International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 10 (2015) pp. 26005-26014

http://www.ripublication.com

Artificial Neural Networks Approach For Predicting The Stability of Cantilever RC Retaining Walls

[1]Rohaya Alias, [2]Anuar Kasa and [3]Mohd Raihan Taha
[1]Faculty of Civil Engineering, Universiti Teknologi MARA Pahang, 26400 Jengka, Pahang, Malaysia.
[1,2,3]Department of Civil and Structural Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor, Malaysia.

Abstract

The determination of the stability of cantilever reinforced concrete (RC) retaining walls is an important task in geotechnical engineering. This paper examines the potential of artificial neural network (ANN) for predicting the external stability of cantilever RC retaining walls. Two types of ANN model used as follows: ANN model (1 output) and ANN model (3 output). ANN model (1 output) involves a separate calculation for each output parameter while ANN model (3 output) involves calculations that take into account all the parameters simultaneously output. There are 235 different designs of cantilever RC retaining walls with three input parameters used for the prediction of safety factors such as height of the wall, angle of slope, and surcharge. The output parameters consist of the external stability namely: factors of safety (FOS) for sliding, overturning, and bearing capacity. Determination coefficient (R^2) and root mean square error (RMSE) have been used for evaluation of prediction accuracy for both ANN models. The results of the study indicated that when compared in terms of R^2 value, ANN model (1 output) shows better performance than ANN model (3 output) does in predicting external stability because the value of R^2 is closer to one for all output parameters. Meanwhile, when compared in terms of RMSE value, ANN model (3 output) shows better performance than ANN model (1 output) since the value of RMSE for output parameters were closer to zero.

Keywords: Artificial neural network (ANN), Cantilever reinforced concrete (RC) retaining wall, External stability, Determination coefficient (R^2), Root mean square error (RMSE).

Introduction

Retaining walls are one of the retaining structures required in most civil engineering projects. The main function is the construction of retaining walls to support land that was in stable condition and holding land banks from collapsing while avoiding landslip on slopes. There are several types of retaining walls and one type is cantilever reinforced concrete (RC) retaining walls. Retaining walls are usually built in areas adjacent to the slopes and in residential areas.

This wall consists of two main parts: the stem and the slab, both are made of reinforced concrete. The stem acts as a vertical cantilever under lateral earth pressure. The slab acts as a horizontal cantilever under soil pressure. The weight of the earth retained helps to maintain the stability of the wall [3]. Walls of this type are usually shaped like an inverted T or L and their size is wider, flattened, and cheaper construction costs for materials of construction with walls lower than gravity [5]. The height of the wall is built to reach up to 6 m and can be constructed in-situ or pre-cast concrete that has been made in a factory and installed only at the construction site to save more time and energy. For heights exceeding 6 m, the use of prestressing techniques are used. Part of the cantilever wall was built to jut out from the base is large and strong enough.

Cantilever RC retaining wall design are more stable than other retaining walls and some have locks that work to strengthen the stability of the walls by generating passive resistance on the front wall. In addition, the backfill provides additional dead load to strengthen the position of the retaining wall. Stability also depends on the base part that bears the volume of its backfill. Therefore, the longer the tread portion projects rearward, the stronger the structure of the walls, which the backfill can touch the ground with more efficiently and thus, provide stability to the wall. Meanwhile the base of the wall that protrudes forward is also important in keeping the entire wall from overturning. Goh [1] indicated that the top end of the cantilever retaining walls tended to rotate when compared with the lower end by the force of the rotation of the horizontal and vertical movement. If the round is over the limit, then the retaining walls will crack and it will break. The whole structure is said to have failed to achieve its function.

Over the last few years, ANNs have been successfully applied to modeling various geotechnical engineering problems. ANNs are used in various subfields of geotechnical engineering including parameter assessment, underground openings, foundations, site investigation, liquefaction, slopes, and ground movement [6]. Other applications of ANNs in geotechnical engineering include retaining walls [2],[8].

ANNs are mathematical models or computational devices that inspire the structure and/or functional aspects of biological neural networks. ANNs are massively parallel systems composed of many processing elements connected by links of variable weights [12]. Leondes [4] indicated that the application of ANNs has great value when it is difficult or impossible to uncover relationships. The method is also helpful even when the data is noisy or incomplete. Ho et al. [13] indicated that ANNs are being used more frequently in the analysis of time series forecasting, pattern classification, and pattern recognition capabilities. ANN used a powerful tool for prediction. ANNs can address prediction problems when the output is continuous or act as a classifier when the output is binary [10].

The main objective of this research is to predict the external stability of cantilever reinforced concrete retaining walls using the ANN model. The predictions made using the two types of ANN model known as ANN model (1 output) and ANN model (3 output).

Materials and Methods

In this study, 235 different designs of cantilever RC retaining walls were created by Prokon (ver 2.1.09) that applied limit equilibrium methods and in accordance with the procedure BS:8110 were used. Input data consists of (i) height of wall, (ii) angle of slope, and (iii) surcharge. Table 1 shows the range of the input parameters. While the output data consists of the external stability namely, FOS for: (i) sliding, (ii) overturning, and (iii) bearing capacity.

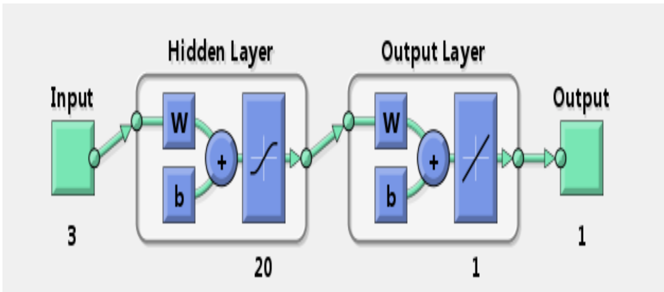
Table 1: Range of input parameters

Parameter	Unit	Range
Height of wall	m	2, 3, 4, 5, 6
Angle of slope	Degree	0, 5, 10, 15, 20, 25, 30, 35, 40, 45
Surcharge	kN/m^2	0, 5, 10, 15, 20

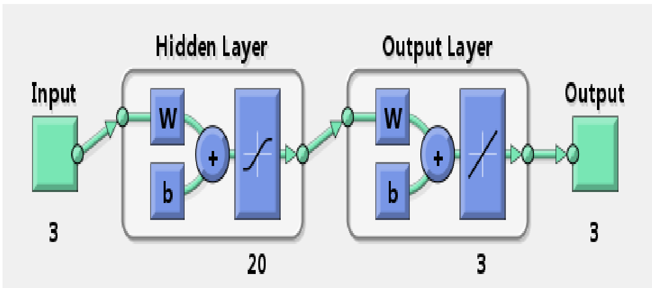
After carrying out the stability analyses, the ANN models were used to predict the result for overall safety factors. Neural network analysis was performed using MatLab (ver 7.6), Neural Networks Toolbox (Mathworks, Inc., Natick, MA, USA). Neural network analysis is a three-layer feed-forward network that consists of an input layer, one hidden layer, and one output layer. These three layers are highly interconnected by nodes and work together to solve specific problems. The input layer is used to present data to the network. The hidden layer is used to act as a collection of feature detectors. The output layer is used to produce an appropriate response to the given input.

In this study, a separate calculation for each output parameters and calculations that take into account all the parameters simultaneously output was done. The ANN model structure used for the calculation separately for each output parameter has three inputs and one output (Figure 1.0 (a)). Figure 1.0 (b) shows the network model that takes into account all three parameters simultaneously output. The numbers of the hidden layer were 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 [11]. The number of hidden layers in the networks used for this study was 20.

Networks used for both cases are feed-forward with tan-sigmoid transfer functions in the hidden layer and linear transfer function in the output layer. The Levenberg-Marquardt back propagation algorithm is used to train the networks. In neural network analysis, the data set is automatically and randomly divided by the software into three subsets as follows: training, validation, and testing. The first step is the training stage, where the network is subjected to a training set of input-output patterns. The second step is the validation stage, where the performance of the network is tested on patterns that have not been 'seen' by the network during the training stage. The third step is the testing stage, where the performance of the network is tested based on the unknown patterns that have not been 'seen' during the previous stages [7]. Shahin et al. [9] indicated that validation is utilized to assess the workings of the model when training has been completed. In this study, input and output vectors are divided into three sets of 70% (165 data) for training, 15% (35 data) for validation, and 15% (35 data) for testing.



(a) ANN model (1 output)



(b) ANN model (3 output)

Figure 1: ANN model structure

An estimated FOS and calculated FOS values for both ANN model were statistically compared and analyzed using determination coefficient (R^2) and root mean square error (RMSE) to examine the performance of a prediction model. 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.

Results and Discussion

Fig. 2 shows a comparison of the accuracy of the ANN model (1 output) and ANN model (3 output) with the target for (a) FOS sliding, (b) FOS overturning, and (c) FOS bearing capacity. Visual comparisons are difficult because the output of both models is almost the same as the target. However, accuracy can be determined by comparing the value of R^2 and RMSE.

Table 2 summarizes the R^2 values that were obtained from the ANN model (1 output). Fig. 3 shows the R^2 values for ANN model (1 output) were generated from the graph of predicted FOS versus calculated FOS. The value of R^2 for FOS sliding and FOS overturning are seen as close with the target and approaching a value of one, namely 0.999 for FOS sliding and 0.998 for FOS overturning. The ANN model (1 output) for FOS bearing capacity is more efficient than the ANN model (3 output) because the value of R^2 was closer to one. The ANN model (1 output) shows excellent performance in predicting the external stability because the R^2 value for each output parameter is higher than 0.97.

Fig. 4 shows the R^2 values for ANN model (3 output) were obtained from graph of predicted FOS versus calculated FOS. Table 1 summarizes the R^2 values obtained from the ANN model (3 output). The R^2 value for the ANN model (3 output) for FOS sliding and FOS overturning is a value of one. This shows the ANN model (3 output) is a good model since the output is equal to the target value. However, the R^2 value for FOS bearing capacity is not approaching the target, namely 0.952. This model shows good performance because the R^2 value is less than 0.97.

Table 3 shows the RMSE values for the ANN model (1 output) and ANN model (3 output). The result shows that the values of RMSE for FOS sliding and FOS overturning was obtained from the ANN model (3 output), which was closer to a value of zero than the ANN model (1 output) was. Meanwhile, the RMSE value for FOS bearing capacity of ANN model (1 output), was lower than the ANN model (3 output). The significant differences in RMSE value can be seen for FOS overturning compared between ANN model (1 output) and ANN model (3 output).

Table 2: R^2 value for ANN model (1 Output) and ANN model (3 Output)

Output parameters	ANN (1 Output)	ANN (3 output)
FOS for sliding	0.999	1.0
FOS for overturning	0.998	1.0
FOS for bearing capacity	0.986	0.952

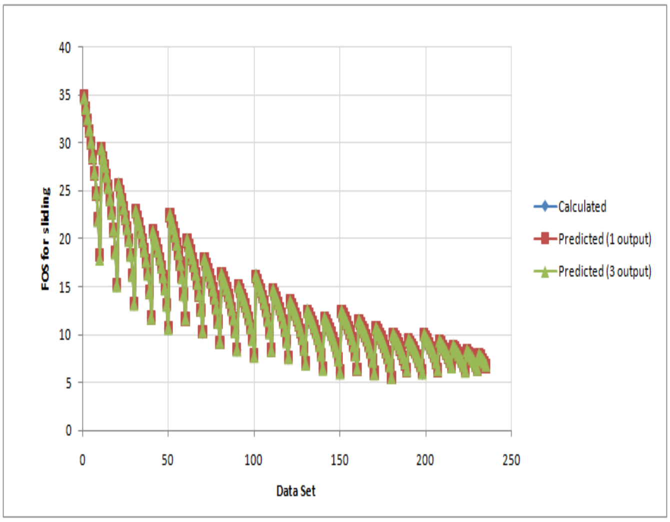
Table 3: RMSE value for ANN model (1 Output) and ANN model (3 Output)

Output parameters	ANN (1 Output)	ANN (3 output)
FOS for sliding	0.059	0.037
FOS for overturning	0.499	0.057
FOS for bearing capacity	0.023	0.042

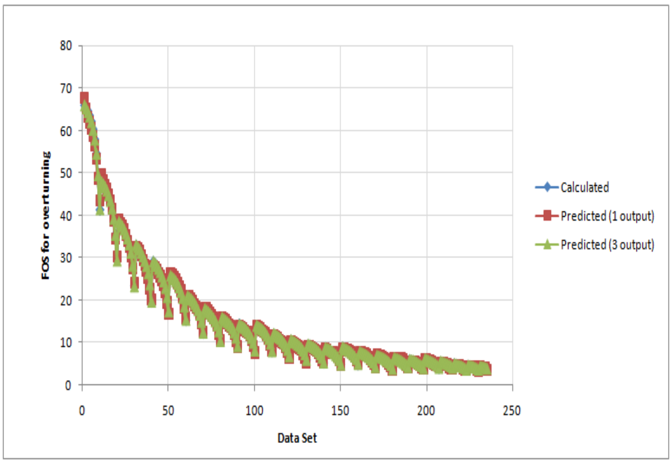
Conclusion

ANNs have the ability to predict the factor of safety of cantilever RC retaining walls for sliding, overturning, and bearing capacity with a high degree of accuracy. When compared in terms of the value of R^2, ANN model (1 output) performed satisfactorily to predict the external stability because the value of R^2 was closer to a value of one for all output parameters. Although the R^2 value of FOS for sliding and overturning of the ANN model (3 output) is one, the R^2 value for the ANN model (1 output) for both the output parameters is close to approaching a value of one. The difference is not significant. When compared in terms of the RMSE value, ANN model (3 output) was the best model since the value of RMSE for output parameters, i.e. FOS for sliding and FOS for overturning was the lowest or closest to zero.

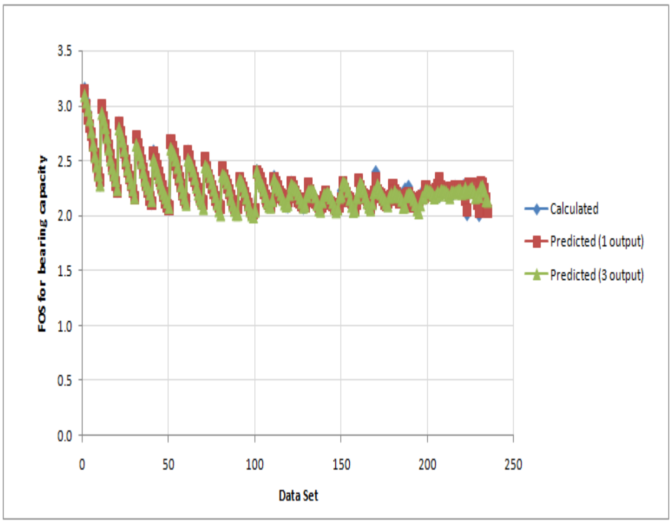
However, to produce better forecasts, some action can be done such as increasing the number of data, using different percentages for training; validation, and testing; increasing the number of hidden layer; do retraining; and train with different methods for ANN.



(a)

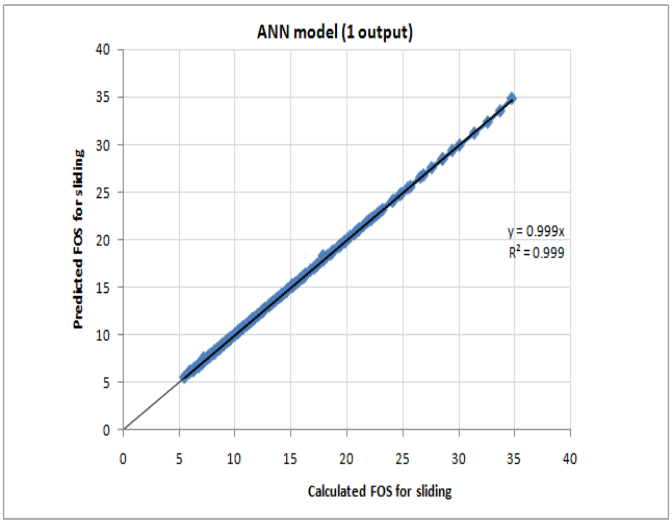


(b)

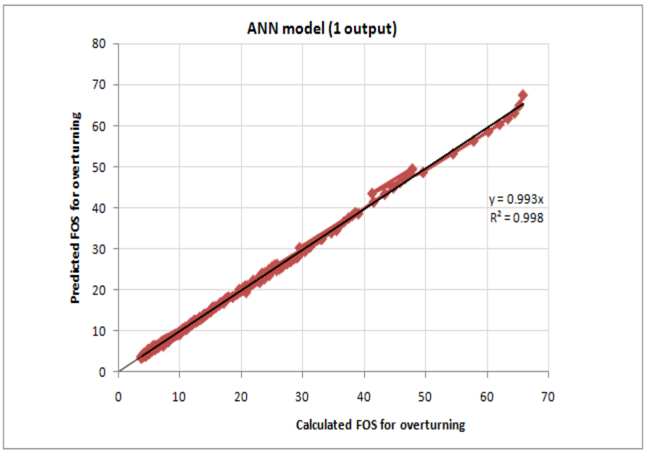


(c)

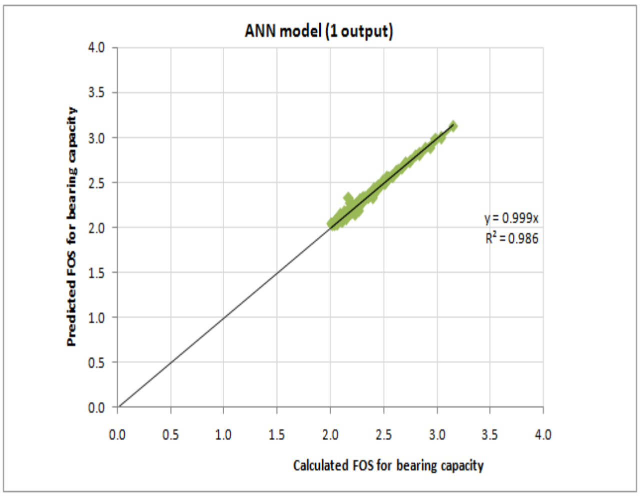
Figure 2: The performance of ANN model: A comparison between the predicted FOS values using ANN model (1 output), ANN model (3 output), and calculated for (a) sliding, (b) overturning, and (c) bearing capacity



(a)

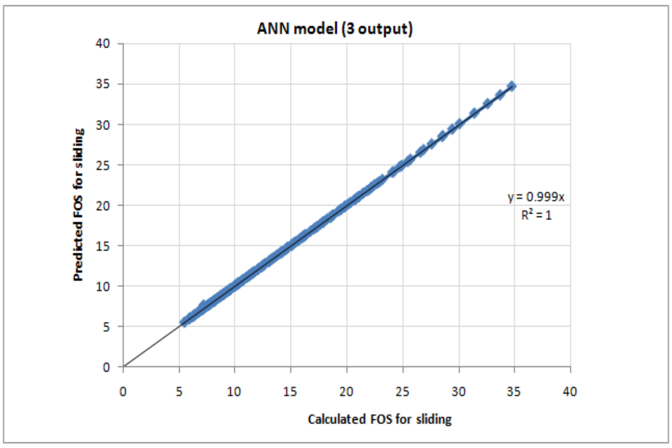


(b)

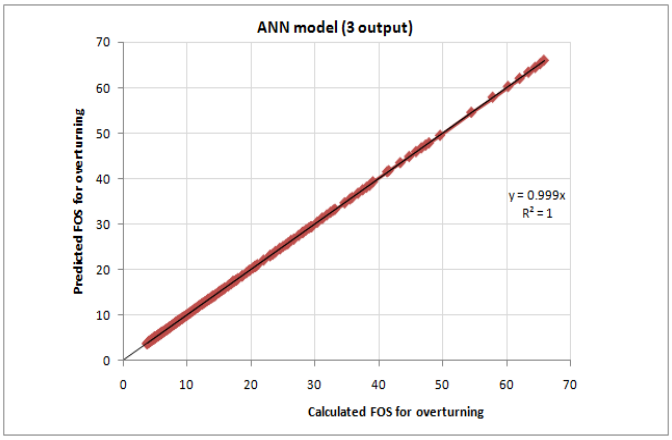


(c)

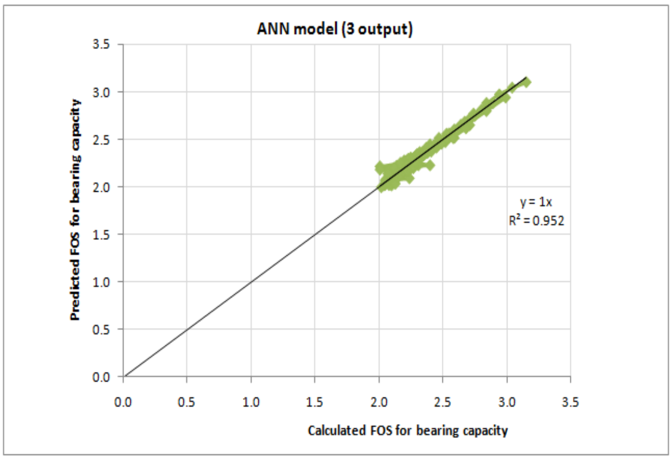
Figure 3: A comparison of the predicted and calculated FOS values for (a) sliding, (b) overturning, and (c) bearing capacity using ANN model (1 output)



(a)



(b)



(c)

Fig. 4: A comparison of the predicted and calculated FOS values for (a) sliding, (b) overturning, and (c) bearing capacity using ANN model (3 output)

References

[1] A.T.C. Goh, Advisory Expert System for Flexible Pavement Design, Artificial Intelligence in Engineering, Vol. 8, pp. 47-56, 1993.

[2] A.T.C. Goh, K.S. Wong and B.B. Broms, Estimation of Lateral Wall Movements in Braced Excavation using Neural Networks, Canadian Geotechnical Journal, Vol. 32, pp. 1059-1064, 1995.

[3] C.R.I. Clayton, J. Milititsky, R.I. Woods, Earth Pressure and Earth Retaining Structures, Spon Press, Taylor and Francis Group, 2nd Edition, pp. 155-161,1993.

[4] C.T. Leondes, Expert Systems: The Technology of Knowledge Management and Decision Making for the 21th Century. San Diego, Academic Press. 2002.

[5] D.P. Coduto, Foundation Design Principles and Practices, 2nd Edition, Prentice Hall, 2001.

[6] D. Toll, Artificial Intelligence Systems for Geotechnical Engineering with Specific Reference to Ground Improvement, 10th European Young Geotechnical Engineers Conference, 1996.

[7] G.J. Bowden, G.C. Dandy and H.R. Maier, Input Determination of Neural Network Models in Water Resources Applications. Part 1- Background and Methodology, Journal of Hydrology, Vol. 301, pp. 75-92, 2005.

[8] G.T. Kung, E.C. Hsiao, M. Schuster and C.H. Juang, A Neural Network Approach to Estimating Deflection of Diaphram Walls Caused by Excavation in Clays, Computers and Geotechnics, Vol. 34 (5), pp. 385-396, 2007.

[9] M.A. Shahin, H.R. Maier, and M.B. Jaksa, Data Division for Developing Neural Networks Applied to Geotechnical Engineering, Journal of Computing in Civil Engineering, Vol. 18(2), pp. 105-114. 2004.

[10] M. Negnevitsky, Artificial Intelligence. A guide to Intelligent Systems, Essex, Pearson Education Limited, 2002.

[11] O. Gencel, The Application of Artificial Neural Networks Technique to Estimate Mass Attenuation Coefficient of Shielding Barrier, International Journal of Physical Sciences, Vol. 4 (12), pp. 743-751, 2009.

[12] R.P. Lippmann, an Introduction to Computing with Neural Net, IEE ASSP Magazine, pp. 4-22, 1987.

[13] S.Y.W. Ho, B. Shapiro, M. Phillips, A. Cooper, A.J. Drummond, Evidence for Time Dependency of Molecular Rate Estimates, Syst. Biol, Vol. 56, pp. 515–522. 2007.