies' existing datasets are an obstacle to implementing and operating BMS software. A large number of bridge datasets for a BMS database are an essential requirement for analyzing a bridge network. Among many BMS input requirements, historical bridge datasets such as bridge element condition ratings and maintenance records from periodic bridge inspection results, are crucial for evaluating up-to-date bridge performance prioritisation for a superlative MR&R decision. However, there are causes of fallibility in the use of BMS software from the perspective of bridge agencies. These are: (1) Commercial BMS software has been used for less than 15 years and even those bridge agencies which implemented BMSs from an early stage, have only approximately 6 to 7 inspection records at their disposal; (2) Bridge condition ratings normally do not change much over short time periods; (3) Approximately 60% of BMS analytical processes rely heavily on periodic bridge inspection results [2].

Numerous bridge condition rating and deterioration models have been developed to reliably determine the bridge life cycle for the remaining years of use for establishing MR&R strategies. Despite many previous research achievements, such fundamental problems as the inadequate number of bridge inspection records for BMS input requirements for estimating future bridge performance still remains an issue to be overcome. Many researchers and infrastructure asset management practitioners also have recognized that deterioration of infrastructure facilities is not deterministic [3]. Thus, current BMS technologies are still not practically reliable.

For effective implementation of BMS software, two important research problems must be solved: (1) Among BMS data requirements, the amount of time-dependent bridge data from periodic bridge inspections for a BMS update is very limited; (2) Bridge condition rating variances in the existing small number of historical data cause inaccurate prediction results from the most important BMS analysis modules, i.e. deterioration model, that require lengthy historical data patterns for their future projections.

This paper presents the bridge asset management methodology for a small bridge network. Key components of the proposed methodology includes: (1) bridge health index for calculating overall condition rating of bridge elements and a bridge; (2) maintenance optimization for the element/project/network level analysis; and (3) AI-based bridge deterioration model for reliable prediction of future bridge performance. The deterioration model described in this paper is based on the Backward Prediction Model (BPM) to address the issue of lacking historical condition ratings for BMSs.

2. BRIDGE HEALTH INDEX

Bridge agencies handle enormous amounts of bridge related data. Even with the best of modelling and computer programmes the outcomes must be clearly communicated to funding agencies and top level decision makers in a simple and easy to understand manner. California Department of Transportation adopted the Bridge Health Index (BHI) to bridge the communication gap between the various stakeholders [4]

BHI will enable the decision makers to easily comprehend and compare the condition of various bridges in the network. BHI will be expressed as a number 1 to 100. BHI of 100 will represent a new bridge and a BHI of 1 will represent the worst condition state. Bridge agencies will calculate the BHI by assigning asset values to the various bridge elements. The current asset value (CAV) of an element will depend on its condition state. As the condition state deteriorates the asset values declines. Table below shows the declining value of the element as a fraction of its 'new asset' value (NAV) for the various condition states CS1 to CS4.

Table 1. Declining Asset Value Factor

Condition State	CS1	CS2	CS3	CS4
CAV/NAV (Declining Asset Value Factor)	1	0.8	0.5	0

The current asset value (CAV) of every element of the bridge will be calculated and aggregated to find the current asset value of the bridge. The ratio between the current asset value of a bridge and the asset value of a new bridge, expressed as a percentage, will be the Health Index of that particular bridge. That is,

$$BHI=(\Sigma\ CAV)/(\Sigma\ NAV)*100$$

Similarly this can be extended to the entire bridges in the network and an aggregated Health Index can be derived for the network. This will be expressed as the Network Health Index (NHI)

3. NETWORK HEALTH INDEX AND BUDGETING

Bridge agencies and funding agencies should come to an agreement as to what will be an acceptable NHI for their network. This will depend on the condition of the bridge stock, repair costs and the availability of funds. A BMS costing module will be a critical tool that will enable informed decision making in this regard.

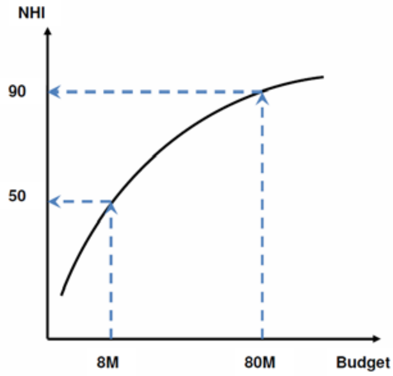


Figure 1. Budget Vs Network Health Index (NHI)

The budget requirements to achieve desired NHI will generate a plot as shown in Figure 1 above. This gives a snapshot of the task in hand and the funding requirements to achieve desired outcomes. For example the agency could set a target to achieve a certain minimum NHI by a certain year and the asset managers could then plan and implement a program to achieve these policy objectives.

4. MAINTENANCE OPTIMISATION

Bridge structures that pose a safety risk must be repaired without delay. Bridge elements that are in a critical condition state must also be repaired as a priority. Critical condition state will be determined by the bridge agency.

The complexities involved in the assessment of bridges in a large network poses significant challenges to decision makers with regards to planning and budgeting for repair and maintenance works programmes. The prioritization of repair works will be governed by a number of factors. The critical factors that influence maintenance prioritization include:

- Current health of bridge element
- Importance of the element within a bridge structure
- Road hierarchy
- Size of the bridge (asset value), and
- Value for money

These critical influencing factors are represented by an Element Health Number (EHN), Element Significance Number (ESN), Socio-Economic Significance Number (SSN) and Value for Money Number (VMN) as described in sections 4.1-4.4.

4.1 Element Health Number

This represents the current health of a bridge element determined by Element Health Index (EHI) as described in section 2 and using the declining asset value factors in Table 1.

$$EHI= CAV/NAV*100$$

Table 2 below assigns EHN values of 2-10 depending on the Element Health Index. A higher EHN is associated with an element that is in good health.

Table 2. Element Health Number (EHN)

EHI	EHN
> 90	10
> 80	9
> 70	8
> 60	7
> 50	6
> 40	5
> 30	4
> 20	3
< 20	2

4.2 Element Significance Number

This represents the importance of a particular element within the bridge structure. A defective main girder, being a critical member of the structure, will require more urgent attention than the bridge barriers or kerbs. The various elements of the bridge and their importance ratings are listed in Table 3 below. The lower numbers are associated with increased importance, as lower the MPN the higher the maintenance priority.

Table 3. Element Significance Number (ESN)

Element	Element Significance Number
Main Girders, Transverse Beams, Piers, Headstocks, Corbels	5
Decks, Bearings, Bracings, Diaphragms	6
Abutments, Foundations	7
Bridge Approach, Wing walls	8
Bridge barriers, Kerbs, Guard rails, Wearing surface, Deck joints	9
Footway, Drainage outlets	10

4.3 Socio-Economic Significance Number

This represents the social and economic impacts of a bridge and is determined by road hierarchy and size of the bridge in terms of asset value (Table 4). Maintenance of a large bridge is critical to preserving the large investment, and closing of a bridge on a highway will have a major social impact. As such the lower numbers in Table 4 are associated with large bridges on major roads.

Table 4. Socio-Economic Significance Number (SSN)

Asset Value	Road Hierarchy			
	Highway, Dual Carriageway	2-Lane Urban Roads	2-Lane Rural Roads	Local Access Roads
>10M	5	5	6	7
5M-10M	5	6	7	8
1M-5M	6	7	8	9

4.4 Value for Money Number

This represents the economics of early intervention and the probability of a worsening condition when maintenance is delayed. If the repair cost of an element in its current state is significantly cheaper compared to the next deteriorated condition state and that it is very likely that this deterioration will occur in the near future, then early intervention will result in significant savings and hence lower the life cycle cost of the network. The lower numbers assigned in Table 5 below correspond to higher priority in this context.

Table 5. Value for Money Number (VMN)

% Increase in Repair Cost	Probability of change in Condition State within 2-years				
	>80	>60	>40	>20	<20
>100	2	3	4	5	6
75-100	3	4	5	6	7
50-75	4	5	6	7	8
25-50	5	6	7	8	9
<25	6	7	8	9	10

4.5 Maintenance Priority Number (MPN)

The maintenance priority number (MPN) integrates all of the abovementioned critical factors that will influence decision making. MPN is calculated as follows:

$$MPN = EHN * ESN * SSN * VMN / 100$$

MPN range is 1-100. The priority for repair increase as the number reduces. This is an easy to comprehend tool that will facilitate bridge/funding agencies to make consistent decisions and set policy objectives backed up by strong rationale.

4.6 Maintenance Programme

Bridge repair and maintenance programme will be influenced by the condition of bridges (MPN) and funding constraints. Repair cost to fix bridges that are below a certain MPN can be calculated and plotted as shown in Figure 2 below. Availability of budget will then set the MPN that will trigger repair works.

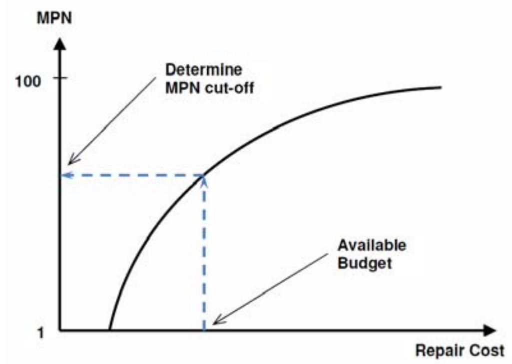


Figure 2. Repair Cost vs Maintenance Priority Number

This process can be repeated after remodeling deterioration for future years. This will then enable bridge authority to determine the MPN 'cut-off' for respective years and in turn identify the bridges that are picked up for repair. Table 6 below, shows a typical bridge repair programme. Alternatively if bridge authority decides to set a target MPN for a particular year, then the budget requirements can be reported.

Table 6. Value for Money Number (VMN)

Bridge ID	Programmed Year of Repair				
	2012	2014	2016	2018	2020
BRDxx1		X			
BRDxx2			X		
BRDxx3	X				
BRDxx4				X	

Bridge agencies typically adopt a 5-10 year forward planning framework. Once the budget requirements are confirmed for the maintenance programme, the corresponding network work health index (NHI) can be predicted over the 5-10 year period. Table 7 below shows the budget and corresponding NHI for a 10-year programme.

Table 7. Maintenance Programme & NHI

Year	2012	2014	2016	2018	2020
Budget	$X1	$X2	$X3	$X4	$X5
Predicted NHI	NHI1	NHI2	NHI3	NHI4	NHI5

5. BRIDGE DETERIORATION MODEL

The outcomes of bridge deterioration model are used to analyse maintenance priority and budget planning. This section presents an AI-based bridge deterioration model to reduce uncertainty in typical long-term predictions caused by insufficient historical condition ratings. A typical approach of deterioration modelling and an outline of the present study are conceptually described in Figures 3 (a) and (b), respectively. Both long-term predictions (years from t_{f1} to t_{fn}) shown in Figure 3 (a) and (b) are based on limited condition rating records only (available from years t_p to t_{pn}).

Figure 3(a) shows a typical deterioration modelling where the long-term prediction of bridge performance is represented by the overall condition rating (OCR). The OCR can not represent individual bridge elements' condition status and is unable to represent detailed condition ratings for a small quantity of bridge elements in lower Condition States (i.e. 3 and 4 CSs). This is a key drawback because bridge collapse usually occurs due to failure of a single element. As a result, all bridge elements need to be analysed at element level in order to reduce such catastrophic risk.

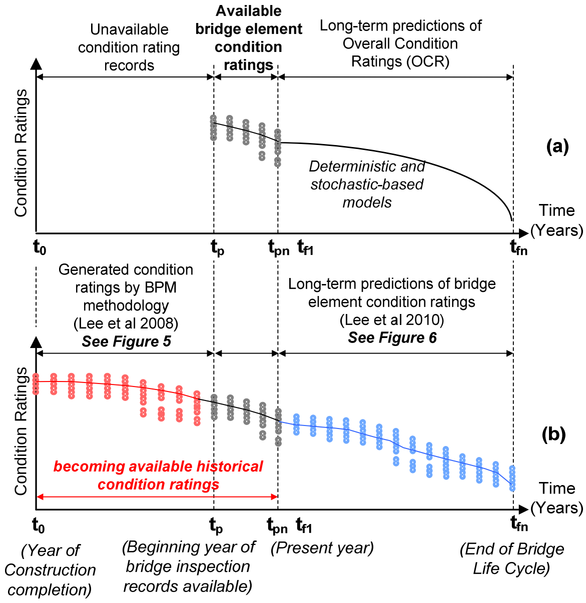


Figure 3. Conceptual diagram for the Long-term bridge performance models: (a) Typical deterioration modeling; (b)AI-based Bridge deterioration model

The recent study by Lee et al [5] and Son et al [6], shown in Figure 3 (b), illustrates that the abovementioned limitations of the current deterioration modelling can be minimised. This study has two major components: (1) generating unavailable historical condition ratings (years from t_1 to t_{p-1}) by using the BPM methodology. It is to establish a comprehensive bridge condition ratings (years from t_0 to t_{pn}) which contains more historical deterioration patterns than the shear amount of available condition ratings (from t_p to t_{pn}); (2) the outcomes from (1) are to predict long-term performance of individual bridge elements using time-series neural network technique.

In order to minimise the problem of insufficient historical condition ratings for a BMS, Backward Prediction Model (BPM) have been established by Lee et al [5]. Figure 4 schematically describes the mechanism of the BPM. It illustrates the main function of the Artificial Neural Networks (ANNs) in establishing the correlation between the existing condition rating datasets (years from year t_p to t_{pn}) and the corresponding years' non-bridge factors such as traffic volume, population growth and climatic conditions. The selection of non-bridge factors is important because all bridge elements are always exposed to local environment conditions and traffic loadings. The non-bridge factors directly and indirectly affect the variation of the bridge conditions thereby the deterioration rate. The relationships established using neural networks are then applied to the non-bridge factors (years from t_1 to t_{p-1}) to generate the unavailable bridge condition ratings (from years t_1 to t_{p-1}). Thus, the non-bridge factors in conjunction with the ANN technique can produce the historical trends that inform the current condition ratings. The input layer in neural network may have such variables as the number of vehicles, climatic conditions and more. This information is used to train the ANN to determine the correlation with currently available bridge condition rating data. The BPM has been tested using two different types of bridge condition rating datasets - the National Bridge Inventory (NBI) and BMS condition rating inputs - for the same bridges provided by the Maryland Department of Transport (DoT), USA.

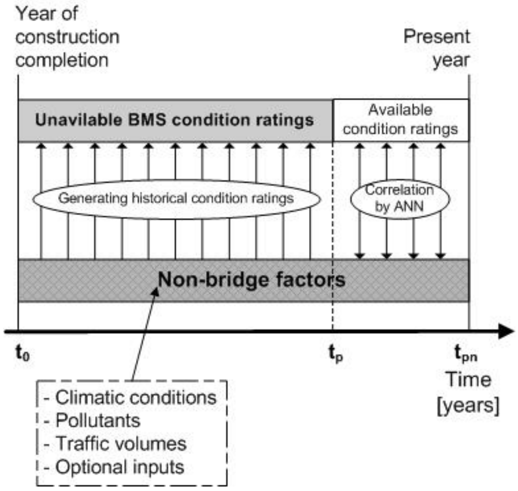
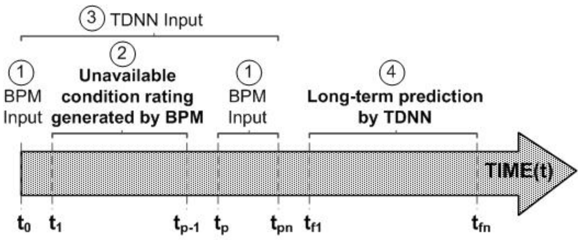


Figure 4. Mechanism of the BPM

The other feasibility study for the AI-based deterioration model is conducted by using the BPM methodology in conjunction with the Time-Delay Neural Networks (TDNNs) technique. A timeframe of input/output and two-stage procedure for the model and is presented in Figures 5 and 6, respectively.



Process	Input/Output	Timeframe
BPM	BPM training	t_0, t_p ~t_{pn}
	BPM testing	t_1 ~t_{p-1}
	BPM training (validation)	t_0, t_1 ~t_{p-1}
	BPM testing (validation)	t_p ~t_{pn}
TDNN	TDNN training (validation)	t_0, t_1 ~t_{p-1}
	TDNN testing (validation)	t_p ~t_{pn}
	TDNN training	t_0, t_p ~t_{pn}, t_1 ~t_{p-1}
	TDNN testing	t_{f1} ~t_{fn}

Figure 5. Timeframe of the AI-based bridge deterioration model

In Stage 1, the BPM methodology [5] is used to generate historical condition ratings. The actual element-level bridge inspection records (years from t_p to t_{pn}) are correlated with relevant non-bridge factors, such as traffic volume and climatic condition, in the neural network training session to generate missing historical condition ratings (years from t_1 to t_{p-1}) in the testing session. The generated condition ratings for each year contain 66 cases which are 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 represents the total quantity of a given bridge element.

In order to confirm the outcome, the BPM need to train the generated condition rating together with non-bridge factors from same years t_1 to t_{p-1} for the prediction of present years condition rating (years from t_p to t_{pn}) in the neural network testing stage. This process is to validate the generated condition ratings (years from t_p to t_{pn}) by simply comparing with actual condition ratings (years from t_p to t_{pn}).

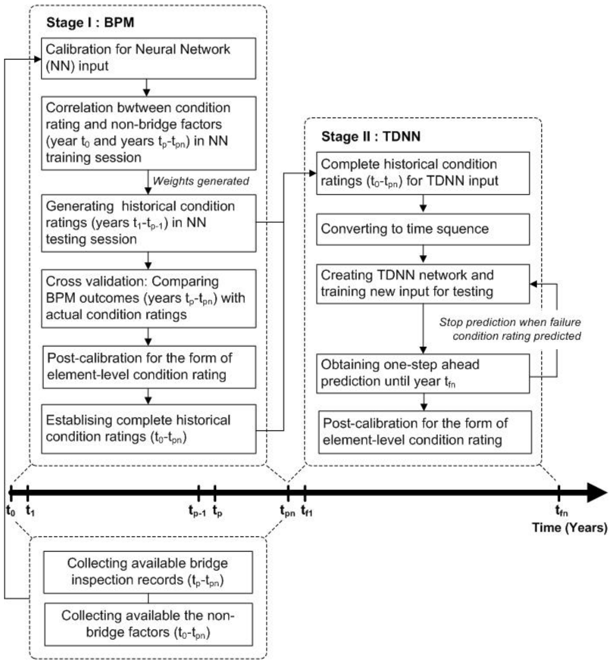


Figure 6. Timeframe of the AI-based bridge deterioration model

In Stage 2, the BPM results (from years t_1 to t_{p-1}) obtained from Stage 1 together with actual condition rating (years from t_p to t_{pn}).are used as TDNN inputs (years from t_1 to t_{pn}) to estimate long-term bridge element performances. It is noted that the feasibility study was only considered "Do-nothing" – no maintenance effects in long-term prediction. This input data is converted to time sequences for time series prediction in the TDNN. The proposed TDNN provides only one-step ahead prediction at a time (one cycle), i.e. a 2-year interval in the actual time domain. The result of the first one-step-ahead prediction (at year t_{f1}) is added on the original TDNN input (from years t_1 to t_{pn}). This means that the amount of input for TDNN increases for the second cycle of the one-step-ahead prediction (at year t_{f2}) to obtain a complete long-term prediction: iterations of the above-described process are required until failure condition rating of element is computed at year t_{fn}. The number of yearly prediction by TDNN is also 66, which is in an identical form as the BPM outcomes obtained in Stage 1. The cross-validation is also necessary to measure the prediction accuracy of TDNN outcomes. In the present study, the results of TDNN predictions (from years t_p to t_{pn}) using BPM outcome only (from years t_1 to t_{p-1}) are compared with the actual BMS condition ratings (from years t_p to t_{pn}). All TDNN outcomes are considered satisfactory if the comparisons are within the error allowances. The maximum yearly prediction errors of three different condition state scales in 3, 4 and 5 CSs are ±16.67%, ±12.50% and ±10% respectively. It should be noted that the final outcomes of the TDNN, upon calibration, are in the same form as the bridge element-level inspection.

8. CONCLUDING REMARKS

A framework for developing a Health Index for Bridges (BHI) and the network as a whole (NHI) is presented. BHI will enable the decision makers to easily comprehend and compare the condition of various bridges in the network. BHI is expressed as a number 1 to 100. BHI of 100 represents a new bridge and a BHI of 1 represents the worst condition state of a bridge. The complexities involved in the assessment of bridges in a large network poses significant challenges to decision makers with regards to planning and budgeting for repair and maintenance works programmes.

The prioritization of repair works is governed by a number of factors. The critical factors that influence maintenance prioritisation were identified as current health of bridge element, importance of the element within a bridge structure, road hierarchy, size of the bridge (asset value), and value for money spent on repair. These critical influencing factors are represented by an Element Health Number (EHN), Element Significance Number (ESN), Socio-Economic Significance Number (SSN) and Value for Money Number (VMN). The methodology for quantifying these critical factors is presented.

The maintenance priority number (MPN) integrates all of the abovementioned critical factors that influence decision making. MPN is calculated as follows: MPN= EHN * ESN* SSN* VMN / 100. MPN range is 1-100. The priority for repair increases as the MPN number decreases. This is an easy to comprehend tool that will facilitate bridge/funding agencies to make consistent decisions and set policy objectives backed up by strong rationale. Bridge repair and maintenance programme is influenced by the maintenance priority number (MPN) and funding constraints. Availability of budget sets the MPN that triggers repair works. This process can be repeated after remodelling deterioration for future years. This will then enable the bridge authority to determine the MPN 'cut-off' for respective years and in turn identify the bridges that are picked up for repair. Alternatively if the bridge authority decides to set a target MPN for a particular year, then the budget requirements can be reported.

The reliability of prioritization depends on the outcomes of long-term structural condition ratings from the deterioration model. The limitation in the current deterioration modelling techniques is the lack of usable bridge element's historical condition rating records. Based heavily on a few sets of recent structural condition ratings, current modelling techniques cannot be expected to produce practically useful outcomes. This in turn leads to an unreliable prediction of future bridge condition ratings. In order to mitigate this drawback, the introduced AI techniques, BPM and TDNN, have been developed to help improve the reliability of the deterioration model for long-term prediction of bridge element performance.

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