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Technical Note

ANN based prediction of moment coefficients in slabs subjected to patch load

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1. Introduction

In civil engineering, there are a number of situations where we have sufficient data in the form of design aids, charts and tables but the use of these data requires manual reading of data and development of a fully computer based design procedure becomes difficult. Bridge decks are subjected to vehicle loads, the tyres of vehicles have finite contact area with the deck and the load is applied on this area. This type of load is known as patch loading. For patch loaded interior panel design, closed form solutions are not available. Pigeaud generated curves to simplify the design of panels subjected to patch loading, he developed curves for symmetrical loaded panels. These curves give moment coefficient in short and long span (m_1, m_2). In actual cases the loading may be unsymmetrical also, apart from this various types of vehicles will be applying different types of patch loads. Hence, the design of interior panel becomes tedious and therefore automation of design process is required. In the computer aided design of interior panel, reading m_1, m_2 values as well as interpolation manually becomes a major hurdle.

In the present work this problem is addressed and an Artificial Neural Network (ANN) is trained to predict moment coefficient in short span m_1 for the interior panel subjected to patch loading. Similarly a different ANN may be trained for moment coefficient in long span m_2 values. The developed ANN is a computationally efficient tool and using this design automation task may be attempted.

Artificial Neural Networks are simplified models of the biological nervous system and therefore, have drawn their motivation from the kind of computing performed by a human brain. ANNs are computing systems made up of a number of simple, highly interconnected processing elements which processes information by their dynamic state response to external inputs. Garrett (1994) has given an interesting engineering definition of the ANN as: *A computational mechanism able to acquire, represent and compute mapping from one multivariate space of information to another, given a set of data representing that mapping.* ANN can be trained with the known values from collected data or from the test data and they can recall full patterns from incomplete, partial, or

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noisy patterns. ANNs have been used recently to recognize complicated patterns and to solve problems too complex to model accurately by traditional computing methods. A state of the art review of journal articles on civil engineering applications of neural networks is presented in a recent article by Adeli (2001). From Civil engineering point of view, ANN has been found to be used for Structural analysis and design (Cheng 1999, Jerzy and Krzysztof 2005, Krishna and Gangadhran 1999, Muhammad Hadi 2003, Taha *et al.* 2003), damage assessment of existing structures (Hsu and Tsai 1997), in bridge engineering (Cevik *et al.* 2002, Sirca and Adeli 2004), image processing (Amerijckx *et al.* 1998) etc.

2. Slabs subjected to patch loading

Interior panel of bridge decks are subjected to patch loads. As the exact formulae are not available, so during the design of interior panels Pigeaud's curves are used. According to Pigeaud's method the moment along the shorter and longer directions depends on the ratios K, u/B and v/L. Bending moment coefficients m_1 and m_2 for different values of K from 0.4 to 1 are presented in the forms of curves, from which the values of m_1 and m_2 for the particular set of u/B and v/L values can be determined, then final moments M_1 and M_2 are calculated from Eqs. (1) and (2).

$$M_1 = (m_1 + \mu m_2)P \tag{1}$$

$$M_2 = (m_2 + \mu m_1)P \tag{2}$$

These curves are generated for symmetrically placed patch loads (Johnson 1980) and hence determination of moment coefficient for unsymmetrically placed patch loads becomes tedious. Use of computer requires an estimator for Pigeaud's curves. ANN is utilized in the present work to overcome this problem.

3. Development of ANN model

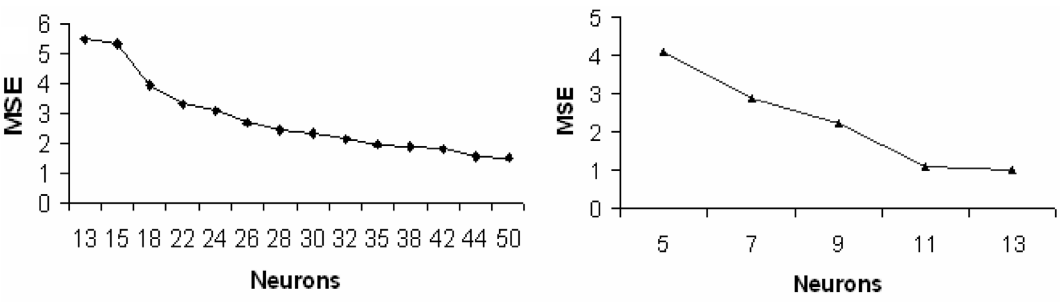
Many applications of neural networks particularly in the areas of nonlinear system identification and control reduce to the problem of approximation of an unknown function, it has been well established that multilayer feed-forward networks with a variety of activation functions can act as universal function approximators (Hornik *et al.* 1989). Most neural network applications are based on the back-propagation paradigm, which uses the gradient-descent method to minimize the error function. The back-propagation neural network and its variants are currently the most widely used networks in applications. Properly trained back-propagation networks tend to give reasonable answers when presented with inputs that they have never seen.

There are generally four steps in ANN modeling process:

- Determination of the training set
- Artificial neural network architecture
- Training and testing of the network
- Generalization capabilities

3.1 Determination of the training set

Patterns chosen for training of ANN are selected accurately by interpolating the values in Pigeaud's curves, these curves are easily available in many text books (Johnson 1980). The training data of K, u/B and v/L and their corresponding target m_1 is obtained from seven curves, where K varies from 0.4 to 1, 2080 data points are generated. For training 80% of the generated data is used, the remaining 20% data is used for testing of the network. The data is normalized before presenting it to the neural network between 0 and 1.



(a) (b)

Fig. 1 (a) Selection of neurons for one hidden layer and (b) Selection of neurons for two hidden layers

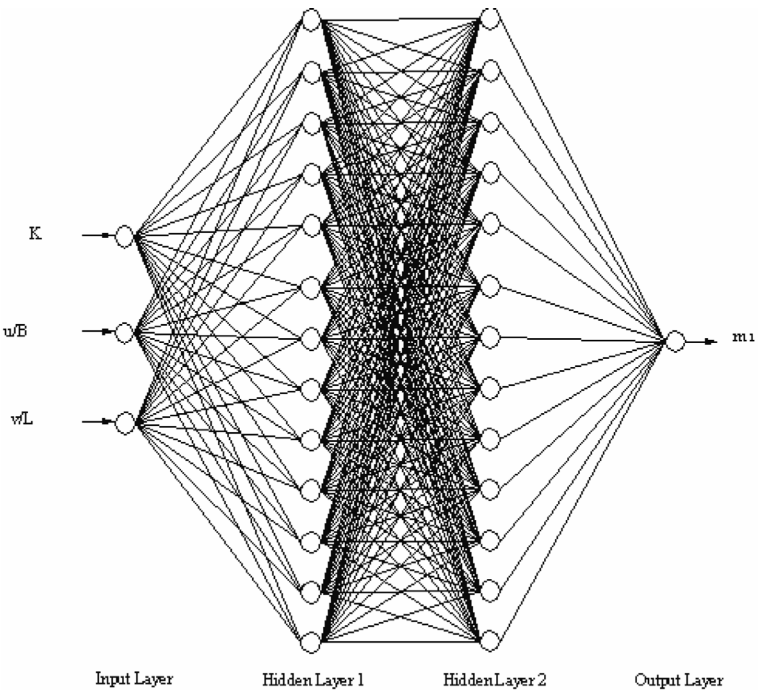
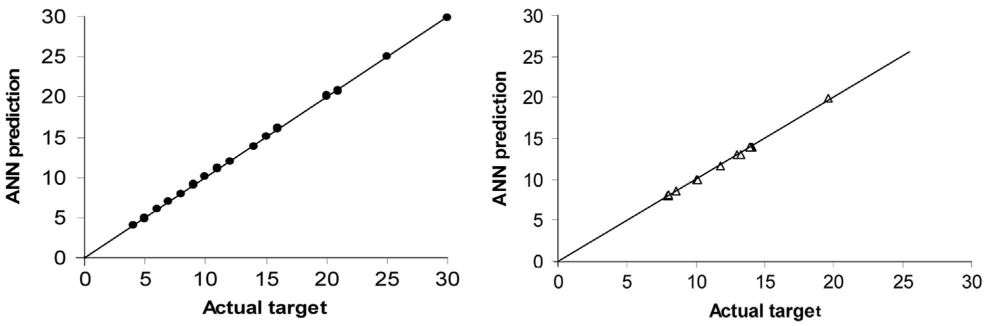


Fig. 2 Artificial neural network architecture

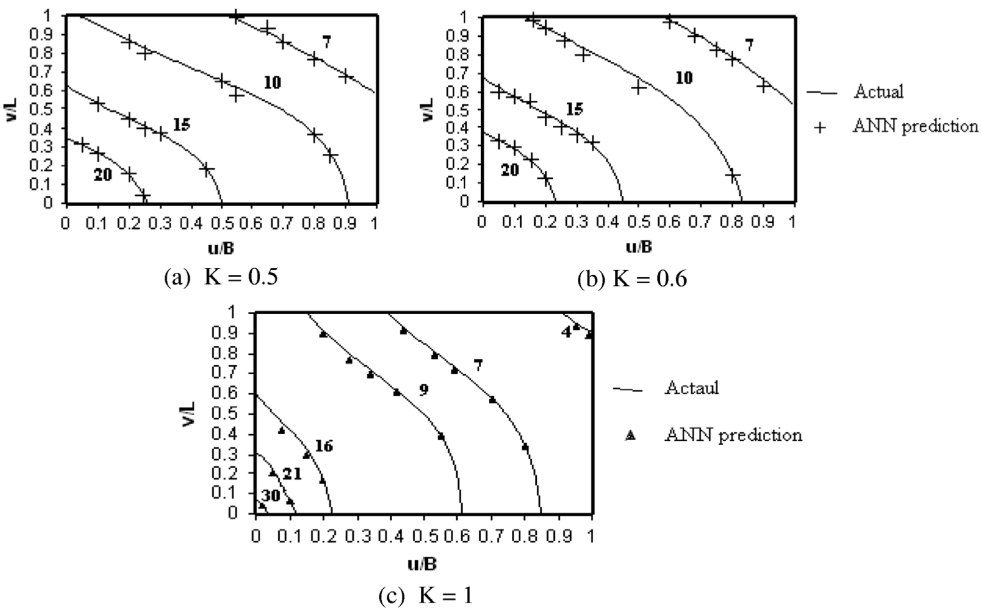
3.2 Artificial neural network architecture

As discussed above the network has 3 inputs and 1 output, the neural network architecture is developed based on observations made in the change of mean square error (MSE) for different neurons in one hidden layer and in two hidden layers, the observations are as shown in Fig. 1, for one hidden layer to converge MSE of 0.00001, the network requires more than 50 neurons and time for convergence is more than 10 minutes, when the network built with two hidden layers requires only 11 to 13 neurons in each layer to converge to the same MSE and the time taken for this convergence is less than 4 minutes. So from the observations 3-13-13-1 architecture is adopted with three neurons in input layer, thirteen neurons in each hidden layer and one neuron in output layer as shown in Fig. 2.



(a) (b)

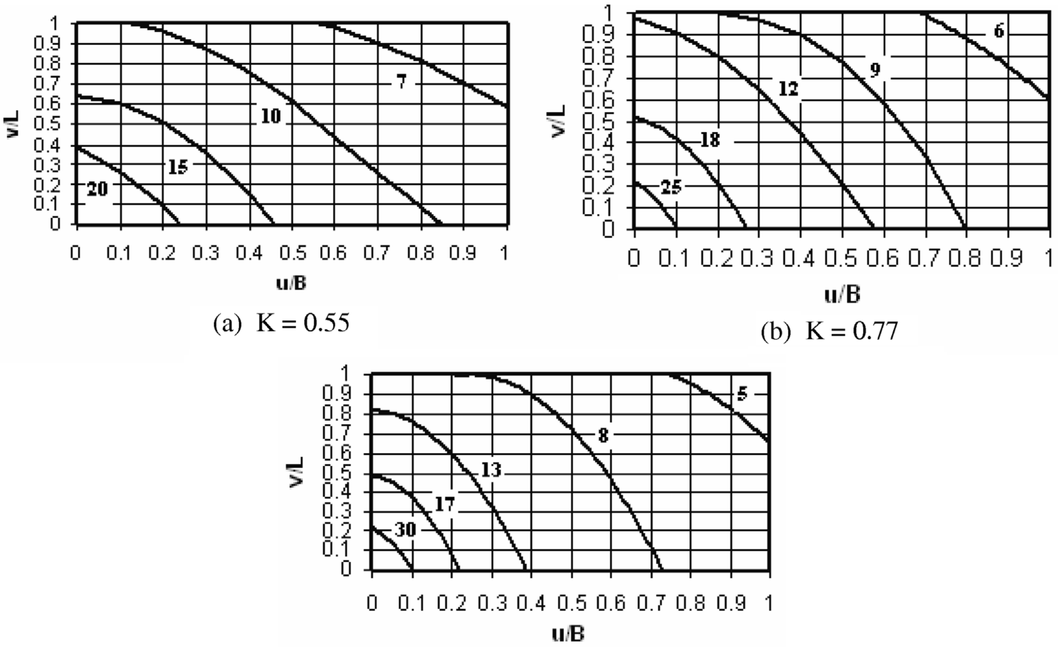
Fig. 3 (a) Training errors and (b) Testing errors



(a) K = 0.5 (b) K = 0.6

(c) K = 1

Fig. 4 (a), (b) Actual and ANN prediction of m_1 in training data, (c) Actual and ANN prediction of m_1 in testing data



(a) K = 0.55

(b) K = 0.77

(c) K = 0.96

Fig. 5 Pigeaud’s curves for intermediate *K* values

3.3 Training and testing of the network

In the present case tansigmoidal function is used as a transfer function in hidden layer neurons and pure linear function used in output layer neurons. Mean square error (MSE) algorithm is taken as network performance function. MATLAB software (Demuth and Beale 2003) used for training and testing of the network, the training rule is Levenberg-Marqudt rule (LM rule has the capability of fast convergence) and the goal is set to 0.00001. Training and Testing errors are as shown in Fig. 3 and Fig. 4. In the present case training error is not exceeding 2.0% and testing error has not exceeded 2.5%.

3.4 Generalization capabilities

Comparison of curves in Fig. 5 with actual Pigeaud’s curves contains the generalization capabilities of the developed ANN.

4. Conclusions

The function approximation capability of ANN has been successfully used in the approximation of Pigeaud’s curves. The developed ANN architecture (3-13-13-1) is computationally efficient as well as it produces reasonably accurate results for moment coefficients (m_1) in short span. The maximum training error is 2%, the maximum testing error is 2.8% and the average training error achieved is 1%. The generalization capability of developed ANN model is very useful in the optimum design of interior panel of girder bridge. Preliminary studies using Pigeaud's curves for determination of moment in short span (m_1) showed promising results. Due to their computational efficiency such type of ANN models will be quite useful in the design optimization.

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