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# Assessment of highway slope failure using neural networks

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**Abstract:** An artificial intelligence technique of back-propagation neural networks is used to assess the slope failure. On-site slope failure data from the South Cross-Island Highway in southern Taiwan are used to test the performance of the neural network model. The numerical results demonstrate the effectiveness of artificial neural networks in the evaluation of slope failure potential based on five major factors, such as the slope gradient angle, the slope height, the cumulative precipitation, daily rainfall and strength of materials.

**Key words:** Neural network, Prediction, Highway, Slope failure

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## INTRODUCTION

Slope failure is a geotechnical phenomenon when a slope collapses abruptly due to weakened self-retainability of the earth during/after an event of liquid precipitation. Rocks, soil, as well as other debris, can fall onto the road surface causing dangerous driving conditions, detours and traffic delays. Typhoons, which cause these problems, strike Taiwan every year during the rainy season. They bring intensive rains and can provoke serious slope failure disasters, such as debris flow and slope sliding, as well as associated calamities, which might include human fatalities and the damage to roadways and bridges. Historical records of natural disasters in Taiwan show that serious slope failures occurred during and after Typhoon Polly in 1992, Typhoon Herb in 1996 and Typhoon Toraji in 2001. Therefore, ways to forecast highway slope failures have been under serious examination by Taiwanese geotechnical engineers.

Many studies in this field are devoted to the relation between slope failures and rainfall (Muller and Hofman, 1970; Varnes, 1978; Caine, 1980; Cannon and Ellen, 1985). The slope failures highlighted in the papers are strongly affected by numerous geologic and geomorphologic factors as well as exogenetic and endogenetic processes, and human activities. In general, slope stability analysis relies heavily on the use of the limiting equilibrium method (Keefer *et al.*, 1987). For many engineering applications, this method has been proven to be quite effective in the assessment of slope failure. Meanwhile there are still many uncertain factors, which may significantly affect slope stability. One of them, for instance, the variability in underlying geologic materials, cannot be taken into account by conventional deterministic methods of slope stability analysis. These uncertainties cannot be handled satisfactorily in the classic theory. A situation like this makes the application of classical estimation procedures extremely difficult. Therefore, of late, risk analysis and assessment have become the imperative tools in addressing uncertainty inherent in slope failures. It is recognized that not all uncertainties are random, and some of them can be objectively quantified, especially those based on incomplete information (Fell and Hartford, 1997).

In the last two decades, the artificial intelligence technique of artificial neural networks (ANNs) has been widely applied in various areas to overcome the problems of nonlinear relationships within geophysical systems (French *et al*., 1992; Campolo *et al*., 1999; Mase and Kianto, 1999; Deo and Naidu, 1998; Makarynskyy *et al*., 2004) and in applications involving diagnosis and forecasting (Lee and Jeng, 2002; Makarynskyy, 2004; 2005; Lee, 2004; 2006; 2008).

ANNs have also been applied to more specific geotechnical engineering problems. For example, Zhang (1996) used an ANN to predict the amount of Chinese colliery roadway surrounding a rock deformation. Yang and Zhang (1998) applied ANNs to Rock Engineering Systems (RES). Lee *et al*.(2001) developed two ANN methods for landslide susceptibility analysis. Jeng *et al*.(2003) used ANNs to assess earthquake-induced soil liquefaction.

This paper describes an original ANN methodology for the investigation of typhoon triggered highway slope failures. Precipitation and slope failure data from the South Cross-Island Highway between the years 1996~2000 are used to test the proposed methodology. In order to assess their relative inputs, the factors determining the slope stability, the slope gradient angle, the slope height, the cumulative precipitation, daily rainfall, the strength of material, the joint number, the condition of the vegetation and slope direction, are investigated. Conclusions are made about the importance of all or some of these factors on the slope stability estimates, employing the saliency analysis of used ANNs of several different structures.

## STUDY AREA AND INITIAL DATA

To illustrate the capability of the proposed neural methodology, highway slopes of the South Cross-Island Highway (Provincial Highway No. 20) between kilometers 90 and 200 are researched in this study.

The South Cross-Island Highway was completed in 1973, but due to the dangers inherent in its treacherous terrain and frequent landslides, it was opened for the public only in 1993. This highway chisels through Tainan, Kaohsiung and Taitung counties and connects southern Taiwan with eastern and western regions (Fig.1). The road zigzags through the Yushan National Park, which possesses precious environmental forests and mountain resources of Taiwan.

The study is based on 340 data sets from in-situ surveys along the South Cross-Island Highway, including 277 data sets without the observed slope failure and 63 data sets when slope failure following precipitation was registered. There are eight different training/validation time series named as Cases A1~A8 in this study. Each considered case involves different numbers of failure/non-failure data sets, e.g., the ANN training for Case A1 employed 15 “failure” and 85 “non-failure” data sets, while validation was performed using 11 “failure” and 29 “non-failure” data series.

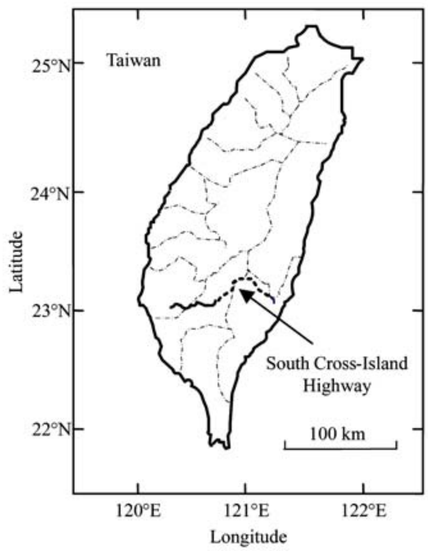


**Fig.1 Southern Cross-Island Highway, Taiwan, China**

## ANNS AND BACK-PROPAGATION TRAINING ALGORITHM

ANNs are the information-processing systems mimicking the biological neural network, or the brain activities, by interconnecting many simple artificial computational nodes, or neurons. A neuron accepts the inputs from a single or multiple sources and produces outputs by processing the information using predetermined linear/non-linear transfer (activation) function. Since the ANN principles have been well documented in the literature (e.g., Haykin, 1999), only a brief survey is given in this section.

A typical three-layered network with an input, hidden and output layers (Fig.2) was adopted in this study. Each layer of such a network usually consists of several neurons and the layers are interconnected using sets of correlation weights. The neurons receive inputs from the external environment or via neuronal interconnections and produce outputs by the transformation using an adequate approach to the imposed tasks transfer function.

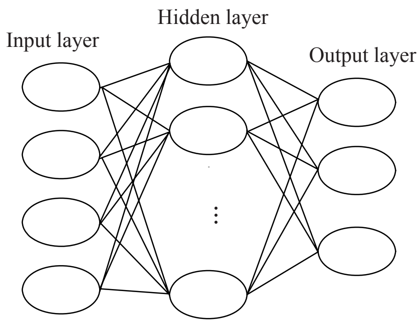


**Fig.2 Commonly used structure of a three-layered artificial neural network**

In geophysical and geotechnical applications, a commonly used transfer function is the sigmoid function expressed by

$$f(x)=(1+e^{-x})^{-1}, \tag{1}$$

and characterized by

$$df/dx=f(x)[1-f(x)]. \tag{2}$$

Importantly, the ANN training (learning) is executed through a series of patterns. In the learning process, the interconnection weights are adjusted to interrelate the input and the target output values.

The back-propagation neural network (BPN) developed by Rumelhart *et al.*(1986) is commonly used as a mode of supervised learning. The BPN is used in the gradient steepest decent method to correct the connection weights. During the learning, the weights are adjusted using an error convergence technique to obtain a desired output for a given input. The error at the output layer propagates backward to the input layer through the hidden layer of the network to correct the outputs to some desired levels of accuracy. The error function at the output neuron is defined as

$$E=\frac{1}{2}\sum_{n}(T_j-A_j)^2, \tag{3}$$

where $T_j$ and $A_j$ are the target and predicated values, respectively.

The gradient error is given by the expression

$$\Delta W_{ij}=-\eta\times\frac{\partial E}{\partial W_{ij}}, \tag{4}$$

where $\eta$ is the learning rate and the general form of the $\partial E/\partial W_{ij}$ term is expressed by

$$\frac{\partial E}{\partial W_{ij}}=-\delta_j^{\,n}A_i^{\,n-1}. \tag{5}$$

Substituting Eq.(5) into Eq.(4), the gradient error is calculated as

$$\Delta W_{ij}=\eta\delta_j^n A_i^{n-1}, \tag{6}$$

where $A_i^{n-1}$ is the output value of the sub-layer related to the connection weight ($W_{ij}$), $\delta_j^n$ is the error signal, which is computed based on whether or not neuron $j$ is in the output layer. If neuron $j$ is one of the output neurons, then

$$\delta_j=(T_j-Y_j)Y_j(1-Y_j). \tag{7}$$

If neuron $j$ is the neuron of the hidden layer then:

$$\delta_j=\left[\sum_j \delta_j(W_{\mathrm{h}y})_{\mathrm{h}j}\right]H_{\mathrm{h}}(1-H_{\mathrm{h}}), \tag{8}$$

where $H_{\mathrm{h}}$ is the value of the hidden layer, $W_{\mathrm{h}y}$ is the connection weight from the hidden layer to the output layer.

Finally, the value of the connection weight can be expressed as

$$W_{ij}^{\,m}=W_{ij}^{\,m-1}+\Delta W_{ij}^{\,m}=W_{ij}^{\,m-1}+\eta\delta_j^{\,n}A_i^{\,n-1}. \tag{9}$$

To accelerate the convergence of the error in the learning phase, the momentum term with the momentum gain $\alpha$ was included in Eq.(9) by Jacobs (1988):

$$W_{ij}^{\,m}=W_{ij}^{\,m-1}+\eta\delta_j^{\,n}A_i^{\,n-1}+\alpha\Delta W_{ij}^{\,m-1}, \tag{10}$$

where the value for $\alpha$ is within 0 and 1. More details of the ANN and BPN algorithms can be found in

Rumelhart *et al*.(1986).

In this paper BPNs are employed to assess the highway slope failure. Initially 8 parameters obtained from the field surveys, including the slope gradient angle, the slope height, daily rainfall, the cumulative precipitation, the surface acceleration, strength of materials, the slope direction, and earthquake magnitudes, were used as the input to 8 input neurons. Hornik (1993) proved that a feed-forward ANN with an arbitrary number of processing units on a single hidden layer is a universal function approximator, so only one hidden layer has been used in this study. Resulting from the ANN processing, the occurrence of highway slope failure was expressed through a single output neuron as a value between 1 and 0, here 1 means that the event of failure takes place, while 0 at the output unit represents the absence of failure.

## ANN PERFORMANCE INDEXES AND PARAMETERS

To assess the performance of the ANN, the success ratio proposed by Derin and Hasan (1998) was used as an agreement index. The success ratio is defined as

$$\text{Success ratio} = \frac{\text{Number of successful trials}}{\text{Total number of trials}}. \tag{11}$$

In their work, Derin and Hasan (1998) used $|E|=0.3$, where $|E|$ is the difference between the value generated by the ANN and 1 in the event of failure, or 0 in the event of non-failure. For instance, when the ANN produces a value equal to 0.92, while the event of slope failure was observed, then $|E|=|0.92-1.0|$. This value of $|E|$ is less than 0.1, so the developed program regards such a prediction as a successful trial demonstrating that the probability of slope failure under the considered conditions is rather high. In the non-failure event, if the ANN result is 0.08, $|E|=|0-0.08|$ which is less than 0.1. Such a simulation is also considered to be successful. After some preliminary studies based on practical requirements for the prediction accuracy (results of which are not shown here), two values for the $|E|$ are selected: 0.1 and 0.2 (Table 1).

Here the effects of the number of hidden units, learning rates ($\eta$), momentum factors ($\alpha$), and the number of training iterations (epochs) for the ANNs performance are estimated. Fig.3a shows the success ratio for 11 different ANNs with the number of hidden neurons changing from 1 to 11. The presented results show that the ANN performance improves to some extent with an increase in the number of neurons (up to 7 hidden units), while larger numbers of neurons affect the performance negatively. This is attributed to the effect of over-learning, which is the inability of an ANN to generalize.

The value of the learning rate $\eta$ affects the convergence of the ANN learning algorithm significantly and may accelerate the convergence of the training process. The momentum factor $\alpha$ is used to avoid stopping the learning process at a local minimum instead of the global one (Jacobs, 1988). After 8 preliminary tests, the highest success ratio of 95.0% for $|E|=0.2$ and 80.0% for $|E|=0.1$ was obtained with the learning rate of 0.01 (Fig.3b). The momentum factor $\alpha=0.9$ demonstrated the best results for Case A3 (Fig.3c). Fig.3d demonstrates that the highest

**Table 1 Training and validation data sets and ANN performance**

| Case | Training | | | Validation | | | Success ratio (%) | |
|---|---|---|---|---|---|---|---|---|
| | Failure | Non-failure | Total | Failure | Non-failure | Total | $\|E\|=0.2$ | $\|E\|=0.1$ |
| A1 | 15 | 85 | 100 | 11 | 29 | 40 | 82.5 | 70.0 |
| A2 | 26 | 124 | 150 | 11 | 29 | 40 | 87.5 | 72.5 |
| A3 | 35 | 165 | 200 | 11 | 29 | 40 | 95.0 | 80.0 |
| A4 | 15 | 85 | 100 | 20 | 60 | 80 | 75.0 | 60.0 |
| A5 | 26 | 124 | 150 | 20 | 60 | 80 | 82.5 | 65.0 |
| A6 | 35 | 165 | 200 | 20 | 60 | 80 | 85.0 | 67.5 |
| A7 | 26 | 124 | 150 | 28 | 92 | 120 | 75.1 | 62.5 |
| A8 | 35 | 165 | 200 | 28 | 92 | 120 | 81.7 | 68.4 |

success ratio for both values of $|E|$ was obtained in 17000 epochs.

Summarizing the above discussions, the ANN architecture selected for Case A3 consists of 8 input nodes (to assimilate the data for the slope gradient angle, slope height, cumulative precipitation, daily rainfall, strength of material, the joint number, the condition of the vegetation and slope direction, as mentioned in the previous section), 7 hidden processing units and 1 output neuron. The learning rate $\eta$=0.01, the momentum factor $\alpha$=0.9 and the number of training epochs=17000 were also determined following the results of multiple numerical tests.

## METHODOLOGY VALIDATION AND SALIENCY ANALYSIS

The length of separate data sets used to train and validate the methodology performance, as well as the success ratio for two different values of $|E|$ are presented in Table 1. An analysis shows that the success ratio generally improves with the increase in the number of training data sets (up to 200 cases in total), though adding even more validation data sets deteriorates the method performance. This might be related to the fact that the additional data sets used for validation were not presented by similar patterns during the stage of ANNs' training. Therefore, an extension of the data archives to include the majority of possible slope failure scenarios might fix this problem.

Figs.4 and 5 visualize some validation results for each of Cases A3, A6 and A8, all trained on 200 data sets, and validated on 40, 80 and 120 data sets, respectively. It is clear that all the results agree reasonably well with the actual observations. These results also confirm that the proposed neural methodology is able of capturing the occurrence of slope failure when adequate initial information is provided. From the analysis of the numerics and graphs, it follows that the best results were obtained for Case A3. Therefore this case was selected for further saliency analysis studies.

Saliency analysis is a technique derived from the idea that an ANN has to stay operational even in the case of incomplete input, or if an internal component faults (Abrahart *et al.*, 2001; Makarynskyy *et al.*, 2005). The technique allows estimation of the relative importance of the input and processing nodes of a

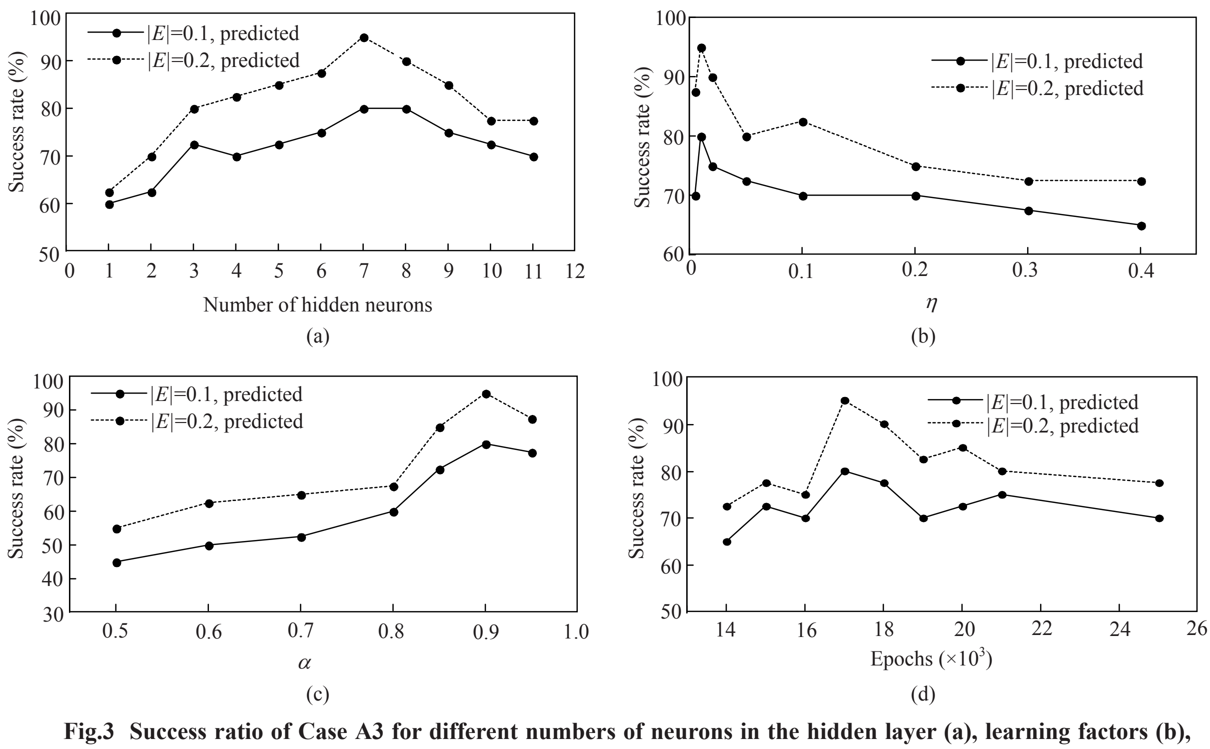


**Fig.3 Success ratio of Case A3 for different numbers of neurons in the hidden layer (a), learning factors (b), momentum factors (c) and numbers of training iterations (d)**

network, as well as its consequent optimization by the intentional introduction of missing neurons. It is different from the standard pruning procedure (Maier and Dandy, 2000), which simply cuts off "excessive" neurons. In this particular study, the importance of ANN input parameters were determined. This might be highly relevant in the situation when the number of observed data is strictly limited, and a question of the data sets sufficiency arises.

In order to found the key success factors of the slope gradient angle, the slope height, the cumulative precipitation, daily rainfall, strength of materials, slope direction, joint number and vegetation condition, there are 8 cases were considered, named as Cases B1~B8 (Table 2). All these cases were based on the outcome of Case A1 with $|E|$=0.2. Each case implies the use of a smaller ANN with 7 input, 7 hidden and 1 output neurons compared to the previously adopted one. The number of input nodes was decreased by 1 (i.e., 1 missing unit is introduced) because instead of 8 previously itemized parameters only 7 of them were used to form the ANN input. The contribution of the missing parameter was calculated as the difference between the highest success ratio (95.0%) and the success ratio computed from each case outcome. Table 2 demonstrates that exclusion of the vegetation condition with a contribution of 7.5% does not significantly affect the success ratio of prediction, which stays reasonably high (87.5%)

In the same way, the 7 (Cases C1~C7) and 6 (Cases D1~D6) parameters could be readily excluded from ANN simulations. A further exclusion of parameters (Tables 3~4) highlights the low level of contribution coming from the joint number (2.5%, Table 3) and slope direction (5.0%, Table 4). After the input neurons were made "missing", the success ratio decreased relatively insignificantly to 85.0% (Table 3) and 80.0% (Table 4), respectively.

The results comparison of Cases A3 (Figs.4a and 5a) and D6 (Fig.6) based on 8 inputs and 5 inputs respectively, shows significant degradation of the estimation outputs attributed to insufficient input information. Nevertheless, it can be concluded that the proposed neural methodology performs well with

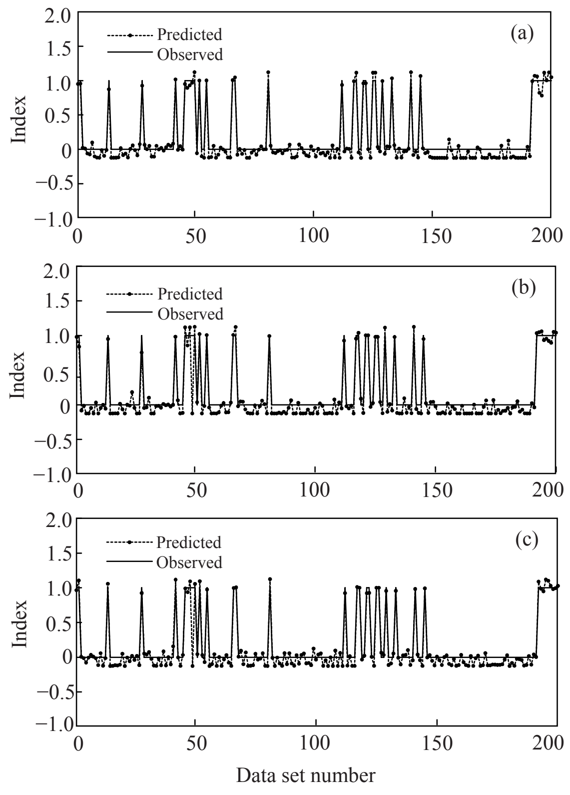


**Fig.4 Results of training vs observations. (a) Case A3; (b) Case A6; (c) Case A8**

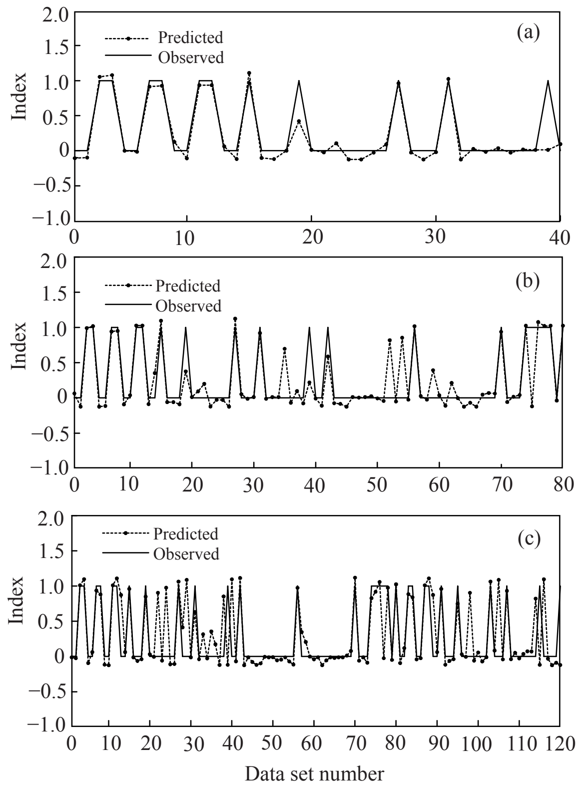


**Fig.5 Forecasts vs observations. (a) Case A3; (b) Case A6; (c) Case A8**

**Table 2 Saliency analysis of initial 8 parameters**

| Case | Missing parameter | Success ratio (%) (\|E\|=0.2) | Contribution ratio (%) |
|---|---|---|---|
| B1 | Slope gradient angle | 77.5 | 17.5 |
| B2 | Slope height | 75.0 | 20.0 |
| B3 | Cumulative precipitation | 75.0 | 20.0 |
| B4 | Daily rainfall | 77.5 | 17.5 |
| B5 | Strength of material | 82.5 | 12.5 |
| B6 | Slope direction | 82.5 | 12.5 |
| B7 | Joint number | 80.0 | 15.0 |
| B8 | Vegetation condition | 87.5 | 7.5 |

**Table 3 Saliency analysis of 7 parameters**

| Case | Missing parameter | Success ratio (%) (\|E\|=0.2) | Contribution ratio (%) |
|---|---|---|---|
| C1 | Slope gradient angle | 72.5 | 15.0 |
| C2 | Slope height | 67.5 | 20.0 |
| C3 | Cumulative precipitation | 72.5 | 15.0 |
| C4 | Daily rainfall | 62.5 | 25.0 |
| C5 | Strength of material | 82.5 | 5.0 |
| C6 | Slope direction | 82.5 | 5.0 |
| C7 | Joint number | 85.0 | 2.5 |

**Table 4 Saliency analysis of 6 parameters**

| Case | Missing parameter | Success ratio (%) (\|E\|=0.2) | Contribution ratio (%) |
|---|---|---|---|
| D1 | Slope gradient angle | 75.0 | 10.0 |
| D2 | Slope height | 60.0 | 25.0 |
| D3 | Cumulative precipitation | 60.0 | 25.0 |
| D4 | Daily rainfall | 65.0 | 20.0 |
| D5 | Strength of material | 72.5 | 15.0 |
| D6 | Slope direction | 80.0 | 5.0 |

a success ratio of 80.0% even in the case where a rather limited number of input data is available. Meantime, it implies that availability of all 8 parameters studied here, or a larger number of inputs, will contribute to a further improvement in slope stability/slope failure estimates.

## CONCLUSION

The traditional method of highway slope failure determination is often based on numerous tedious field tests in order to produce an empirical expression of limited applicability. In this paper an alternative methodology built on the artificial intelligence technique of BPNs was proposed and successfully implemented to assess highway slope failure. The survey data from the South Cross-Island Highway in southern Taiwan were used to test the performance of the neural methodology.

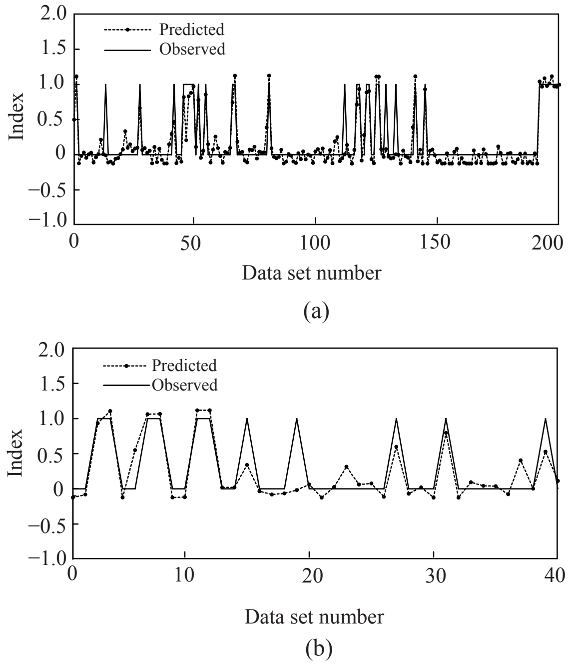


**Fig.6 ANN performance with five input parameters in Case D6. (a) Training; (b) Predicting**

Such vital information concerning ANN performance and optimal data for the case parameters such as the number of hidden processing units (7), learning rate (0.01), momentum factor (0.9) and the number of training epochs (17000), were determined in multiple numerical tests.

It was demonstrated that the availability of 8 observed parameters, namely the slope gradient angle, the slope height, the cumulative precipitation, daily rainfall, strength of materials, the joint number, the condition of the vegetation and slope direction provide a success ratio of 95.0% in neural simulations of slope failure.

The technique of saliency analysis applied to the used ANN structure showed the ANNs ability to perform well with a success ratio of 80.0% with much fewer input parameters, employing only the slope gradient angle, the slope height, the cumulative precipitation, daily rainfall and strength of materials. The case study presented here clearly showed that this neural methodology could be successfully applied to slope failure estimates. It also implies that, before employing it in other areas and under different conditions, the methodology must be trained and validated on site-specific data sets.

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