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THE APPLICATION OF ARTIFICIAL NEURAL NETWORK IN PREDICTING BRIDGE CONDITION BASED ON SEISMIC ZONATION

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ABSTRACT:
In this study, artificial intelligent methodology is applied to bridge inspection system. Artificial neural network (ANN) is developed to predict bridge condition rating based on different intensity of seismic zonation. Inspection results from nondestructive evaluation are used as an indicator to the structural condition. Numbers of systems are developed to determine the effective parameters and neural network structure in order to build the most predictive ANN system. Backpropagation algorithm with one hidden layer is used to develop the neural network and Borland C++ is used as the programming language. 75 concrete bridges under the supervision of Public Works Department, PWD (Malaysia) have been selected for further inspection using nondestructive evaluation technique which includes the rebound hammer test, Ultrasonic Pulse Velocity, and electromagnetic cover meter. These tests were conducted to determine the bridge strength, structural damages, and level of the damages. Results from this inspection are then applied to the ANN together with the seismic zonation parameter and other bridge parameters in order to develop the intelligent system. Generally, this study showed that the ANN has a potential to be used to predict the condition rating based on different seismic intensity. Prediction values are up to 90% correct. Linear correlation coefficient between the prediction and actual value ranges from 0.5 to 0.8, which shows a strong relationship between these two values. This intelligent system can help the authority to forecast bridge condition after tremors. Critical bridges can be short listed and prioritized for the allocation of maintenance budget. The intelligent system has large potential to be used as inspection aided tool in bridge monitoring and thus any attempt to enhance the system are very much recommended.

KEYWORDS:
Seismic zonation, earthquake monitoring system, artificial neural network, nondestructive evaluation.

1. INTRODUCTION

1.1. Background

Assessing the condition of a structure is necessary to determine its safety and reliability. Ideally, structural health monitoring should be similar to medical health monitoring of the body. In medical health monitoring, the life signs such as pulse and blood pressure give an overall indication of the overall health of the body. This is analogous to global health monitoring, in which damage to the structure can be identified by measuring changes in the global properties of the structure. Once the body signs show an anomaly, we do a battery tests to determine the cause of the anomaly. Analogously in structural health monitoring, nondestructive evaluation can be used to determine the nature of the damage.

Concrete bridges are exposed to numerous environmental stressors and traffic loads which increases from time to time. These can cause a reduction in overall strength and lead to eventual failure of the bridge. Periodic bridge inspections are therefore necessary to assess the extension, implications, and current state of the deterioration process. Inspections not only help to prevent failure but also deliver information necessary to effective administration of the bridge network. Thus, the administrative bodies can further define priorities and establish programs to apply available resources to the most critical bridges.

Currently bridges are evaluated through either a visual inspection or structural analysis. Visual inspections are commonly used nowadays. When bridge evaluation is conducted using this method, rating will be assigned to the bridge components by a responsible inspector. Major problem with visual inspection is the inherent variability that naturally occurs when subjective observations are converted to a numerical rating. Bridge evaluation based on this method may vary according to personal judgment. Thus, large uncertainties exist in the interpretation of inspection data.

Nondestructive evaluations are one of the techniques suggested by researchers to overcome the limitations faced by the existing rating system. This method has gained interests among researchers due to its effective ability in determining damages inside the structure that are not visible. Previous researches show a good potential of nondestructive testing to be used in evaluating structural condition of existing structure. Thus several trials were carried out to correlate data from nondestructive testing with visual inspection in order to enhance the existing evaluation process.

Despite of all the advantages of using the nondestructive testing, this method is not always readily available and there may be problems occur with the lack of experienced inspectors to conduct the test. Hence, the implementation of this method in routine inspection may be limited. The strong capability of artificial neural networks in predicting fuzzy data and the success applications of this approach in various fields give an idea to implement ANN to predict bridge condition based on nondestructive testing data and visual inspection. In other words, nondestructive tests may not be necessarily conducted in each routine inspection; previous nondestructive testing results will be used to predict the condition rating of a bridge. It is hope that this system will assess the current inspection process and thus lead to a more thorough yet uncomplicated evaluation.

1.2. Problem Statement

Existing practice in evaluating bridge condition through visual inspection has been identified to have few limitations. Despite of their role as the first step of any condition assessment procedure, this type of evaluation is subjected to large uncertainties and depends primarily on a personal judgment of responsible inspector. Ratings assigned to the bridge component are subjective and may vary according to the visual observation. Due to these limitations, few researches have been conducted to support assessment made using visual inspection.

In recent years, researchers and industrial practitioners has turn to nondestructive testing (NDT) method to evaluate their structure due to the ability of this method in determining invisible defects inside the structure that is not possible to be evaluated through visual inspection. Therefore, the NDT method has been chosen in this research to support evaluation made in the existing practice. However, despite of their masses advantages, this method is not always readily available and there may be problems occur with the lack of experienced inspectors to conduct the test. Hence, the implementation of this method in routine inspection may be limited.

If the NDT results can be predicted, the bridge condition can still be assessed without even conducting the test during inspection. The strong capability of artificial neural networks (ANN) in predicting fuzzy data and the success applications of this approach in various fields give an idea to implement ANN to predict bridge condition based on previous inspection data. If this approach success, there will be less works need to be done during inspection and yet the evaluation is still thorough. This will benefit lots of people involved in bridge inspection especially the bridge authority. This system can help the authority to forecast bridge condition at any given time. Critical bridges can be short listed and prioritized for the allocation of maintenance budget.

1.3. Objectives

This study is conducted to comply with the following objectives:

i) To conduct nondestructive testing (NDT) on selected bridges to evaluate the bridge condition
ii) To find the correlation between NDT results and visual inspection (VI) ratings
iii) To determine NDT results and VI ratings using Artificial Neural Network (ANN)
iv) To find the correlation between NDT results and VI ratings from field test (manual process) and ANN

2. BACKGROUND OF RESEARCH

2.1. Artificial Neural Network

From the time of the first primitive computing machine, their designers and users have been trying to push computers beyond the role of automatic calculators and into the realm of "thinking" machines. Thus, the emergence of "artificial intelligence" (AI) has brought up new transformation to the computer applications. Different approaches using the concept of AI have becoming more popular and beneficial to industrial practitioners and researchers.

The human senses detect stimuli, and send this "input" information (via neurons) to the brain. Within the brain, neurons are exited and interact with each other. Based on the input, a conclusion is drawn, and an "output" is sent from the brain in the form of an answer or response. The interaction between neurons is not seen by anyone, but manifests itself as identifiable intelligent behavior.

The same type of structure can be developed for a computer modeling of intelligent behavior. Neurologists and AI researchers have proposed a highly interconnected network of "neurons" or nodes for this purpose. Information is applied as an input to a network of nodes. The nodes mathematically interact with each other in a manner unknown by the users. Eventually, based on the input, an output arises that maps the expected, macroscopic input-output pattern.

In other words, the development of ANN are intended to mimic the behavior of biological learning and the decision making process without being biologically realistic, in detail (Kim et al. 2003). Neural networks represent simplified methods of a human brain and may be used to solve problems that conventional methods with traditional computations find difficult to solve.

3. METHODOLOGY

3.1. Programming Phase

The aim of this phase is to develop the artificial neural network system to determine conditional ratings. The development consists of few stages which may vary according to the programmer. However, each set of stages shared the same basic fundamental in ANN development. For instance, Wu and Lim (1993) applied five stages in developing a neural network model which include: data acquisition, architecture determination, learning process determination, training the network, and finally testing the trained network for generalization evaluation. Timothy (1993) classified ANN development phase in three steps; training or learning phase, testing phase, and validation phase. Whereby, Elazouni et al. (1997) classified ANNs modeling into three main phases; design, implementation, and recall or use for problem solving. The design phase consists of two aspects; problem analysis and problem structuring. The implementation includes three main tasks; data collection, selecting the network configuration, and training and testing the network.

In this study, three main phases are applied in the application of neural network model, in which each phase consists of few steps as shown in Figure 4.32. The phases are as listed below:

i) Analyzing data
ii) Developing ANN structure
iii) Operating the ANN

In the first phase; data involved in developing the network are analyzed to determine their characteristics and correlation between input and output data are evaluate. Data samples are divided into two groups; one group is to be used in training and testing phase, and another one is for the validation phase. Normalization process is conducted to the data before it is applied to the network.

In developing the ANN structure (phase ii), parameters involved in the network need to be finalized. In this phase numbers of trial and error process are conducted to determine the effective input variables and number of hidden neurons needed in developing the neural network. Other parameters such as weights and biases, functional forms, learning rate, and momentum of coefficient will also be outlined.

When the network structure has been concluded, operating process (phase iii) can now be proceed. This phase consists of three process; training, testing, and validation. Network performances in each process are analyzed to determine the network's ability in providing output based on the data it is subjected to. The above mentioned phases are discussed further in the following sub-topic. Figure 1 graphically illustrates the phases involved in the programming phase.

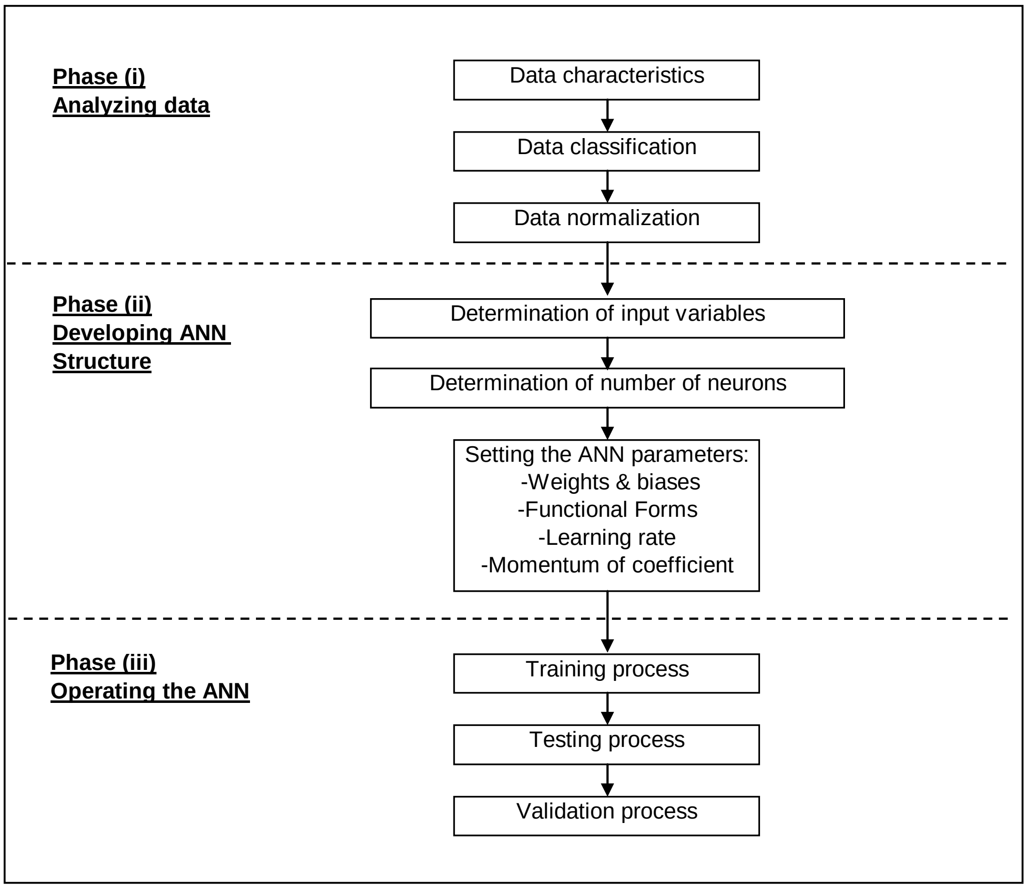


Figure 1: Stages involved in the programming phase

3.1.1 Analysing Datafor Seismic Zone

The data used in developing the neural network is limited to the data gathered during site survey phase. These include the data from bridge inventories, visual inspection report, and nondestructive testing. There are nine parameters applied to the ANN model which includes the parameter based on the seismic intensity at the bridge site. Peak ground acceleration, PGA value used is based on 2% probability of accidence in 50 years (return period equal to 2500 years). The PGA value for each bridge sample is determined using the macrozonation map shown in Figure 2. Road maps for each district as attached in Appendix 4D are referred to get the exact location of the bridge samples.
The above parameters are classified into specific groups to characterize their types and variety. Each group will be represented by a particular code to be used in the ANN development. Table 1 to 5 shows the classification made to the parameters.

As mentioned, the PGA values shown in Table 1 are determined from the macrozonation map shown in Figure 2. Referring to the map, PGA values for Peninsular Malaysia ranges from 40 to 200 gal, whereas for Johor state it ranges from 60 to 140 gal. For programming purposes, the PGA values are classified in ten groups starting from 0 to 200 gal with an interval of 20 gal.

Table 1: Seismic zonation

PGA Value (gal)	Group Code
0-20	1
21-40	2
41-60	3
61-80	4
81-100	5
101-120	6
121-140	7
141-160	8
161-180	9
181-200	10

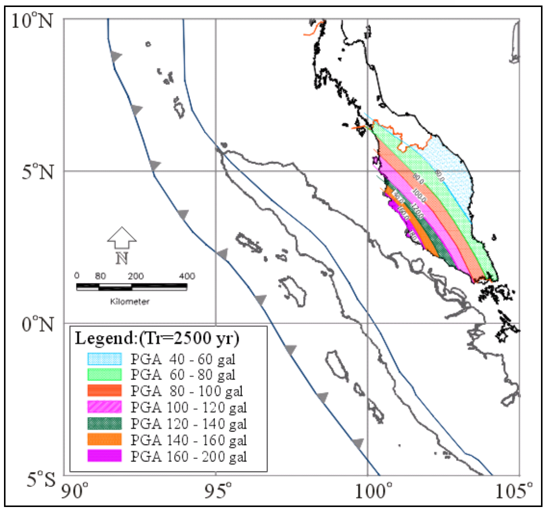


Figure 2: Macrozonation map at 2% PE in 50 years on rock site conditions for the Peninsular Malaysia (TR=2500year), Adnan et. al. (2006).

Although bridges can be classified according to different aspects such as their function, form of superstructure, as well as material and method used in construction, interspan relation is used to classified bridge types in this study. There are three major classification made as shown in Table 2.

Table 2: Classification of system type

System Types	Group Code
Simply supported	1
Continuous	2
Cantilever	3

Bridge samples used in this study are limited to concrete bridge only. Basically, deck type for the bridge samples can be classified in six groups as shown in Table 3.

Table 3: Classification of bridge deck

Bridge Decks	Group Code
Prestressed concrete I-beam	1
Reinforced concrete beam	2
Prestressed inverted T-beam	3
Prestressed concrete M-beam	4
Concrete box-girder	5
Reinforced concrete slab	6

Abutment types are categorized in four groups as shown in Table 4.

Table 4: Classification of abutment

Abutment Types	**Group Code**
Bank seat	1
Wall abutment	2
Skeleton abutment	3
Wing wall	4

As for the pier structure, six groups are identified to classify the pier type. This classification is shown in Table 5.

Table 5: Classification of piers

Pier Types	**Group Code**
Solid pier	1
Leaf pier	2
Single leg pier	3
Multi column pier	4
Portal pier	5
V-pier	6

As mentioned earlier, data involved in developing the neural network needs to be analyzed first. This analysis consists of three stages;

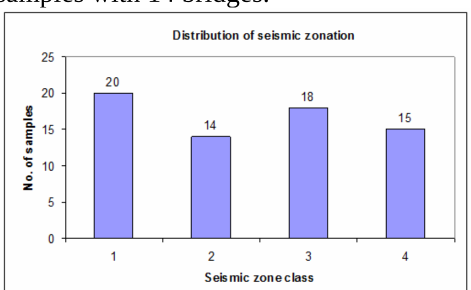
i) analyzing the characteristics of data involved
ii) classification of data
iii) data normalization

4. RESULT AND DISCUSSIONS

4.1. Data Characteristic

Characteristic of each data used in developing the neural network needs to be defined due to the random process applied to extract the data. The distributions of each inputs and outputs are defined through histograms and the relationships between these two variables are determined using linear correlation coefficient, *r*. Figure 3 shows the distribution chart for each parameter.

Figure 3 shows the distribution of seismic zone at bridge sites. There are four zones involved with peak ground acceleration ranges from 61 to 140 gal. The distributions are quite even between the bridge samples. Zone class 1 shows the highest readings with 20 bridge samples, followed by class 3 and 4 with 18 and 15 samples respectively. Zone 4 has the least samples with 14 bridges.



Legend:

Seismic Zone Class	Seismic Intensity (PGA)
1	61-80
2	81-100
3	101-102
4	121-140

Figure 3: Distribution of seismic zonation on bridge site

4.2. Data Classification

After knowing the distribution of input and output parameters used in this study, it is important to evaluate the classification made to these parameters. Data involved are classified in two groups; 1) training and testing phase, 2) validation phase. From 75 samples of concrete bridges involved in this study, 52 samples are used in the training and testing phase while 15 samples are used in the validation phase. These validation samples can never be applied in the training and testing phase. This selection is based on a random process. Another 8 samples have incomplete details and inadequate to be used in the ANN system. Appendix 6A shows the whole input and output data used in training and testing phase, as well as in the validation phase. Figure 4 graphically shows the distribution of data used in both categories.

Figure 4 shows the distribution of seismic zonation for training and validation phase. Classifications of seismic zones in this figure are the same with Figure 3. Training and validation data are represented in all categories. Since the data distributions are uniform, the differences between training and validation data set are uniform as well. Seismic zone class 1 with PGA between 61-80 gal, has the highest number of samples in both phases.

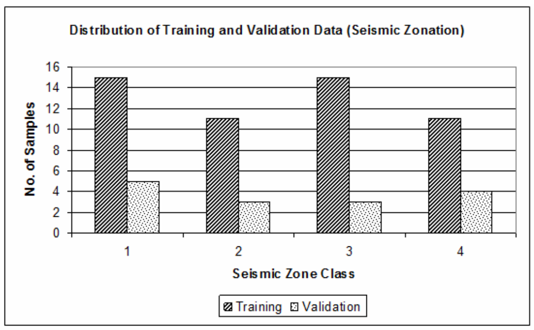


Figure 4: Distribution of training and validation data

4.3. Result and Discussion

In this section, result from the application of ANN in each rating prediction is discussed. In this stage, the final ANN structure is used in which all seven input parameters and 15 hidden neurons are applied to the network. Mean square error between the actual output and output given by the ANN are discussed to evaluate the training phase. Linear correlation coefficient between the actual output and output given by the ANN is analyzed.

4.3.1 Rating Prediction for Bridge Deck

Figure 5 shows the plotted values of actual rating and rating predicted by the neural network in the testind phase for bridge deck. The VI rating gives r equal to 0.758.Out of 52 samples used in the testing phase, 48 samples were predicted accurately for the VI rating which presents 92% from the total data used. Rating 1 dominated the samples for VI rating and this rating had the highest number of samples predicted without error. Rating 4 had a lowest number of samples and it was predicted with more than 1 rating difference.

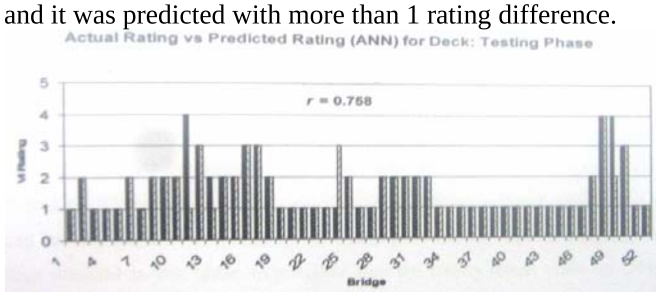


Figure 5: Plotted actual rating and predicted rating by ANN during testing phase for deck ratings, VI

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5. CONCLUSIONS

This study involved two major aspects; 1) conducting nondestructive testing to evaluate bridge condition, and 2) applying artificial neural network methodology to predict the bridge condition. Conclusion from the bridge inspection conducted in this study and ANN that had been developed can be summarized as follows:

1) Based on the visual inspection conducted by PWD, most of the bridge samples were rated 1 and 2. It can be observed that the VI rating ranged differently based on each district. In other words, the rating assigned during visual inspection was dependent on the inspector's evaluation and judgment.
2) Based on the artificial neural network developed in this study, it can be concluded that the ANN predictions were very much affected by the data applied to the network. These included the total samples used in the training and validation phase, number of samples in ach rating type, and the distribution pattern of the data. Increasing the number of output parameter will improve the ANN performances.
3) The ANN models used in the rating prediction were capable to predict the condition ratings with high accuracy. Results show that the VI rating can be predicted between 67% correct. The linear correlation coefficients between the actual rating and rating predicted by the network were up to 0.9 which shows a very strong relationship between these two ratings. These results prove the capability of the network to recognized data pattern and provide accurate prediction even when the correlation between input and output data is very weak.
4) However, the development of the model needs extra consideration on the most effective parameters and number of neurons to be applied to the network. Both of these aspects are important and affect the network prediction significantly. Based on findings obtained in this study, the ANN can best perform when all of the bridge parameters are applied as input to the network.

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