OPEN ACCESS
International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-7 Issue-2, December 2017

Comparison of ANN and ANFIS Models for Stability Prediction of Cantilever Reinforced Concrete Retaining Walls

Rohaya Alias, Anuar Kasa, Siti Jahara Matlan

Abstract*: *Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) models are used to predict the external stability of cantilever reinforced concrete (RC) retaining walls. A total of 235 different designs of cantilever RC retaining walls using procedure of BS: 8110 were used. Three input parameters were used namely; height of wall, angle of slope, and surcharge, while the output parameters consist of the external stability namely: factors of safety (FOS) for sliding, overturning and bearing capacity. The output data generated through design is used as a target for both models. Two criteria involving the determination coefficient (R^2) and root mean square error (RMSE) were used to evaluate the accuracy of prediction models. The results showed that prediction made using ANFIS more accurate compared with ANN.

Index Terms*: *Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial neural network (ANN), Retaining wall, Stability.

I. INTRODUCTION

The cantilever reinforced concrete (RC) wall is the most common type of retaining structure and usually shaped like an inverted T or L. Generally, the height of the wall is built can reach up to 6 m. The determination of the stability of cantilever RC retaining wall is an important task in geotechnical engineering practice. Design of cantilever retaining walls involves stability checks for overturning, sliding and bearing capacity.

Over the last few years or so, the use of artificial neural networks (ANNs) has increased in many areas of engineering. In particular, ANNs have been applied to many geotechnical engineering problems and have demonstrated some degree of success [1]. There are many different types of ANNs, the variety of ANNs is correlated with certain important factors occur in each computational element, such as arrangement, the connectivity degree and the calculation types [2]. According Lippman [3], ANN are massively parallel systems composed of many processing elements connected by links of variable weights. ANN is being used more frequently in the analysis of time series forecasting, pattern classification and pattern recognition capabilities [4].

Besides ANN, one of the prominent method of computing today is fuzzy and neuro computing that produce neuro-fuzzy system. Neuro fuzzy system is a combination of the fuzzy logic for explicit knowledge representation and the learning capability of neural network [5]. ANFIS is a branch of fuzzy inference system (FIS) which mostly utilizes Sugeno and Takagi's of fuzzy reasoning [6]. Given an input/output data sets, ANFIS constructs fuzzy inference system (FIS) whose membership function (MF) parameters are adjusted using back propagation algorithm or other similar optimization techniques [7]. ANFIS is capable of approximating any real continuous function on a compact set to any degree of accuracy [8]. The difference between the common neural network and the ANFIS is that, while the former captures the underlying dependency in the form of the trained connection weights, the latter does so by establishing the fuzzy language rules [9].

In many applications, ANFIS modeling was found better than ANN modeling [10]. In this context, the main objective of this study was to analyze the predictive ability of ANN and ANFIS models by comparing the predicted with target values in order to identify which method was more accurate and reliable to predict the external stability of cantilever RC retaining wall.

II. MATERIALS AND METHODS

In this study, 235 different designs of cantilever RC retaining walls were created by Prokon software (ver 2.1.09) that applied limit equilibrium methods (LEM) were used. Designs of cantilever RC retaining wall accordance with the procedure of BS: 8110. ANN and ANFIS prediction behavior utilized input and output parameters. The input data consists of a variety of (i) height of wall, (ii) angle of slope, and (iii) surcharge. While the output data consists of the external stability namely; FOS for (i) sliding, (ii) overturning, and (iii) bearing capacity. The output data generated by the LEM design was used as a target. The MATLAB Neural Networks Toolbox was used to analyze the ANN model. In this study, ANN model structure used is three inputs and one output, as shown in Fig. 1. The selection of the model input variables have the most significant impact on the model performance. A large number of inputs to ANN model increase the model size which in turn decreased the processing speed and reduces the network efficiency [11].

Manuscript published on 30 December 2017.
* Correspondence Author (s)
Rohaya Alias*, Faculty Department of Civil Engineering, University Teknologi MARA Pahang, 26400 Bandar Tun Razak Jengka, Pahang, Malaysia, E-mail: rohaya_alias@uitm.edu.my
Anuar Kasa, Department of Civil and Structural Engineering, Faculty of Engineering and Built Environment, University Kebangsaan Malaysia, UKM Bangi, Selangor, Malaysia, E-mail: iranuar@yahoo.com
Siti Jahara Matlan, Department of Civil Engineering Program, Faculty of Engineering, Universiti Malaysia Sabah, Kota Kinabalu, Malaysia, E-mail: jahara@ums.edu.my

The feed-forward network with tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer is used. The number of hidden layers in the networks used for this study was 20. The number of hidden layer was determined after trying various network structures, since there is no theory yet available to tell how many hidden units are needed to approximate a given function [12]. The number of hidden layers and their neurons are often determined by trial and error [13]. In the present study, Levenberg-Marquardt (LM) algorithm is used to train the network. LM algorithm is specifically designed for the squared error function and is used because of its faster convergence as compared to the most commonly used back propagation algorithm [14–17]. Input and output vectors are divided into three sets of 70% for training, 15% for validation and 15% for testing.

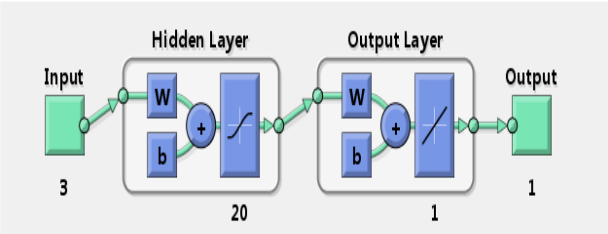

Fig. 1: ANN Model Structure

The MATLAB ANFIS Editor GUI Toolbox was utilized in order to apply a fuzzy system into the ANFIS model. The structure of the ANFIS is adopted Sugeno type fuzzy logic systems. In the present study, the ANFIS model structure is used as shown in Fig. 2. The system has three inputs, nine membership functions (MF) inputs, 27 rules and 27 membership functions (MF) outputs to produce an output. The number of input membership functions has a great influence on the ANFIS training process. If a model uses too many membership functions, the inference rules will be more complicated and the training time will increase [18]. The Gaussian membership function was chosen to train input/output data. The usual studying algorithms utilizing a mixture of least square procedures and gradual descent back propagation procedure to identify FIS parameters that are Sugeno type utilized for studying and the number of epoch is set at 100 and the tolerance of the error at zero.

The accuracy of prediction between ANN and ANFIS models are evaluated by comparing the predicted output with the target using determination coefficient (R^2) and root mean square error (RMSE). The value of R^2 should be near a value of one to be a good model. The following classification is used to examine the accuracy of the model as follows: excellent ($R^2 \geq 0.97$), good ($0.90 \leq R^2 < 0.97$), medium ($0.80 \leq R^2 < 0.90$), weak ($0.70 \leq R^2 < 0.80$), very weak ($0.60 \leq R^2 < 0.70$), and failed ($R^2 < 0.60$). Meanwhile, an RMSE value of zero indicates the highest level of efficiency for the model.

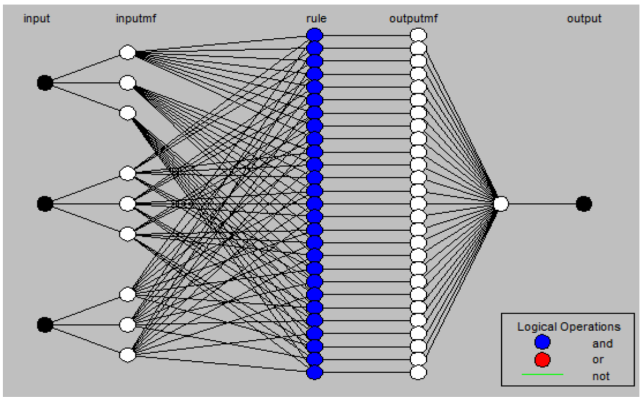

Fig. 2: ANFIS Model Structure

III. RESULTS AND DISCUSSION

Fig. 3 shows a comparison between ANN output, ANFIS output and target for (a) FOS for sliding, (b) FOS for overturning, and (c) FOS for bearing capacity. No significant difference between the output and the target for both of models because the data seems to overlap with each other. Visual comparisons are difficult because the output of both models is almost the same as the target. However, the differences can be seen more clearly by comparing the value of R^2 and RMSE.

R^2 values for ANN and ANFIS models for all output parameters shown in Table 1. The ANN and ANFIS models show excellent performance in predicting the external stability because the R^2 value for each output parameter is higher than 0.97. However, prediction made using ANFIS model more accurate compared with ANN model because the R^2 value of ANFIS model for FOS for overturning is one. The ANFIS model also was predicted the FOS for bearing capacity more efficiency than the ANN model because the value of R^2 was closer to one.

Table 2 summarizes the RMSE values were obtained from the ANN and ANFIS models. The result shows the RMSE values for FOS for overturning and FOS for bearing capacity were obtained from the ANFIS model was closer to zero. This result shows that ANFIS model performed better than the ANN model. Significant differences in RMSE value can be seen for FOS for overturning compared between ANN and ANFIS models. However, the RMSE value for FOS for sliding of ANN model was lower than the ANFIS model.

Table 1: R2 values for ANN and ANFIS models

Output parameters	ANN	ANFIS
FOS for sliding	0.999	0.999
FOS for overturning	0.998	1.0
FOS for bearing capacity	0.986	0.996

Table 2: RMSE values for ANN and ANFIS models

Output parameters	ANN	ANFIS
FOS for sliding	0.059	0.062
FOS for overturning	0.499	0.097
FOS for bearing capacity	0.023	0.012

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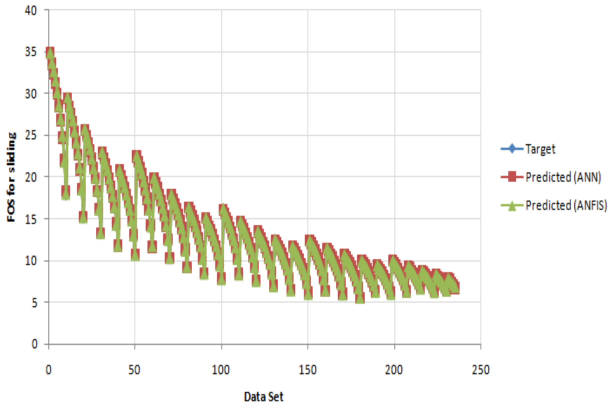
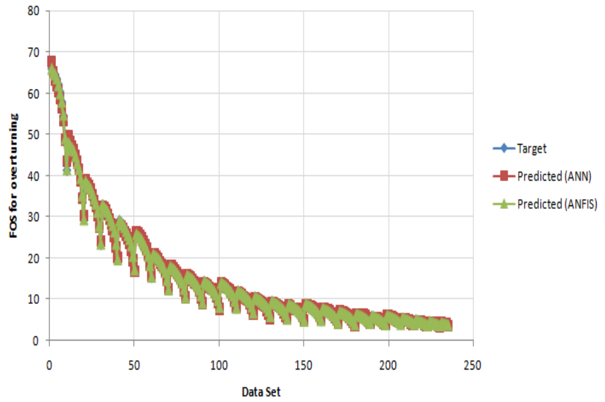
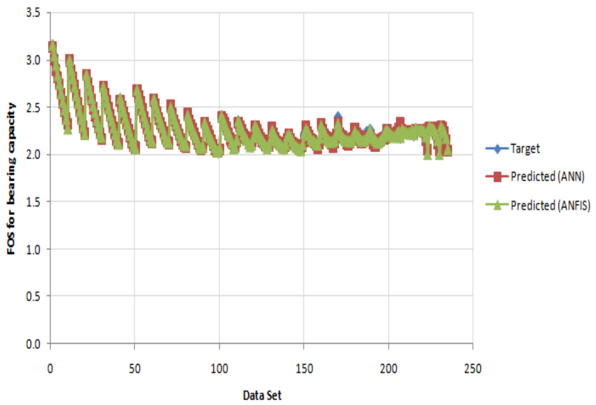


(a)



(b)



(c)

Fig. 3: A Comparison Between ANN Output, ANFIS Output and Target for (a) FOS for Sliding, (b) FOS for Overturning, and (c) FOS for Bearing Capacity

IV. CONCLUSION

ANFIS and ANN techniques were used for prediction of external stability of cantilever RC retaining walls namely, FOS for sliding, overturning, and bearing capacity. The model with maximum R^2 and minimum RMSE was selected as best model. Analysis of R^2 values showed the ANFIS model generally performed better than the ANN model in predicting the external stability of cantilever RC retaining wall. Analysis of RMSE values also showed the ANFIS model was able to produce more accurate predictions than the ANN model in terms of FOS for overturning and bearing capacity, but not FOS for sliding.

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