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PREDICTION OF BRIDGE DECK CONDITION RATING BASED ON ARTIFICIAL NEURAL NETWORKS

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Abstract

An accurate prediction of the future condition of structural components is essential for planning the maintenance, repair, and rehabilitation of bridges. As such, this paper presents an application of Artificial Neural Networks (ANN) to predict future deck condition for highway bridges in the State of Alabama, the United States. A library of 2572 bridges was extracted from the National Bridge Inventory (NBI) database and used for training, validation, and testing the ANN model, which had eight input parameters and one output being the deck rating. Specifically, the eight input parameters are Current Bridge Age, Average Daily Traffic, Design Load, Main Structure Design, Approach Span Design, Number of main Span, Percent of Daily Truck Traffic, and Average Daily Traffic Growth Rate. The results indicated the obtained ANN model can predict the condition rating of the bridge deck with an accuracy of 73.6%. If a margin error of ±1 was used, the accuracy of the proposed model reached a much higher value of 98.5%. Besides, a sensitivity analysis was conducted for individual input parameters revealed that Current Bridge Age was the most important predicting parameter of bridge deck rating. It was followed by the Design Load and Main Structure Design. The other input parameters were found to have neglectable effects on the ANN's performance. Finally, it was shown that the obtained ANN can be used to develop the deterioration curve of the bridge deck, which helps visualize the condition rating of a deck, and accordingly the maintenance need, during its remaining service life.

Keywords: condition rating; bridge deck; deterioration curve; artificial neural networks; sensitivity analysis.

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1. Introduction

According to the American Society of Civil Engineers' 2017 Infrastructure Report Card [1], about one in 11(9.1%) of the bridges in the United States were rated to be structurally deficient. "Almost four in 10 (39%) are over 50 years or older, and an additional 15% are between the ages of 40 and 49. The average bridge in the U.S. is 43 years old. Most of the country's bridges were designed for a lifespan of 50 years, so an increasing number of bridges will soon need major rehabilitation or retirement." [1]. It is known that, in order to have an optimum repair strategy, the future condition rating of the bridges needs to be predicted with a high level of accuracy.

At present, the visual inspection technique is the most commonly used method to determine the condition rating of a bridge structure in the United States [2]. During the examination, the inspectors gather a large amount of information related to operational, geometric, and defects/condition of the

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bridges. Those inspection data are then archived in the NBI database. For each bridge structure, such data reflect the condition ratings of superstructure, substructure, and bridge deck. More specifically, the deck condition rating is stored in item No. 58 of the NBI records.

The bridge deck is rated as an integer number between 0 and 9, in which 0 means a bridge being in a failed condition while 9, on the other hand, indicates an excellent condition. The bridge with a component's condition rating of 4 or lower will be considered as structurally deficient. The deck condition rating is performed for the entire deck, i.e., deck surface, sides and deck bottom. Table 1 shows a detailed description of the bridge deck in various ratings, which was taken from the Michigan Department of Transportation's guidelines [2]. Such an overall deck rating will be employed as the prediction output of this study.

Table 1. Bridge deck condition rating (NBI item 58)

Code	Description
N	NOT APPLICABLE. Code N for culverts and other structures without decks, e.g., filled arch bridge.
9	NEW CONDITION. No noticeable or noteworthy deficiencies which affect the condition of the deck.
8	GOOD CONDITION. Minor cracking less than 0.8 mm wide with no spalling, scaling or delamination on the deck surface or underneath.
7	GOOD CONDITION. Open cracks less than 1.6 mm wide at a spacing of 3 m or more, light shallow scaling allowed on the deck surface or underneath. Deck will function as designed.
6	FAIR CONDITION. Deterioration of the combined area of the top and bottom surface of the deck is 2% or less of the total area. There may be a considerable number of open cracks greater than 1.6 mm wide at a spacing of 1.5 m or less on the deck surface or underneath. Medium scaling on the surface is 6.4 mm to 13 mm in depth. Deck will function as designed.
5	FAIR CONDITION. Heavy scaling. Excessive cracking and up to 5% of the deck area are spalled; 20–40% is water saturated and/or deteriorated. Disintegrating of edges or around scuppers. Considerable leaching through deck. Some partial depth fractures, i.e., rebar exposed (repairs needed).
4	POOR CONDITION. Deterioration of the combined area of the top and bottom surface of the deck is between 10–25% of the total area. Deck will function as designed.
3	SERIOUS CONDITION. The deck is showing advanced deterioration that has seriously affected the primary structural components. Deterioration of the combined area of the top and bottom surface of the deck is more than 25% of the total area. Structural evaluation and/or load analysis may be necessary to determine if the structure can continue to function without restricted loading or structurally engineered temporary supports. There may be a need to increase the frequency of inspections.
2	CRITICAL CONDITION. Deterioration has progressed to the point where the deck will not support design loads and is therefore posted for reduced loads. Emergency deck repairs or shoring with structurally engineered temporary supports may be required by the crews. There may be a need to increase the frequency of inspections.
1	IMMINENT FAILURE CONDITION. Bridge is closed to traffic due to the potential for deck failure, but corrective action may put the bridge back in service.
0	FAILED CONDITION. Bridge closed.

In the current practice, the operational and physical characteristics of bridge components (superstructure, substructure, and deck) are evaluated visually by a bridge inspector based on his or her own assessment. Such visual inspection requires the inspector to assign a subjective rating for each bridge component. The overall rating of a bridge is then calculated through the integration of those component ratings. Since for each bridge, the instant rating indicates the immediate level of repair needed for its structure, it is important to predict accurately the future ratings of a bridge, and accordingly, its components, so that bridge engineers can develop an effective bridge repair/rehabilitation plan.

In the literature, several deterioration models of bridge decks based on chemical and physical processes have been proposed [3–6]. Other research applied stochastic models such as Markov chains, or reliability-based methodology [7, 8]. In recent years, an alternative approach using an Artificial Neural Network has been widely applied to structural condition assessment. For example, Cattan and Mohammadi [9] used an ANN model to predict the condition rating of railway bridges in the Chicago metropolitan area. Al-Barqawi and Zayed [10] predicted the condition of underground water main pipes with the ANN model. The application of ANN model has also been expanded to predict the condition rating of a certain component of a bridge such as abutment [11], bridge deck [12–15].

In this study, a supervised learning ANN model was developed and used to predict the condition rating of bridge decks using available information in the NBI database. In addition, a similar methodology was also utilized to analyze the sensitivity of the input parameters in predicting the future condition of bridge decks. Dataset used for training, validation, and testing the proposed ANN model is the NBI data from the State of Alabama in 2018. This dataset was downloaded from the Federal Highway Administration (FHWA) website [16]. Original data were refined before being used to develop the ANN model. The subsequent section provides details on the data refinement.

2. Database preparation

The original NBI data obtained from the FHWA website comprises valuable information about the United States' bridge network. However, based on the initial analysis, the NBI database also contained multiple errors and data outside a normal range, i.e. outliners. In order to minimize the potential negative effects of such data on the performance of the ANN model, the refinement of original data was carried out. Specifically, the original data were filtered with consideration to a number of criteria as discussed in the following paragraphs.

The initial refinement focused on removing the records containing flawed data. The original dataset was checked for errors such as zero or negative *Average Daily Traffic*, zero *Number of main Span*, negative *Ages*. The bridges with those errors were removed from the database. The refinement also targeted at the bridges with reconstruction and repaired records. In this study, the authors used the ANN model to predict the condition rating of bridge decks without previous intervention, i.e., previous repair or replacement. Thus, the bridges with repair and reconstruction activities were also removed from the database. In another refinement step, the bridges with an overall deck rating of 1 or 2 or no rating were considered not being qualified for the inputs, and therefore they were also removed from the database.

The next refinement was aimed to remove the input parameters those are likely not important. According to the previous study [14], 11 NBI items were considered to have a significant influence on concrete bridge deck performance. Those variables were: *Age, Year Built, Average Daily Traffic, Percent of Daily Truck Traffic, Average Daily Truck Traffic, Number of main Span, Region, Steel Reinforcement Protection, Structure Design Type, Design Load, and Approach Surface Type* [14]. However, due to the uncertainty in the NBI data, the number of items used in this study was reduced to seven items as following: (i) *Year Built* (item 27), (ii) *Average Daily Traffic* (item 29), (iii) *Design Load* (item 31), (iv) *Main Structure Design* (item 43B), (v) *Approach Span Design* (item 44B), (vi) *Number of main Span* (item 45), (vii) *Percent of Daily Truck Traffic* (item 109).

The overall condition rating of bridge deck was the output of the ANN model, thus the *Deck Condition Rating* (item 58) was utilized for a supervised learning of the ANN. In addition, the *Current Bridge Age* item was created to replace the *Year Built* item from NBI database. The age of a bridge was equal to the subtraction of 2019 and the year that the bridge was built (*Year Built*, item 27). Furthermore, a new item, *Average Daily Traffic (ADT) Growth Rate*, was added to the inputs. This parameter and the *Current Bridge Age* item were used later as the variable parameters for constructing the deterioration curve of bridges. The *ADT Growth Rate* parameter is the annual growth rate of ADT. It was calculated by the following equation.

$$\text{AGR} = \frac{\text{FADT} - \text{LADT}}{\text{FDT} - \text{LDT}} 100\% \tag{1}$$

where AGR = Percent of annual *ADT Growth Rate*; FADT = Future *ADT* (item 114); LADT = Latest *ADT* (item 29); FDT = Future year of *ADT* (item 115); LDT = Latest year of *ADT* (item 30).

In the last refinement, the old bridges with abnormal ratings were removed from the database. This refinement was performed to ensure that the rating records reflect the reasonable typical deterioration for a bridge deck. To perform this refinement, the records were removed if they met one of the following conditions: (i) age ≥ 30 and deck rating ≥ 6, (ii) age ≥ 25 and deck rating ≥ 7, (ii) age ≥ 20 and deck rating ≥ 8, and (iv) age ≥ 15 and deck rating ≥ 9 [14].

After performing refinement, the final dataset was a matrix that contains 2572 rows and 9 columns. The range of the input and output parameters is listed in Table 2. Some bridges were forecast with a reduction in the number of average daily traffic, and as a result, the value of the additional parameter (ARG) was negative, as seen in Table 2. The classification of the deck condition rating is presented in Table 3. This dataset was used for the ANN model with the inputs were the data from column 1 to column 8 and the outputs were the data from column 9.

Table 2. Characteristics of input and output

No.	Parameter	Item	Contraction	Unit	Min.	Max.
1	Current Bridge Age	-	CBA	year	2	119
2	Average Daily Traffic	29	ADT	No.	4	157350
3	Design Load	31	DLD	-	0	6
4	Main Structure Design	43B	MSD	-	0	22
5	Approach Span Design	44B	ASD	-	0	22
6	Number of main Span	45	NMS	No.	1	48
7	Percent of Daily Truck Traffic	109	PDT	%	1	75
8	ADT Growth Rate	-	AGR	%	−2.78	26.5
9	Deck Condition Rating	58	DCR	-	3	9

Table 3. Number of records in each specific range the bridge deck rating

Condition Rating	3	4	5	6	7	8	9	Total
Number of records	9	65	1136	128	602	479	153	2572

3. Methods

As mentioned earlier, the ANN model was used to predict the condition rating for bridge decks. Artificial Neural Network is an adaptive system using a number of fully connected neutrons to process the data and then establish the relationship between the inputs and outputs. A typical neutron often consists of five components as depicted in Fig. 1. The input section provides information (triggering signals) for the neutron. The information is then going through an evaluation system where a weight is assigned to each input depending on the importance of the inputs. After that, a summation is performed to obtain a net input that comes to a neuron. The net input is then processed in the determination section to produce value in the output neuron [17].

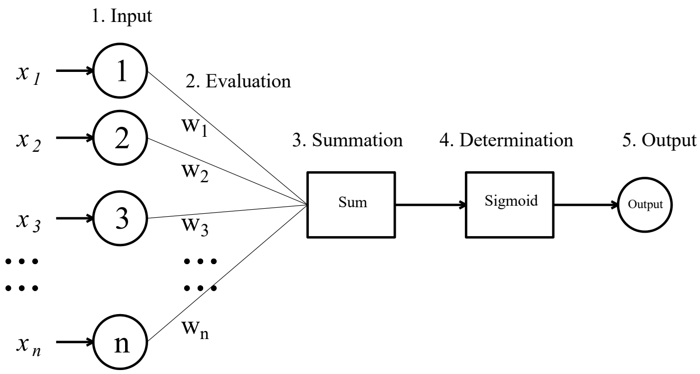


Figure 1. Components of a simple neuron

Neural networks learn to map between input and output through a common learning process called error back-propagation. It works by using the errors presented in the network output to adjust the weights between two adjacent layers. The error back-propagation consists of two different processes, in which one is a feed-forward process and the other is a back-propagation process. In the feed-forward process, the inputs are used to obtain the outputs based on the weights initially assumed or obtained from the previous adjustment. The errors are then passed backwards to the input layers through the back-propagation process, the weights are adjusted during this process to minimize the network errors to an acceptable level.

The ANN model often contains multiple neutrons with an input layer, multiple hidden layers, and an output layer, as shown in Fig. 2. In this study, the input layer consisted of eight parameters/neutrons,

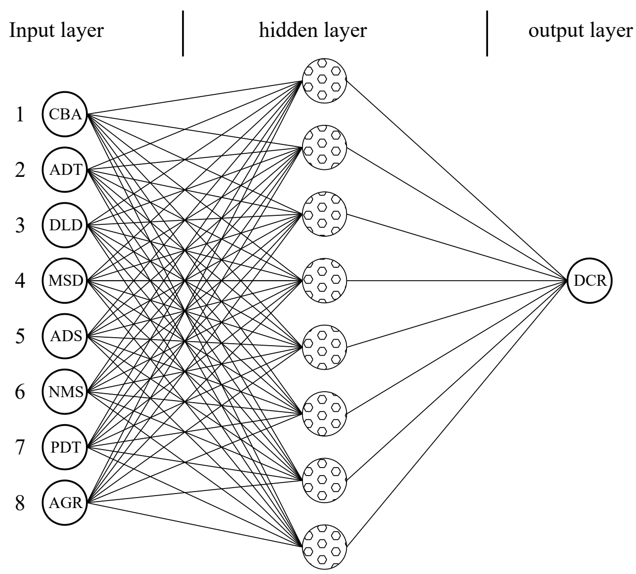


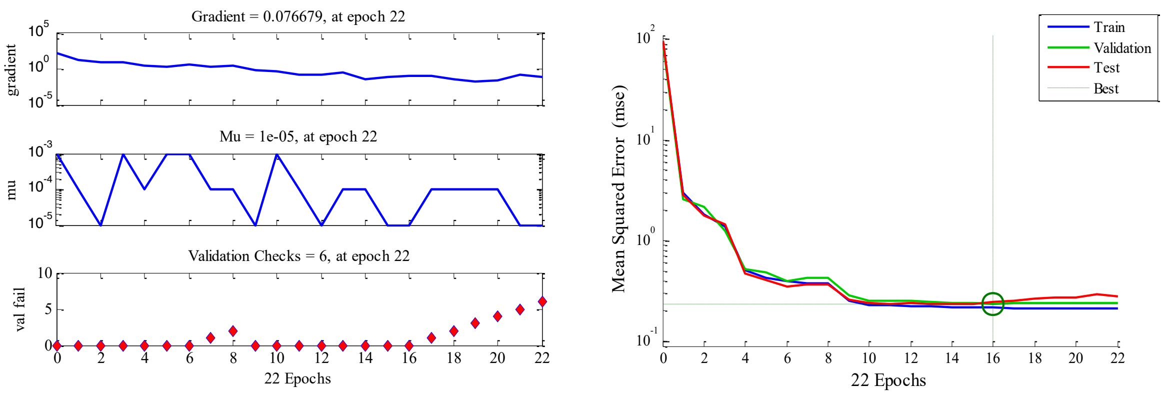
Figure 2. Structure of ANN model

namely *Current Bridge Age* (CBA), *Average Daily Traffic* (ADT), *Design Load* (DLD), *Main Structure Design* (MSD), *Approach Span Design* (ASD), *Number of main Span* (NMS), *Percent of Daily Truck* (PDT), and *ADT Growth Rate* (AGR). The output of the ANN model was the *Deck Condition Rating* (DCR). The dataset was divided arbitrarily into training, validation, and testing data subsets. The training subset consisted of 70%, i.e. 1800 bridges, of the entire database. The validation subset contained 15%, i.e. 386 instances, of the entire database. The remaining, i.e. 386 samples, were used for testing the proposed ANN model. The trained ANN model was then utilized to develop a degradation curve for a specific bridge.

In addition, the ANN models were also employed to study the importance/effects of each input parameter to the output. To perform this task, each ANN model was trained and used to predict the output with a single input parameter. The performance of the model with that input was then evaluated and recorded. Repeated this task for all the input parameters. The results were then ranked to explore the importance of each input to the output of the ANN model.

4. Results and discussion

The ANN model in this study has eight neutrons in the input layer, ten neurons in the hidden layer, and one neuron in the output layer. It employs the sigmoid activation function. The regression method is used to generate output for the ANN model. The output (condition rating) is rounded up or down to the nearest valid rating. For instance, if the condition rating of a bridge obtained from the ANN is 6.51, it will be rounded up to 7. Fig. 3 shows some information about the training and performance of the proposed ANN model. After training was completed, the ANN model was used to predict the output with the testing dataset. It is worth noting that the testing data is a set of data that was not included in the training set. A detailed discussion about the performance of the ANN model can be found in the subsequent sections.



(a) Training (b) Validation

Figure 3. Information of the proposed ANN model

4.1. Model performance

In order to evaluate the performance of the proposed ANN model, a confusion matrix and a bubble plot were used. The confusion matrix is often applied for classification problems to report numerical results thanks to its ability to show the relations between classified outputs and the true ones [18]. The bubble plot (scatter plot) provides a visualization of the confusion matrix with the number of instances were presented via the diameter of the dot [19]. The details of those two methods were presented in the following sections.

a. Confusion matrix

The confusion matrices were created for both training and testing data sets. The columns of a confusion matrix represent the true rating value from the manual inspection, and the rows show the predicted rating values by the proposed ANN model. Two indicators, *Correct Rating* (CR) and *Acceptable Rating* (AR), were used to evaluate the performance of the network. The CR is the percentage of predicted ratings that accurately matched the visual inspection rating. The AR is a ratio of predicted values within a rating margin of error over the actual rating values.

Table 4. Confusion matrix of bridge deck rating in training

	Manual Inspection							
Prediction	3	4	5	6	7	8	9	SUM
3	1	0	3	0	0	0	0	4
4	0	3	40	1	0	0	0	44
5	0	0	810	5	1	0	0	816
6	0	0	1	49	37	8	0	95
7	0	0	0	19	254	138	1	412
8	0	0	0	0	88	222	12	322
9	0	0	0	0	0	88	19	107
SUM	1	3	854	74	380	456	32	1800
CR (%)	100	100	94.8	66.2	66.8	48.7	59.4	75.4
AR (%)	100	100	99.6	98.6	99.7	98.2	96.9	99.2

Table 5. Confusion matrix of bridge deck rating in the test set

	Manual Inspection							
Prediction	3	4	5	6	7	8	9	SUM
3	1	0	1	0	0	0	0	2
4	0	1	10	0	0	0	0	11
5	1	1	172	2	1	0	0	177
6	0	0	0	8	6	1	0	15
7	0	0	0	6	52	30	0	88
8	0	0	0	0	25	49	0	74
9	0	0	0	0	2	16	1	19
SUM	2	2	183	16	86	96	1	386
CR (%)	50.0	50.0	93.9	50.0	60.5	51.0	100	73.6
AR (%)	50.0	100	99.5	100	96.5	98.9	100	98.5

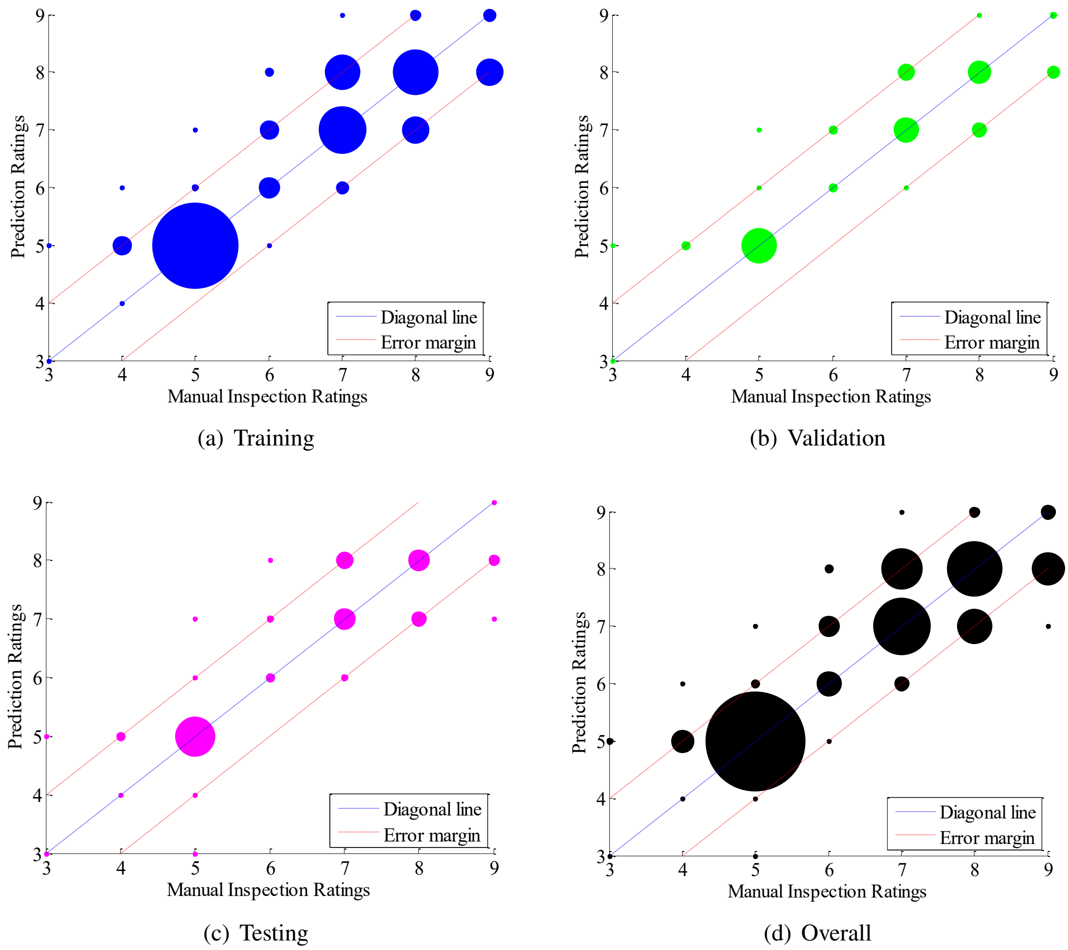
In the confusion matrix, the element a_{ij} (i is the row, and j is the column) indicates that the proposed ANN model predicted the rating as i while the true rating values as recorded in the database is j. The elements in the diagonal of the confusion matrix (a_{ii} in the bold gray cells) are the elements correctly classified by the network. These elements were used to calculate the CR for each individual rating, and for the overall network. As presented in Table 4, the proposed ANN had an overall CR of 75.4% for the training data subset.

The subjective rating of the visual inspection process is well recognized, therefore a margin error of ±1 is selected in this study to account for that subjectivity. The light gray cells in the confusion matrix represent the values of ratings within the margin of error. The AR indicator was calculated for the overall network and for the individual ratings. Taking into account this margin, the overall prediction ratings of the proposed ANN model for the training data subset significantly increased to 99.2%, as shown in Table 4.

Table 5 presents a confusion matrix for the bridge deck condition ratings in the test set. The proposed ANN model performed well for the new/unseen data in the testing data set with the overall CR of 73.6%, as seen in Table 5. When the margin error of ±1 was applied, the overall value of AR was increased to 98.5%. The results show the great potential of the ANN model at predicting ratings within a ±1 rating interval.

b. Bubble plots

An alternative technique to present the classification results is a bubble plot. Fig. 4 shows the bubble plots for the performance of the ANN model in different data sets with an identical scaling factor. In those plots, the diameter of the dots represents for the number of cases with an identical rating at each point. Because the number of samples in the validation and testing data subset is approximately



(a) Training (b) Validation

(c) Testing (d) Overall

Figure 4. Bridge deck ratings – Bubble plots

half of the size of the training subset, the size of the bubbles in validation and testing plots are smaller. The dots on the diagonal line indicate the number of accurate predictions, and the dots within the limit of upper and lower error margin line represent the number of instances within a ±1 rating interval.

4.2. Deterioration curves

The deterioration curve for bridge deck was created using the proposed ANN model. This curve can be used to predict the performance of the bridge deck during its service life. In the development of the deterioration curve for a specific bridge, two parameters, *Current Bridge Age* (CBA) and *Average Daily Traffic* (ADT) were changed in each step, other parameters were kept constant. While the increment of bridge age was 1 year, the change of average daily traffic was calculated by using the following equation

$$ADT_{next} = (1 + ARG)\, ADT \tag{2}$$

where ADT is the average daily traffic of the current year; ADT_{next} is the average daily traffic of the next year; ARG is the annual average daily traffic growth rate. To obtain the deterioration curve for the deck of a specific bridge, the following steps were applied.

1. Obtain the initial value of inputs of the bridge of interest from the database.
2. Decide the number of years to be simulated.
3. Apply the inputs to the proposed ANN model for the rating prediction.
4. Increase the age by 1 year and calculate ADT_{next}.
5. Repeat steps 3 and 4 for the entire life of simulation.

Fig. 5 shows an example of the bridge deck rating projection using the proposed ANN model. In Fig. 5, a circle dot represents the overall deck rating predicted by the ANN model. The square dots and diamond dots represent the upper limit and lower limit of the predicted condition rating, respectively. This bridge was seven years old with a current rating (DCR) of 8 and an AGR of 2.5%. The simulation was performed to predict the condition rating for the bridge deck over 60 years. Details of the initial input parameters of this bridge can be seen in Table 6.

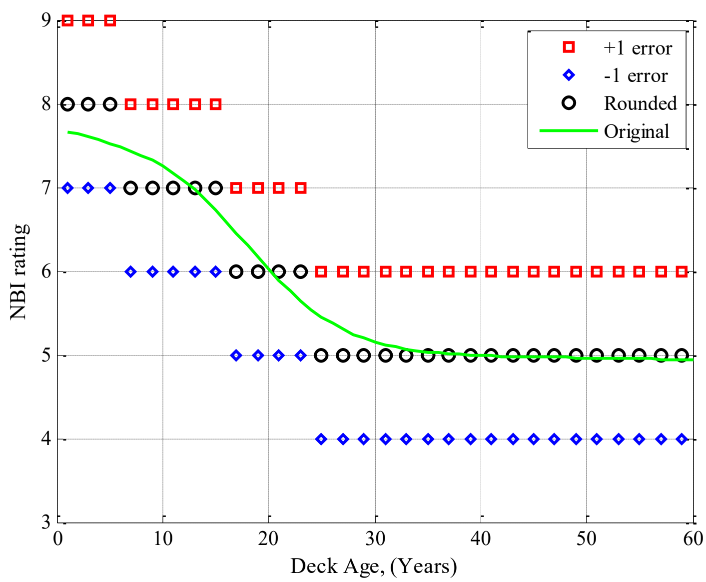


Figure 5. Lifetime bridge deck ratings prediction

Table 6. Initial input parameters from the database

Input	CBA	ADT	DLD	MSD	ASD	NMS	PDT	ARG
Value	7	17503	5	2	0	2	10	2.5

4.3. *Input sensitivity analysis*

To study the influence of a single input parameter to the overall deck rating for the bridges, the ANN model was used to run the sensitivity analysis. In each case, a single input was used with the ANN model to predict the output. The performance of each simulation instance was evaluated using the coefficient of determination (R^2). The coefficient of determination measures the correlation between input and output variables using equation (3)

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{3}$$

where y_i is the i^{th} actual output, $\bar{y}$ is the mean of the actual outputs, $\hat{y}_i$ is the i^{th} predicted rounded outputs, and n is the total number of samples. The results of the input analysis simulation are shown in Table 7.

Table 7. Sensitivity analysis for the inputs

Input	R^2	Ranking
CBA	0.93	1
ADT	0.18	5
DLD	0.60	2
MSD	0.52	3
ASD	0.23	4
NMS	0.08	7
PDT	0.14	6
AGR	0.05	8

As can be seen in Table 7, the most influential input parameter for the proposed ANN model was the *Current Bridge Age* (CBA) with a value of R^2 was 0.93. The *Design Load* (DLD) and *Main Structure Design* (MSD) came in the second and third place with an R^2 of 0.60 and 0.52, respectively. The results were reasonable since the performance of a bridge deck was likely linearly dependent on time. In addition, the design load was related to the type of load that applied to the bridge decks, thus a strong relationship between the design load parameter and the performance of a bridge deck was comprehensible. Other input parameters presented the limited correlation to the output.

5. Conclusions

In this paper, an ANN model was developed for predicting the condition rating of bridge deck using the available information in the NBI database. The bridge data in the State of Alabama were used to train, validate, and test the proposed ANN model. The model worked well with the new data in the testing data set with the percentage of prediction accuracy of 73.6%. Within the margin error of ±1, the prediction accuracy of the model can achieve 98.5%. The trained ANN model can be used effectively to develop the deterioration curve for the bridge deck. With such a curve, the future condition rating of the bridge deck can be easily predicted. In addition, a sensitivity study of the input parameters revealed that the *Current Bridge Age* (CBA) is the most important predicting factor to the bridge deck condition rating/deterioration. Other factors such as *Design Load* (DLD) and *Main Structure Design* (MSD) also had some significant effects on the deck deterioration.

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