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Artificial Neural Network Model for Bridge Deterioration and Assessment

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Abstract: Missouri has the seventh largest number of bridges nationwide, yet must maintain its inventory with funding from just the fourth lowest gasoline tax in the country. Estimation and prediction of the condition of bridges is necessary to create and optimize future maintenance, repair, and rehabilitation plans as well as to assign the necessary associated budgets. Previous studies have used statistical analysis, fuzzy logic, and Markovian models to develop algorithms for predicting future bridge conditions. Due to the non-linear nature of the relationship between the characteristics of bridges and their deterioration behavior, Artificial Neural Networks (ANN) have shown to be more suitable for discovering and modeling such relationship. As such, there is a gap in the literature when it comes to the ability of bride condition estimating. The goal of this research is to develop an ANN deterioration assessment model in Missouri. To this end, data on long span bridges was used where 80% of the data points were used for training and 20% were used for testing. In addition, a linear regression model was developed to act as a benchmark to assess the performed of the proposed ANN. The developed framework was successfully able to predict future condition of bridges. By using the developed model, the Missouri Department of Transportation will have a better ability to optimize their funding allocation and timing of bridge maintenance, repair, and rehabilitation. While this model was applied to bridges in Missouri, it can be tailored for other bridge assessment operations nationwide.

1 INTRODUCTION

According to the American Society of Civil Engineering (ASCE) report card (ASCE 2017), the infrastructure systems in the US scored an overall grade of D+ with predicted costs equal to $4.59 Trillion Dollars and bridges scored a C+ grade. The U.S. has 614,387 bridges, and of those bridges, almost four in ten of which are 50 years or older, and 56,007 (9.1%) were structurally deficient (i.e. they require repair and more frequent inspection) in 2016. The most recent estimates put the nation's backlog of bridge rehabilitation needs at $123 billion (ASCE 2017). For Missouri, the situation is even worse as 3,195 of the 24,468 bridges are structurally deficient; this is equal to 13.1 percent of total bridges in Missouri. In addition, Missouri is considered the seventh largest bridge inventory in the nation. This equivalent to say that one out of every 25 bridges in the country are in Missouri. Furthermore, bridges are inspected regularly, and their deterioration condition and efficiency are recorded. The most important elements of bridges include: superstructure, substructure, and deck. Based on the inspection reports, authorities determine the recommended actions for the maintenance and rehabilitation of bridges. The recommended actions include regular maintenance, more exhaustive rehabilitation, or even decommission and demolishment of the bridge. The data is recorded and managed in a Bridge Management System (BMS). BMSs are used to study the deterioration of bridges, to schedule their maintenance, and to prioritize which bridge has the most critical condition to allocate funds for maintenance and repair. When used, BMSs normally contain the current state of bridges, but they do not predict the state of the bridge nor prioritize which bridge(s) should be repaired first. Estimation and prediction of the condition and sufficiency rating of bridges is necessary to create and optimize future maintenance, repairs, and rehabilitation plans for bridges, and to assign budgets for that. There exist many research studies that examined several methods to predict the deterioration of bridges using the data from BMSs. These methods include traditional regression techniques, artificial neural networks (Huang 2010; Cattan and Mohammadi 1997), Markov Chains (Cesare el al. 1992), among many others. However, there is a lack of research that compares different modeling methods. In addition, there is an urgent need to implement robust model for the predictions of bridge deterioration in the state of Missouri. This research intends to study and compare two methods of bridge deterioration: linear regression and Neural Networks (NN). These two methods were applied to bridges in the state of Missouri.

2 GOALS AND OBJECTIVES

The goal of this paper is to study the deterioration of the superstructure, substructure, and deck conditions of bridges in the state of Missouri. The objectives of this research work is to: 1) Develop a statistical linear model (LM) using linear regression to be used as a benchmark for assessing the performance of NN, 2) Develop NN and experiment different configurations in order to achieve a satisfactory performance, and finally, 3) Compare the accuracy of the LM and the NN. A flowchart of the objectives of the research is shown in Figure 1.

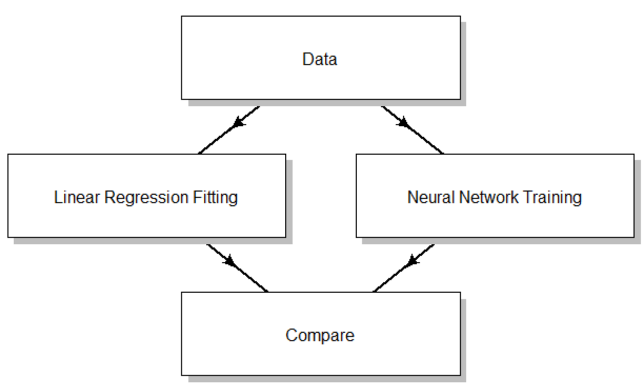

Figure 1: Flowchart of the Objectives of the Research

The model is expected to be useful to (1) estimate the sufficiency rating of a bridge given required characteristics, (2) predict the future rating of a bridge (superstructure, substructure and deck conditions), and (3) create/optimize maintenance and rehabilitation plans. The developed model predicts the deterioration of bridges and provides necessary information for decision making and maintenance planning for individual bridges or a network as a whole. Ultimately, the developed model can output the conditions of bridges based on selected parameters that affect the deterioration of bridges. In order to achieve that goal, a multistep methodology is implemented. This research is directed at construction management, infrastructure management, and computational science researchers.

3 METHODOLOGY

3.1 Used Software

This project uses the programming language R, also known as Cran R (R Core Team 2018) and the package “neuralnet” (Fritsch and Guenther 2016). R is a language that is widely used for statistical data analysis, data mining, and machine learning. It implements a wide variety of statistical and graphical abilities. The package “neuralnet” is available in the Cran R repository. It is used to train neural networks with given configuration of neurons, activation function(s), stopping criteria, etc.

3.2 Data Collection

The data was retrieved from the US. Department of Transportation, Federal Highway Administration (FHWA 2018). Data for bridge inspections in the US are submitted annually to FHWA by the different states, federal agencies, and tribal governments in accordance with the National Bridge Inspection Standards and the Recording and Coding Guide for the Structure Inventory and Appraisal of the Nations Bridges.

3.3 Inputs

The data collected contains several properties for each bridge, as well as its condition. The definitions and possible values of those properties are in accordance with the National Bridge Inspection Standards (FHWA 1995). After reviewing all the supplied standards, properties that are relevant to the condition of bridges were selected to be used as inputs for the model. The inputs and their descriptions are shown in Table 1.

Table 1: Inputs of the model

Input index	Name	Description
1	Year Built	The year on which the bridge was built
2	ADT	The average daily traffic
3	Year ADT	The year on which the ADT is calculated
4	Service On	The type of service on the bridge. Example: highway, railroad, etc.
5	Structure Kind	The material of the structure. Example: concrete, steel, etc.
6	Structure Type	The type of the structure. Example: slab, arch, truss, suspension, etc.
7	Max Span Length	The maximum length of any span
8	Structure Length	The total length of the bridge
9	Deck Width	The width of the deck on the bridge
10	Year Reconstructed	The year on which the bridge had heavy rehabilitation
11	Deck Structure Type	The material of deck. Example: concrete, steel, wood, etc.
12	Surface Type	The type of the deck surface. Example: concrete overlay, steel, bituminous, epoxy, etc.
13	Membrane Type	The type of the membrane on the deck. Example: built-up, epoxy, none, etc.
14	Deck Protection	The type or method of protection for the deck. Example: epoxy coated reinforcing, cathodic protection, etc.
15	Percent ADT Truck	The percentage of the trucks in the ADT

3.4 Outputs

Three conditions were selected to be the outputs of the model. They are: (1) the deck condition, (2) substructure condition, and (3) superstructure condition. These elements were selected because they are considered the major structural elements of a bridge. In the data collected from the FHWA, the condition ratings can be any option from “9” being in excellent condition, to “0” which means that the element is in a failed condition. The list of condition ratings as defined by the FHWA is shown in Table 2.

Table 2: Condition ratings as defined by FHWA (1995)

Condition Code	Notes
N Not Applicable	-
9 Excellent Condition	-
8 Very Good Condition	No problems noted.
7 Good Condition	Some minor problems.
6 Satisfactory Condition	Structural elements show some minor deterioration.
5 Fair Condition	All primary structural elements are sound but may have minor section loss, cracking, spalling or scour.
4 Poor Condition	Advanced section loss, deterioration, spalling or scour.
3 Serious Condition	Loss of section, deterioration, spalling or scour have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present.
2 Critical Condition	Advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support. Unless closely monitored it may be necessary to close the bridge until corrective action is taken.
1 "Imminent" Failure Condition	Major deterioration or section loss present in critical structural components or obvious vertical or horizontal movement affecting structure stability. Bridge is closed to traffic but corrective action may put back in light service.
0 Failed Condition	Out of service, beyond corrective action.

3.5 Data Preparation and Pre-Processing

For the purpose of this research, short-span bridges are excluded from the data to maintain a relevant length for the bridges included in the developed model. Short span bridges are the one possessing a length between 20 and 600 feet. Therefore, only bridges that are longer than 600 feet are selected. Also, bridges that have a condition of “N”, which is “Not Applicable”, were removed from the data because their condition is missing. Additionally, the data is randomly split into 80%-20% training and testing sets, respectively. The training set is used to train the NN, and fit the LM. While testing set is used to test the forecasted output of the NN and the LM. Before inputting the data into the NN, whether for training or testing, data pre-processing is performed to normalize it. The used pre-processing normalization method allows the data to be limited between zero and one. The equation for the pre-processing function is shown in Equation 1.

[1] $f(x_k) = \frac{x_k - \min(x_k)}{\max(x_k) - \min(x_k)}$

Where Xk is value of each parameter of the model before normalization.

Equation 1 is repeated for each column k in the data (which are, for example, the year built, the ADT, etc.). This equation yields a scaled data with a mean of 0 and a standard deviation of 1. The normalization was performed to ensure easier data processing for the development of the NN. The outputs of the model (conditions of superstructure, substructure, and deck) were then “un-scaled” using the same token, as shown in Equation 2.

[2] $f(x_k) = x_k \times [\max(x_k) - \min(x_k)] + \min(x_k)$

4 RESULTS AND ANALYSIS

4.1 Correlation Analysis

Pearson correlation analysis was performed between the inputs and the outputs. This analysis reflects the relationships between any two variables. The correlation value ranges from -1 to 1. A correlation of 1 means that a perfect positive linear relationship exists between the two variables. While a correlation of -1 mean that there is a perfect negative linear relationship. A value of zero means that there is no relationship at all. The results of the correlation analysis between the inputs and the outputs are shown in Table 3. It is to be noted that the rows in Table 3 are sorted by the absolute average of the correlation values, from highest to lowest. It is observed that the “year built” and the “surface type” are the most highly correlated inputs, followed by the “structure kind”, “structure type”, “year reconstructed”, “and the “deck structure type”.

Table 3: Correlation analysis results

Input	Substructure Condition	Superstructure Condition	Deck Condition
Year Built	0.551	0.626	0.376
Surface Type	-0.346	-0.392	-0.446
Structure Kind	0.264	0.308	0.271
Structure Type	-0.17	-0.242	-0.063
Year Reconstructed	-0.179	-0.278	0.049
Deck Structure Type	-0.11	-0.147	-0.124
Deck Width	0.043	0.065	0.157
Structure Len	-0.107	-0.131	-0.011
Max Span Len	-0.09	-0.067	0.028
Year ADT	-0.062	-0.009	-0.057
Percent ADT Truck	-0.041	-0.075	0.01
ADT	-0.023	-0.097	0.016
Service On	0.049	-0.01	0.035
Membrane Type	0	-0.052	-0.002
Deck Protection	0.006	-0.014	0.049

4.2 Linear Model (LM)

The linear model is implemented by performing linear regression. The linear regression calculates the coefficients for each input, and the y-intercept for each one of the 3 outputs. After fitting the model, it was found that the fit residuals are equally spread without having recognizable arrangement. In addition, the obtained residuals followed a normal distribution, which indicates that the developed LM could be used as a benchmark for assessing the performed of NN. Moreover, the developed LM shows an acceptable distribution of residuals where most of the residuals are between -1 and 1. Considering that there are ten conditions for a bridge, an error of plus or minus one condition is considered acceptable. Histograms of the obtained residuals are shown in Figure 1. Regarding the P-values of the coefficients, the variables: “Year Built”, “ADT”, “Structure Kind”, “Structure Length”, “Deck Width”, “Year Reconstructed”, “Deck Structure Type”, and “Surface Type”, have a p-value ≤ 0.05. This indicates that these inputs are highly significant to the predicted output. The R squared values for the developed LMs are as follows.

- Deck Condition:
  - Multiple R-squared: 0.3497
  - Adjusted R-squared: 0.328
- Superstructure Condition
  - Multiple R-squared: 0.4692
  - Adjusted R-squared: 0.4515
- Substructure Condition:
  - Multiple R-squared: 0.3747
  - Adjusted R-squared: 0.3539

The obtained R^2 values are considered to be in the acceptable mid-range. However, it is to be noted that these R^2 values should not be taken as the sole indicators of the performance of the developed LMs. Nevertheless, from a holistic view on the accuracy of the LM, it can be concluded that the fit of the linear model is acceptable. Hence, the LMs can be used for comparison with the NN.

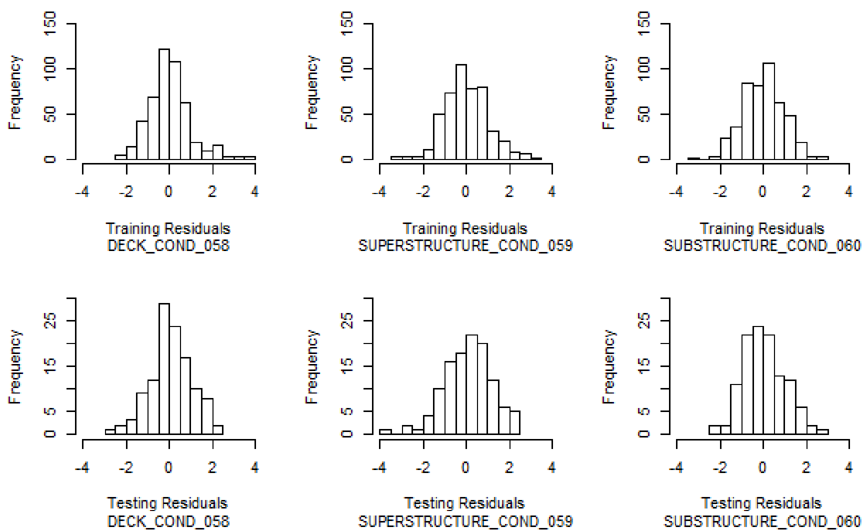

Figure 2: Histograms of the residuals for the deck, substructure, and superstructure for the LM

4.3 Neural Network (NN)

Several NN configurations were tested, the residuals of those configurations were investigated, and comparisons with the LM were performed, in order to select the best model. An example configuration of an NN, with ten neurons on one hidden layer, is shown in Figure 3. One key point to avoid while developing an NN is the over-training of the model. As such, an appropriate selection of the number of layers, number of neurons, and stopping criteria should be well established to avoid over-training. An over-trained NNs output very good results for the training set; however, they perform badly with the testing set, which is considered to assess the performance of the NN with new data set. An example of the outputs of an over-trained NN is shown in Figure 4. Several configurations of the NN were experimented. In addition, the used activation function is the logistic function. The inputs are the same inputs for the LM, and the outputs are the conditions of the deck, superstructure, and the substructure, each with its own output neuron in the output layer. It is to be noted that the output layer of the developed NN is linear; this means that they are not affected by the activation function. This is done because the condition ratings are numerically and logically linear, where they range from 9, which is the best condition, to 0, which is the worst condition. The inputs and outputs are subject to pre-processing, where they are “scaled” and “un-scaled” using Equations 1 and 2. In order to ensure that the training of the NN was completed successfully, tests were performed on the training test first to investigate the residuals.

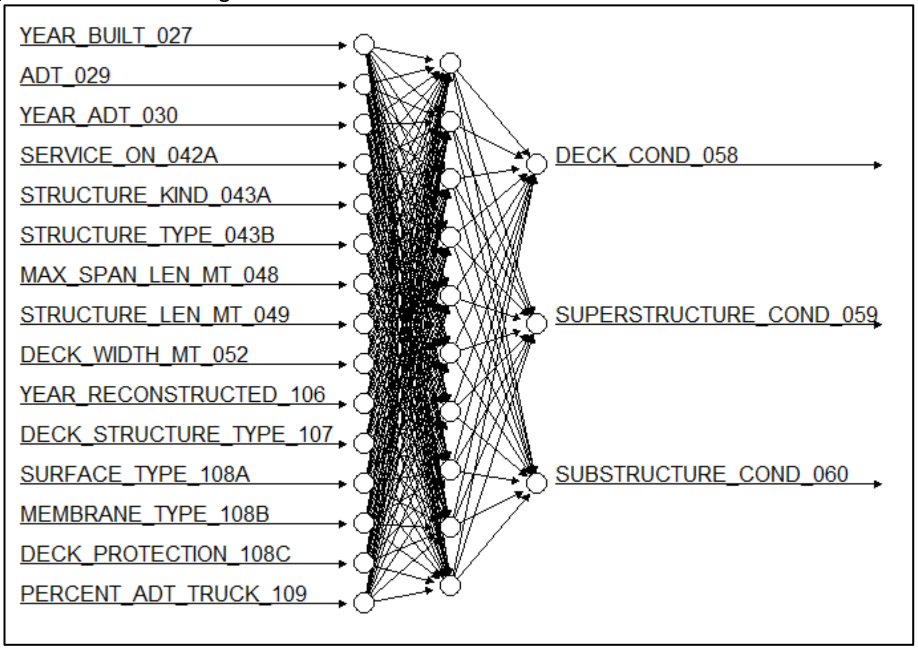

Figure 3: Sample configuration of the NN

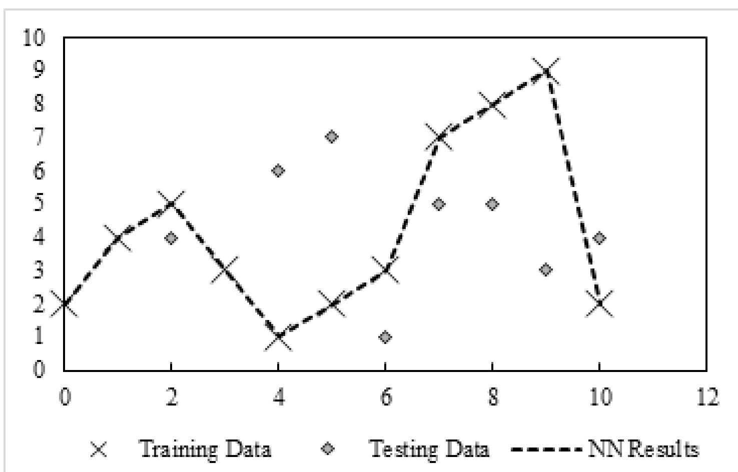

Figure 4: Example results of an over-trained NN

4.4 Comparing Results of LM and NN

Several NN configurations were tested in order to identify the best-performing NNs against the training and testing sets. The NN configuration is represented as NN(x) where x shows the number of neuron in each hidden layer. For instance NN(3,3,1) means that there are 3 hidden layers with 3 neurons in the first one, 3 neurons in the second one, and one neuron in the last one. A comparison of the Mean Squared Errors (MSE) for the LM and several NNs is shown in Table 3. It can be seen that as the complexity of the NN increases, the errors for the training set generally decrease, but the errors for the testing set increase. By checking the errors for the testing, the NN with only one neuron preforms better that the LM. The best performing NN, by average MSE for the testing set (that NN with the lowest value in the last column of Table 3), is the NN with a [3,3,1] configuration. This configuration of the NN is shown in Figure 5. A histogram of the errors of this NN(3,3,1), is shown in Figure 6. Most of the errors lie in the [-2,2] range. In practice, and taking into consideration that there are ten conditions, the error is acceptable. Overall, it could be concluded that developed NN(3,3,1) performs slightly better that the LM.

Table 3: Comparison of MSEs for LM and NN trials

Model	MSE							
	Training				Testing			
	Deck	Super-structure	Sub-structure	Average	Deck	Super-structure	Sub-structure	Average
Linear	0.857	0.997	0.813	0.889	0.903	1.248	0.904	1.018
NN(1)	1.004	0.999	0.855	0.953	0.989	1.231	0.877	1.032
NN(5)	0.56	0.728	0.605	0.631	1.406	1.478	1.043	1.309
NN(10)	0.461	0.698	0.487	0.549	1.219	1.125	1.097	1.147
NN(3,1)	0.852	0.796	0.651	0.766	0.965	1.268	1.108	1.114
NN(5,1)	0.748	0.741	0.644	0.711	1.13	1.98	1.387	1.499
NN(5,5)	0.605	0.647	0.486	0.579	0.888	1.41	1.141	1.146
NN(3,3,1)	0.823	0.774	0.611	0.736	0.933	1.119	0.973	1.008
NN(5,5,1)	0.797	0.644	0.542	0.661	0.985	1.361	1.037	1.128
NN(3,3,3,3)	0.626	0.787	0.634	0.682	0.942	1.366	0.928	1.079
NN(3,3,3,3,3)	0.638	0.732	0.561	0.644	0.878	1.464	0.922	1.088

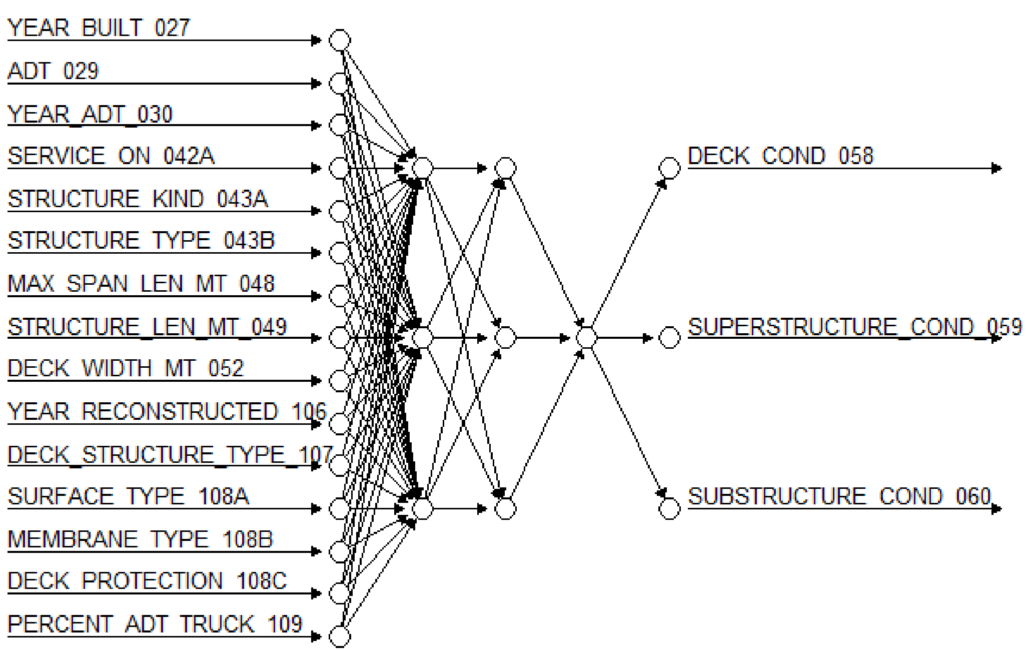

Figure 5: Configuration of the best performing NN (Configuration 3,3,1)

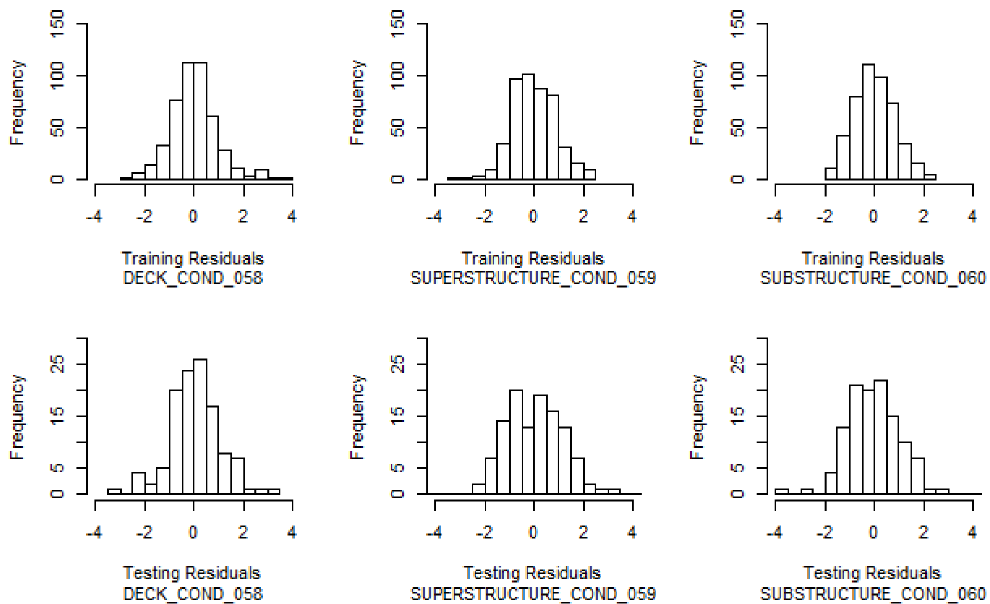

Figure 6: Histograms of the Residuals of the best performing NN (3,3,1)

5 CONCLUSION

Estimation and prediction of the condition and sufficiency rating of bridges is necessary to create and optimize future maintenance, repairs, and rehabilitation plans for bridges, and assign budgets for them. This paper developed an NN model to study the deterioration of the superstructure, substructure, and deck conditions of long bridges in the state of Missouri. The developed model was compared with a LM that acted as a benchmark to assess the performance and reliability of the proposed framework. The developed model in this paper is perceived to help in providing the optimal plan to schedule for the maintenance of bridges, and to prioritize which bridge has the most critical condition to allocate the proper funds for its maintenance and repair. The paper investigated several NN that output the condition of bridge elements based on selected parameters. In addition, the accuracy of both models were compared. Furthermore, it was found that both methods have almost the same accuracy. However, the accuracy of the NN is slightly better.

6 LIMITATIONS AND FUTURE WORK

There are some limitations to this work, such as this model is best applicable for long span bridges. Although this study was performed for bridges in the state of Missouri, it can be easily extended to neighboring states or even applied to all the US states, especially that the environmental and weather conditions are considered as factors affecting the output of the model. As for future work, the authors recommend the performance of further research in the area of modeling deterioration of bridges using NN. Further testing is needed on the settings and configuration of the NN, such as changing the number of neurons used, adjusting the number of hidden layers, using different activation functions, and manipulating the stopping criteria so that the model can provide better results.

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