AN ARTIFICIAL NEURAL NETWORK MODEL FOR THE CONDITION RATING OF BRIDGES

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ABSTRACT : An outline of an Artificial Neural Network (ANN) model for bridge condition rating and the results of a pilot study are presented in this paper. Most BMS implementation systems involve an extensive range of data collection to operate accurately. It takes many years to effectively implement a BMS using existing methodologies. This is due to unmatched data requirements. Such problems can be overcome by adopting the ANN model presented in this paper. The objective of the proposed model is to predict bridge condition ratings using historical bridge inspection data for effective BMS operation.

Key words : Bridge Management System (BMS), Condition Rating Model, BMS Implementation, Artificial Neural Networks (ANNs)

1. INTRODUCTION

The prime objective of bridge asset management is to maintain a satisfactory level of safety in bridges with optimal life cycle cost. This is a complex task requiring the management of conflicting resource requirements. Computerised Bridge Management Systems (BMSs) can assist to determine the best possible maintenance strategy. However, in order to effectively use a BMS, a large amount of historical and technical bridge information is required. This data must be collected over a period of several years, before a BMS can be effectively implemented.

Fundamentally, comprehensive bridge information is essential to operate a Bridge Management System (BMS). Lack of bridge data is a major problem for many bridge agencies as they try to implement the BMS. This study aims to resolve the problem and enable the effective implementation of a BMS. An efficient methodology for extracting information from existing historical data, which in most cases are not comprehensive, is of much interest to bridge agencies.

This study aims to improve the existing BMS implementation process, by resolving insufficient historical data problems, using Artificial Neural Networks (ANNs). The focus will be on the development of a model to predict time series data of bridge elements. This in turn will lead to the establishment of a bridge condition rating model.

Preliminary results indicate that the level of accuracy in the prediction is satisfactory.

1.1 General background

The concept of infrastructure asset management is to systematically approach maintenance, keeping up-to-date bridge information, and cost effective physical operation. The activities under those concepts are a combination of engineering principles with business practices and economic theory to provide tools for effective decision-making [1]. The following BMS definition is one of those available from numerous leading authors to emphasize a comprehensive necessity of BMS:

"The goal of bridge management is to determine and implement the best possible strategy that ensures an adequate level of safety at the lowest possible life-cycle cost" [2]

1.2 Necessity of a BMS

The road transportation network is extremely important to national economic and social development. A bridge is one of the most crucial elements in transportation networks as a functional, valuable, and expensive asset. In terms of the bridge aging process, its life cycle cost (LCC) increases continually due to its heavy duties such as: increased amount of traffic, environmental condition and other direct and indirect factors. However, bridges must be durable enough at all times to provide satisfactory service so that proper maintenance, repair and rehabilitation (MR&R) can be carried out. However, in a large bridge network with limited maintenance funds, it is difficult to make the right decisions as a bridge asset engineer. For that reason, bridge asset management techniques have been widely developed and used by transportation organizations such as local, highway, and railway bridge authorities. Well developed management practices and skills can provide an effective methodology to assist bridge asset management activities. Currently, a systematic BMS has become more popular and crucial to effectively manage a large bridge network.

1.3 Structure of a BMS

A component of a computerised bridge management system is similar to an ordinary Information System (IS) for operation of the business process. However, the BMS is not just used to control management processes, it also provides future planning, which could not be done in conventional computer systems. A typical structure of a BMS is shown in Figure 1 and according to the guidelines of bridge management systems[3]. It is suggested that the system include four essential components such as data storage (database (DB)), cost, deterioration and optimisation models for running the system.

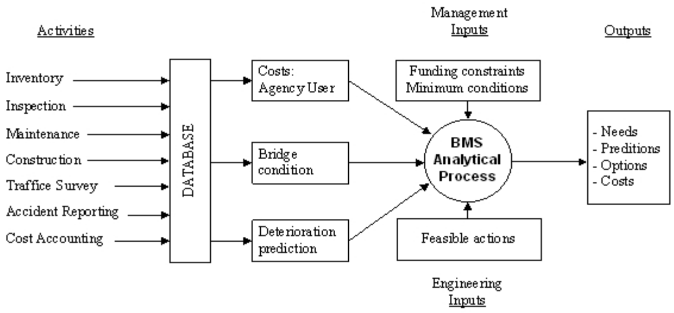


Figure 1. Typical Structure of BMS [4].

2. OBJECTIVES AND SCOPE

Although BMS developments over the last decade have been remarkable, the system implementation methods are still problematic. For that reason, implementing a BMS requires the collection of massive amounts of historical bridge inspection information and other quality BMS relevant data. Bridge inspection data is mainly used to calculate the bridge condition rating model. The outcomes of this are directly and indirectly linked with other BMS modules as input data. According to the summarized relationship between the BMS input source and BMS outputs, 60 percent of BMS outputs (6 out of 12 project level and 12 out of 18 network-level outputs) are affected by inspection data. It is evident that the operations of those BMS modules are difficult without historical inspection information[5]. As a result, many studies have been conducted in the field of bridge condition rating models to provide better quality bridge condition rating outputs that may improve the overall quality of BMS outputs.

Hence, the proposed research is focused on how to compute the bridge condition rating as well as resolving insufficient data problems by using neural network models employing existing historical bridge inspection data. This ANN technique has the ability to recognise historical data patterns (maintenance patterns) that enable predictions of future events. The establishment of this particular model is believed to achieve an initial bridge condition rating without physical data collections for operating a BMS to shorten the BMS implementation period by generating required missing bridge elements' condition rating data.

3. BRIDGE CONDITION RATING MODEL FOR EFFECTIVE BMS IMPLEMENTATION

3.1 Proposed Strategy for BMS Implementation

This section details the three stages of the proposed BMS implementation strategy, shown in Figure 2. The first Phase requires the bridge agency to collect available data from a specified region of their bridge network. This data can be used to build up a basic BMS Database (DB). From the collected existing data sets, condition rating-related resources will be used as input data in a bridge condition rating prediction model.

Bridge condition rating-related data such as bridge inspection reports, which possess periodic maintenance records, are not comprehensive and thus cannot be used to extract the input data required to determine a bridge's condition rating. This problem can be overcome by the proposed model to predict the condition rating values. The condition rating DB in this phase is therefore based on a combination of outputs generated from the ANN model and the actual data obtained from element-level inspection reports. At this stage a trial implementation of a BMS for a specific region of the bridge network is possible.

As new and up-to-date inspection data become available, the agency can periodically replace predicted data with the actual data during Phase II, thus refining the prediction model. As more and more actual data gradually replaces the predicted data for each bridge, the reliability of the BMS database will increase. At this stage the bridge agency enters phase III and is in a position to fully adopt a commercial BMS package for its entire bridge-network.

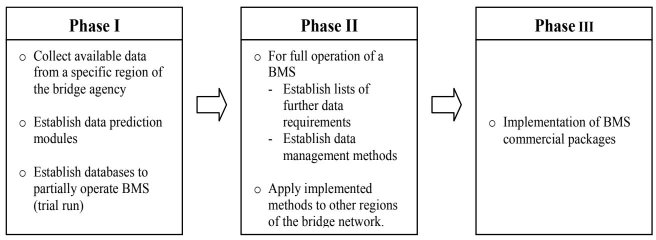


Figure 2. Proposed Strategy for BMS Implementation

3.2 Why ANNs for BMS Implementation

Historical bridge inspection data are a major source for the bridge condition rating module in a BMS and is a significantly important source to produce various BMS outputs. Insufficient amounts of these data cause the slow adoption of a BMS implementation or in same cases makes it impossible to fully implement the BMS. This has been reported in many BMS implementation cases worldwide.

These typical problems have encouraged more research in this field to improve the condition rating module by using other bridge information. For example, using bridge inventory data[6] and reduction of the number of bridge element items[7] have been used to determine a bridge condition rating and its future predictions. Those attempts were an expedient method against lacking bridge inspection records and minimizing further data collections. This minimizing process is only available to element-level type of inspection methods.

Historical bridge inspection data were widely used in other BMS modules. According to Godart and Vassie[5], input data required to satisfy project- and network-level outputs are very useful to BMS analysts for tracking the input data of a particular model. It provides a relationship between the BMS input data-set, which includes historical inspection data, and BMS outputs. 60 percent of BMS outputs (6 out of 12 project level and 12 out of 18 network-level outputs) are affected by inspection data. It is evident that the operations of those BMS modules are extraordinarily difficult without historical inspection information.

Consequently, historical bridge inspection records are crucial to operate BMSs. Previous research has concentrated on the development of particular models by using substitution data, instead of inspection data. These are not very effective for a fully operational, BMS implementation. The proposed ANN model overcomes some of the problems encountered.

ANNs have attracted world-wide attention over the last decade, because they are simple and effective tools for examining data and developing models. It can be used to extract patterns or detect trends in data, which are useful for future prediction. Many different ANN models have been developed to achieve various predictions such as: (1) learning to predict events based on observation of patterns in historical data; (2) learning to classify unseen data into predefined data-sets based on observations in characteristics of the data; (3) learning to cluster the training data into natural groups based on similarity of characteristics [8].

An Artificial Neural network and its support techniques, such as GAs (Genetic Algorithms) and Fuzzy theory, have been used in bridge condition rating modules and optimisation modules in bridge management systems. Past research was mainly focused on improving the accuracy of indicated BMS modules, which are based on comprehensive bridge information. The rationale of this is to prevent the receipt of imprecise results from the system. Although neural networks are able to detect historical data patterns, it has not been applied to improve BMS implementation processes.

Existing BMSs require a large amount of bridge information to analyze bridge networks accurately. If the existing data in bridge agencies do not match with BMS requirements then they need to physically carry out further data collections, which require significant time and cost. However, by using the proposed ANN model, a satisfactory quality level of prediction in bridge condition ratings is achieved as if physical data collection were used.

Accordingly, indicated typical BMS implementation problems motivate the use of ANN models to improve the efficiency of bridge condition ratings, which is a core part of a BMS implementation.

3.3 Process of an ANN model

The significant advantage of an ANN is that it can control many input elements and effectively classify different objects. The proposed study uses the back-propagation algorithm, which is mainly used in non-linear engineering problems. The ANN model process consists of two steps, training and testing. To perform specific tasks using neural networks requires varying the network's weights during the training process. The computation of this process is an error derivation of the weights between the desired output and actual output. All input elements are connected to one another by weighted connections [9].

There are several parameters to consider in the training step such as the number of hidden unit(s), hidden layer(s), learning rate, and the momentum coefficient. Different combinations of those parameters yield different weighting factors. The training process can be divided into 2 main types, supervised and unsupervised. The supervised training process compares the ANN's actual output with that of the desired output until the desired result is obtained at a specific combination of parameters (i.e. as in backpropagation). The unsupervised training process does not require inspection on each result of the weighting factor. The network finds out optimal parameters for itself, which is convenient when the user is unable to predict the result from the network.

3.4 ANN Embedded Bridge Condition Rating Model

From the 3 phases of implementation strategies in Section 3.1, the major technical part is involved in Phase I for establishment of a bridge condition rating model using an ANN. The condition of each bridge element belongs to 5 or 6 groups of bridge components, such as superstructure, substructure, deck, and slab. A condition rating for the element is an interim process to achieve a bridge component's condition rating. In the following, Section 4 mainly focuses on procedures of ANN modeling for future bridge element condition rating, using imported historical bridge inspection data sets to yield preliminary investigations.

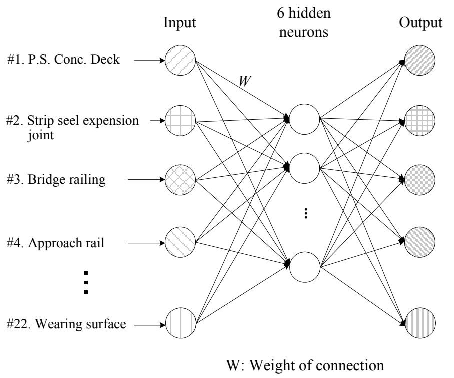


Figure 3. Architecture of the Proposed ANN Model for Bridge Element Condition Ratings

4. PRELIMINARY INVESTIGATION

4.1 Historical Bridge Inspection Data for the ANN model

The inspection data was provided by KICT (Korea Institute of Construction Technology) for 24 prestressed concrete girder bridges. Three bridges, which are simply supported one span bridges, have been selected for the pilot study. The imported bridge data has been evaluated at 5 different levels of condition rating such as level A to E. The assumptions for the proposed ANN model are as follows:

1. Inspection has been made regularly;
2. Inspector(s) have equivalent level of knowledge and experience so that inspection quality and judgment skills are approximately equivalent;
3. Inspection item(s) have been recorded only for defective bridge element(s), hence, the condition of unrecorded inspection items are deemed to be in good condition, which are at least ranked at level C;
4. In addition to assumption number 3, supplementary items, the unrecorded item(s), will be added by using element-level inspection items to provide more extensive consideration in each of the bridge components in the ANN model.

From assumption number 4, the historical inspection data has been recorded only for defective element(s) and are not comprehensive enough to adopt for the current condition rating model. As shown in Table 1, inspected bridge items in the imported data did not meet the bridge element-level inspection format, which are currently most commonly used as a bridge data collection method for BMS operation.

The ANN model is not able to predict future element conditions with only defect-based inspection records. It requires a conversion process such as the form of a bridge element-level inspection to attach supplementary inspection items to the sample data, because it helps to obtain more extensive historical patterns of each nominated bridge element. For example, if the inspection results of a particular bridge in a certain year show defect elements only in the superstructure and deck, the ANN model is not able to predict the condition in other components of the bridge elements. Adding the unrecorded bridge items as a normal condition rating are important as it sets sufficient bridge elements in each component to provide full consideration to the ANN model. Therefore, for the ANN training stage, this prerequisite process (assumption #4) is crucial.

Table 1. Bridge Inspection Items for the ANN Model

Bridge components	I^1	I^2	ID	inspection items
Deck	A^1	B^1	1	P.S. Conc. Deck
Other	A^2	B^2	2	Strip Seel expension joint
	A^3	B^3	3	Bridge railing
	A^4		4	Approach rail
	A^5		5	Approach slab
	A^6	B^4	6	Bearings
		B^5	7	Drainage
Smart Flags	A^7		8	Deck Cracking
	A^8		9	Impact damage p.s.
	A^9	B^6	10	Soffit_underside of conc. Deck/slab cracking
Substructure	A^{10}		11	Abutment_R/C
	A^{11}	B^7	12	Wingwalls_R/C
	A^{12}		13	Bent cap
	A^{13}		14	Tie-beam
	A^{14}	B^8	15	Column_R/C
	A^{15}	B^9	16	Piling
	A^{16}		17	Riprap
	A^{17}		18	Retaining wall
Superstructure	A^{18}	B^{10}	19	Secondary member
	A^{19}	B^{11}	20	P.S. conc. Beam_mid. point
		B^{12}	21	P.S. conc. Beam_ends point
Wearing surface	A^{20}	B^{13}	22	Wearing Surface (ACP)

(Note: I^1 represents element-level inspection items and I^2 is obtained inspection items)

Table 1 shows the list of bridge elements established from two different categories such as commonly used in element-level type inspections (I^1: 22 items, A1~A20) and the imported normal inspection information (I^2, 13 items, B1~B13) for prestressed concrete bridges.

In addition, for the superstructure category, there are two different considerations under the same bridge element such as the prestress concrete beam (A19). This has been considered as two items in the imported data i.e. the “mid point” (B11) and “end point of beam” (B12). In this case, imported items have more consideration than element level inspection items. For the proposed ANN model, item number B11 and B12 will be used instead of A19. Therefore, the total number of inspection items per bridge for sample data of prestressed concrete bridges is 22 inspection items for the proposed ANN model as given in Table 1.

As Figure 4 illustrates, a simple encoding process is required in the existing data (currently, evaluated at Levels A~E) to convert to numerical values, which can be

0.2. The median values in each level will be used in the ANN models. For example, for level A (0.8 ~ 1.0) evaluations in the actual data, the median value of 0.9 is used for the ANN input value.

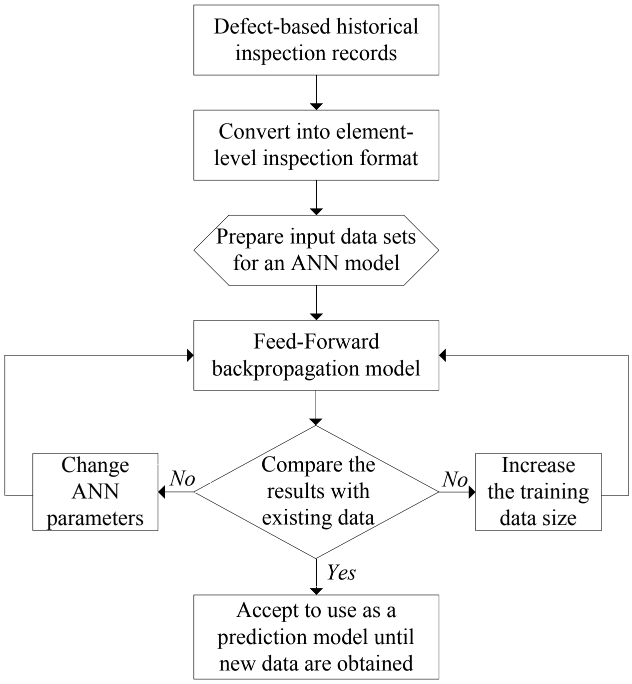


Figure 4. Flow Chart for the Proposed ANN Model

4.2 Proposed ANN model

The ANN model requires data sets for training (input and output) and testing (input). The training input data set contains a 6 by 66 matrix; each row is an array of 66 elements, consisting of 3 years of inspection records (each year of inspection has 22 elements). The training output data, corresponding to the training inputs, is a 6 by 22 matrix. Similarly for the testing model, the testing input and testing output is a 1 by 66 and 1 by 22 matrix, respectively.

In this preliminary investigation, was used up to the 9th year of inspection information for the ANN model training and then the 10th year of inspection results were compared with ANN prediction results.

A feedforward backpropagation algorithm needs manual adjustments of parameters such as the number of hidden units, learning rate (lr) and momentum coefficient (mc). The number of hidden units has been set at 6 through experimental tests, which means that the model has optimal performance when the network has 6 hidden neurons. The best possible combinations of the remaining parameters (lr and mc) are timely to determine by using experimental selections for optimal network performance.

Hence, all possible cases, 66 combinations of lr (0.0-0.5) and mc (0.0-1.0), were examined. The network will subsequently display the results of 66 different weighting factors. Afterwards, those weighting factors were used in the ANN testing model continuously to predict the bridge condition ratings. And then the best prediction result and its weighting factor was selected, which was used for future predictions on a particular bridge until new data was obtained.

5. PRELIMINARY RESULTS

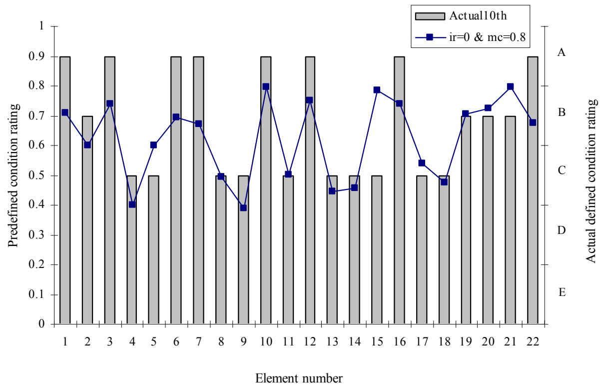
528 processing elements for training (396: input and 132: output) at each bridge were applied to an ANN-embedded bridge element condition rating model to determine the weighting factor for future prediction. Three simply supported prestressed concrete bridges among the imported bridge data were selected for the proposed ANN models. Comparisons of the 10th year's prediction with real data and its predictive performance on each bridge are shown in Table 2. Performance is measured in percentage ratio of the element's portion and correctly predicted value at each level of the original condition rating scale. The best weight factor was found in trial prediction number 46 (lr=0.4 and mc=0.1) in bridge #10 and 25 (lr=0.2 and mc=0.2) in bridge #13. Based on this weighting factor, the performance of each network is 81.82 % and 86.31 % in bridge #10 and bridge #13 respectively.

Table 2. Overall Predictive Performance

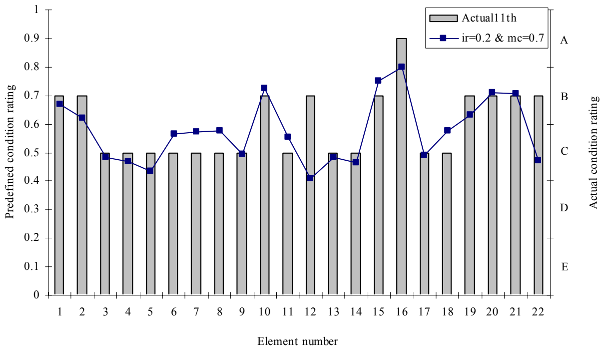
Subjective rating	*Performance (%)*		
	Bridge #10	*Bridge #13*	*Bridge #14*
Level A (0.81-1.00)	0.00	0.00	4.55
Level B (0.61-0.80)	40.91	40.91	18.18
Level C (0.41-0.60)	40.91	45.45	36.36
Level D (0.21-0.40)	-	-	-
Level E (0.00-0.20)	-	-	-
Total	*81.82*	*86.36*	*59.09*

However, the optimal weighting factor for bridge #14 was found in trial prediction number 9 (lr = 0.0 and mc = 0.8) for the 10th year's prediction. This weighting factor reflects unsatisfactory prediction results. The overall network performance is 59.09 percent. It is not acceptable to use for future elements prediction because there are many elements predicted inaccurately. The main reason is that unexpected maintenance activities were performed in year 10 for a number of elements. As a result, the ANN model was unable to predict this unusual historical pattern.

For example, element number 6 has a historical maintenance pattern for the condition rating from 0.7 (year 5) to 0.9 (year 6). However, this element has never had a condition rating from 0.5 (year 9) to 0.9 (year 10). The condition rating 0.5 has not occurred in this element, thus triggering the error in the prediction of the 10th year's condition. To solve this problem, two alternative methods are suggested: 1. another trial by using an increased training data set to obtain a new set of weights; 2. adjustment of ANN parameters as shown in Figure 4.



(a) Comparison in 10th Year



(b) Comparison in 11th Year

Figure 5. Actual Data vs Predicted Data on Bridge #14

The first method was applied to improve prediction performance. The input data for training needed to increase up to the 10th year's inspection results so that the ANN model is able to detect more accurately the maintenance behavior of each element. The model can recognise a new pattern such as the condition rating from 0.5 (year 9) to 0.9 (year 10) in element # 6. It provides a better prediction for year 11. As a result, the prediction in year 11 can be more effectively obtained by using a more comprehensively trained network. Also, other elements (1, 3, 7, 12, 16, and 22) have similar problems as element # 6 in this bridge. This can be overcome by increasing the size of the training set. As a result, the performance of prediction for year 11 is greatly improved and it is acceptable for future element conditions in this bridge.

6. CONCLUSION AND FURTHER STUDY

The proposed prediction models were a first step in the establishment of bridge condition rating models, which provide essential information for BMS operations during the implementation period. Difficulties were encountered relating to the size of training data sets and selection of appropriate ANN parameters. Further studies and a comprehensive investigation are required to refine the proposed bridge component condition rating model.

Analysing current MR&R strategies of bridge agencies is crucial for improving the bridge condition rating model. A variety of input information in connection with MR&R activities such as risk factors, safety, time, and cost will have to be considered. The relationship between bridge elements and historical MR&R activities will enable condition rating of the bridge components to be developed. Case studies will have to be carried out to validate the model.

Although further study is required to refine the proposed approach, effective use of defect-based bridge inspection data for the proposed bridge condition rating model will bring a significantly positive effect on current BMS implementations.

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