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ASSESSING LANDSLIDE HAZARD USING ARTIFICIAL NEURAL NETWORK: CASE STUDY OF MAZANDARAN, IRAN

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Abstract: Investigations of soil failures are subjects touching both geology and engineering. These investigations call the joint efforts of engineering geologists and geotechnical engineers. From the studies of field case records at least two types of soil failures have been distinguished, namely "shear failure" which is main concentration of the current research and "liquefaction failure". Shear failures along shear planes occur when the shear stress along the sliding surfaces exceed the effective shear strength. These slides have been referred to as landslide. An expert system based on artificial neural network has been developed for use in the stability evaluation of slopes under various geological conditions and engineering requirements. The Artificial neural network model of this research uses slope characteristics as input and leads to the output in form of the probability of failure and factor of safety. It can be stated that the trained neural networks are capable of predicting the stability of slopes and safety factor of landslide hazard in study area with an acceptable level of confidence. Landslide hazard analysis and mapping can provide useful information for catastrophic loss reduction, and assist in the development of guidelines for sustainable land use planning. The analysis is used to identify the factors that are related to landslides and to predict the landslide hazard in the future based on such a relationship.

Keywords: Landslides, Expert system, Artificial neural network, Geology, Mazandaran.

1. INTRODUCTION

From the studies of field case records at least two types of soil failures have been distinguished, namely "shear failure" and "liquefaction failure". To indicate the characteristics of shear failure and liquefaction failure, the words "landslide" and "flow slide" have been used, respectively. To distinguish these two types of failures it should be noted, that shear failures along shear planes occur when the average shear stress along the sliding or slip surfaces tends to exceed the effective shear strength. Liquefaction failures occur as a consequence of large excess pore pressure build up under mainly undrained conditions (Roscoe, 1967).

Sliding of masses of soil, primarily resulting from the shear failures along shear planes forming the boundaries of the moving masses, may take place during a very long time. Some of these slips started more than ten thousands years ago and are still continuing (Christiansen, 1983). Table 1 shows the cause and failure time of some typical cases.

A landslide or landslip is a geological phenomenon which includes a wide range of ground movement, such as rock falls, deep failure of slopes and shallow debris flows, which can occur in offshore, coastal and onshore environments (Bishop et al., 1969). Although the action of gravity is the primary driving force for a landslide to occur, there are other contributing factors affecting the original slope stability. Typically, pre-conditional factors build up specific subsurface conditions that make the area/slope prone to failure, whereas the actual landslide often requires a trigger before being released (Bishop, 1955).

Landslides occur when the stability of a slope changes from a stable to an unstable condition. A change in the stability of a slope can be caused by a number of factors, acting together or alone (Duncan, 1996).

Table. 1. The cause and failure time for different cases of failures.

Problem	Mechanism	Cause	Failure time
Denholm Saskatchewan Landslide	shear failure	erosion at toe	12000 years
Coastal flow slides in Zeeland	liquefaction failure	erosion, tidal current, geometry change	about 1.5 minutes
Fort Peck dam flow slide	liquefaction failure	increase of total load during construction	about 3 minutes
The flow slide of 1966 at Aberfan	liquefaction failure	additional load, change of geometry	about 2.5 hours
Lower San Fernando dam flow slide	liquefaction failure	Earthquake	about 2 minutes
Flow slides in model experiments	liquefaction failure	steady increase of pore pressure	about 40 seconds
Quick clay flow slide at Furre	liquefaction failure	increased pore pressure	about 2 minutes
Quick clay flow slide at Baastad	liquefaction failure	stream erosion, leaching	about 1 minute

From table 1 it can be seen, that natural causes of landslides include: groundwater (pore-water) pressure acting to destabilize the slope, loss or absence of vertical vegetative structure, soil nutrients, and soil structure (e.g. after a wildfire), erosion of the toe of a slope by rivers or ocean waves, weakening of a slope through saturation by snowmelt, glaciers melting, or heavy rains, earthquakes adding loads to barely-stable slopes, earthquake-caused liquefaction destabilizing slopes and volcanic eruptions (Eckersley, 1990). Also landslides are aggravated by human activities such as deforestation, cultivation and construction, which destabilize the already fragile slopes, vibrations from machinery or traffic, blasting and earthwork which alters the shape of a slope, or which imposes new loads on an existing slope (Gokceoglu & Sezer, 2009; Sassa et al., 2004). However, there are a number of external or internal causes which may be operating either to reduce the shearing resistance or to increase the shearing stress. There are also causes affecting simultaneously both terms of the factor of safety ratio. Table 2 shows brief lists of landslide casual factors (Varnes, 1978; Cruden & Varnes, 1996).

Table 2. A brief list of landslide casual factors.

Ground Conditions	Geomorphological Processes	Physical Processes	Man-Made Processes
(1) Plastic weak material (2) sensitive material (3) Collapsible material (4) weathered material (5) Sheared material (6) Jointed of fissured material (7) Contrast in permeability and its effects on ground water contrast in stiffness (stiff, dense material over plastic material)	(1) Tectonic uplift (2) Volcanic uplift (3) Glacial rebound (4) Fluvial erosion of the slope toe (5) Wave erosion of the slope toe (6) Glacial erosion of the slope toe (7) Erosion of the lateral margins (8) Subterranean erosion (solution, piping) (9) Deposition loading of the slope or its crest (10) Vegetation removal (by erosion, forest fire, drought)	(1) Tectonic uplift (2) Volcanic uplift (3) Glacial rebound (4) Fluvial erosion of the slope toe (5) Wave erosion of the slope toe (6) Glacial erosion of the slope toe (7) Erosion of the lateral margins (8) Subterranean erosion (solution, piping) (9) Deposition loading of the slope or its crest (10) Vegetation removal (by erosion, forest fire, drought)	(1)Excavation of the slope or its toe (2)Loading of the slope or its crest (3)Defective maintenance of drainage systems (4)Irrigation (5)Water leakage from services (water supplies, sewers, storm water drains) (6)Vegetation removal (7)Mining and quarrying (open pits or underground galleries) (8)Creation of dumps of very loose waste (9)Artificial vibration (including traffic, pile driving, heavy machinery)

Forgoing discussions indicate that there is a big complexity involved in the analysis of landslide failures. In the following, artificial neural network will be used to overcome this complexity. Recently, extensive studies have been done on application of ANN to geotechnical engineering problems; (Chan et al., 1995, Lees, 1996, Teh et al., 1997, Sivakugan et al., 1998, Ellis et al., 1995). Sidarta & Ghaboussi (1998) employed an ANN model within a finite element analysis to extract the geometrical constitutive behavior from non-uniform material tests. Penumadu & Jean-Lou (1997) used neural networks for representing the behavior of sand and clay soils. Sidarta & Ghaboussi (1998) used neural networks to model both the drained and undrained behavior of sandy soil subjected to triaxial compression-type testing. Penumadu & Zhao (1999) also used ANNs to model the stress-strain and volume change behaviour of sand and gravel under drained triaxial compression test conditions. Zhu et al. (1998a and 1998b) used neural networks for modeling the shearing behavior of a fine-grained residual soil, dune sand and Hawaiian volcanic soil.

Simplified methods in assessing slope stability are popular among practicing engineers. These procedures are very useful at the preliminary design stages to assess landslide risk. If the landslide risk is high, then a detailed analysis can be carried out to obtain the stability of slope, which is necessary in subsequent design of structures in study area (Hornik, 1991). In more details improving the reliability of landslide risk, may lead to cost reduction and helps to operation planning (Remondo et al., 2005).

Data collection in explored soils is important for assessing of landslide as well as estimation of strata thickness, soil type, groundwater table and etc (Champati ray et al., 2007). It is also time consuming and often expensive process, which includes many field and laboratory experiments (Ayalew et al., 2004). Therefore reliable prediction of landslide asks for carefully planning of sampling, testing and exploration methods (Cal, 1995).

Successful prediction of slope stability in soil deposit using the existing data leads to improve the reliability of data which will be used for construction in future (Saha et al., 2005). Such approach is presented in the following text that generally comprises presentation of the study area, description and selection of the neural model, its training, improving, and developing of final model used for prediction of slope stability by specific ANN.

To this end, first the study area and its geological setting will be considered, taking into account the experimental and laboratory tests performed in the landslide regions. Then, by considering the advantages of these data, the structure of the ANN model is completed. In the next step, the ANN model will be adapted by training process. It follows by validation process in which the generality of the models for future prediction is increased. At the final stage, the predictive capability of the ANN model is controlled by comparing the calculated results with corresponding actual slope conditions failure. This is followed by the concluding remarks of the present research work.

2. STUDY AREA AND GEOLOGICAL SETTING

The study area is located in central part of Mazandaran province in north of Iran. The geomorphology of this region has been formed under the impact of neighborhood with the Caspian Sea heights, local climate, geology and earth structuring. The northern foothills of this mountain range, overlooking the Caspian depression, are covered by forest and have been cut by many rivers (Asadian et al., 2010). The authors focused on 3 zones in this study area named Flourd, Hollar and Noabad. The Flourd site is located at Savadkouh Azad University grounds in the rural surroundings of Savadkouh, 5 Km from Pol-Sefid city in the northern part of Iran (Fig. 1).

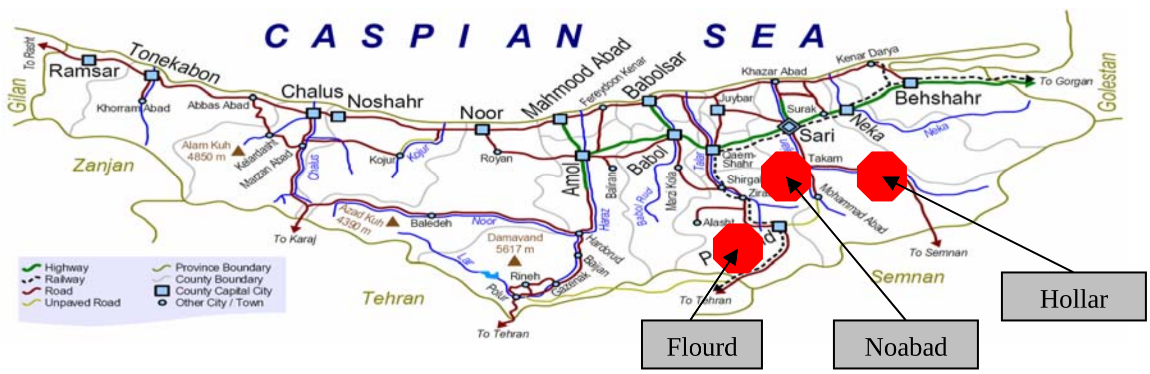


Figure 1. Geographical map of Flourd landslide, Northern part of Iran.

(a) Extent of damage.

(b)Tilting trees and visible roots.

Figure 2. A view of the active slide at the Flourd site.

The elevation of the site is 350 m above sea level. Like the surrounding lands, a forest vegetation cover and a mountainous morphology is dominant. Figure 2 shows a scarp of the landslide along with the tilted trees, indicating the extent of the slide damage. The area investigated consists of an old slide mass which experienced several slides during the quaternary period, associated with saturated conditions and dynamic loading caused by severe earthquakes. Peat, lignite remains, and coal remains from Alder trees were revealed from boreholes at the site. These findings indicate that the site had several previous slides and, generally similar geographical conditions existed in the past.

Subsurface site investigations indicate that no stable underground water table exists. However, underground seepage flow seems to exist within the silt and gravel lenses which exist in the stratification. Bore pits dug in the area showed that seepage water exists at the depth of three to five meters below ground surface. Water level was observed in several observation wells at depths ranging from 10 to 15 meters, at the interface between the slide mass and the underlying bedrock.

Site investigation revealed that part of the surface water run-off from adjacent areas to the active landslide mass, leaks into the sliding area. This trapped surface water eventually infiltrates into the ground and accumulates with the existing rainfall induced seepage from surface water absorption within the sliding mass. The slide mass is, therefore, considered to be saturated at the time of landslide activation (Havenith et al., 2006).

One of the important factors affecting a landslide risk assessment is the engineering geological parameters and characteristics of the site. In this context, the parameters considered usually consist of site geometry, failure mechanisms observed, effect of slide on existing structures, assessment of the causes and the risks for future occurrence of slides, classification of the landslide, and in-situ soil conditions. All these have been studied in Flourd landslide and have revealed the high landslide hazard risk of the site. Figure 3 shows geological map of Flourd landslide and Pol-Sefid (Choobbasti et al., 2009a).

As previously mentioned, the slide mass at the university site is part of a sliding slope facing the south eastern direction. The sliding mass extends to the calcareous sediments on the south west side, and finishes off to the river at its toe. Steady state seepage conditions prevail below the ground surface down to the underlying bedrock. A volume of 15 to 20 liters per second were predicted for the seepage flows. The slide mass does not have any visible surface flow paths and the existing paths are rather scattered in the whole region. From the lateral scarps, silty clay along with boulders is visible. The slide initiated at the point where little vegetation existed. Surface water from rainfalls directly penetrated the underlying soils at these surfaces and reached the shear zone of the sliding mass. The upper surface of the slide has a concave form which gathers rainfall water into the sliding mass. Therefore, each period of heavy rainfall causes a reactivation of the slides. Tilting of the existing trees indicates that a progressive and creep type of active slide is dominant in the area. The effect of landslide on existing geotechnical structures in the area was generally in the form of slides in the slopes, creep, tilt and structural cracks in the soil retaining structures.

On January, 2004 a large landslide on a layer of mainly clayey soil took place at Hollar (Fig. 1), in Mazandaran, northern part of Iran. Landslides in the province of Mazandaran constitute a major threat to both lives and property. The falling and sliding of some of Hollar trenches (Fig. 4) is a research subject that attracted a group of geological investigators for a time about at least ten years.

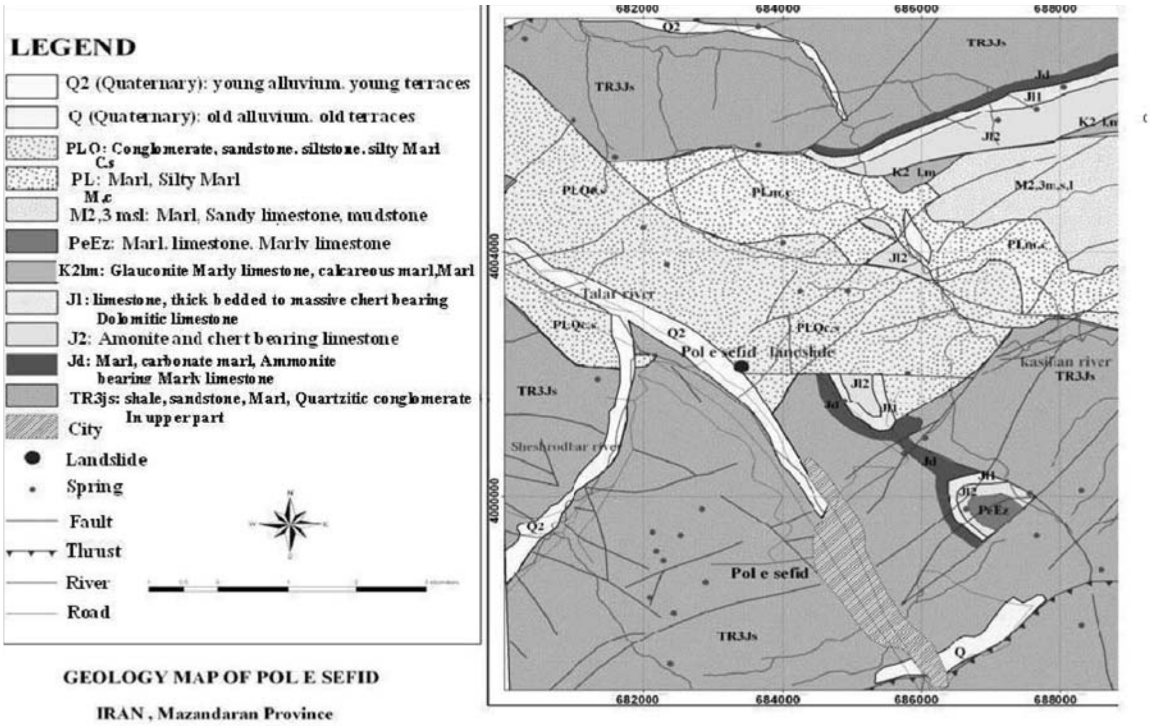


Figure 3. Geological map of Flourd landslide and Pol-Sefid.

(a) Extent of damage on infrastructures.

(b) Extent of damage on properties.

Figure 4. A view of the active slide at the Hollar site.

Table.3. Physical and mechanical characteristics of soils.

K (m/day)	φ°	ψ°	C (KN/m^2)	υ	γ_{sat} (KN/m^3)	E (KN/m^2)	γ_{dry} (KN/m^3)	Soil type
0.0001	20	0.0	5	0.35	11.5	800	7	peat
0.0001	24	0.0	2	0.33	17	2000	15	clay
0.01	25	0.0	4	0.33	17.5	20000	16	Stone clay

The investigation shows that three kinds of materials dominated the site. The lower one is stone clay over the whole area. The upper one is clay with adenitis fragment. The average thickness of clay layer in this area is investigated about 25-30 m. Another material is found as alluvium, which is the minority of the material type. The corresponding values being shown in the table 3.

Rainfall is one of the main factors governing the landslide occurring in the Hollar region. Average annual rainfall between 800-1000 (mm) has been recorded in this region. As a result of this regional meteorological event, flooding and landslide began to occur on January 2004. In fact, these changes in environmental conditions caused abnormally high groundwater levels and subsequently the initiation of the slide.

As mentioned above, Noabad landslide area is also located in north of Iran, Mazandaran. The annual mean temperature of the terrain is 12.5 °c and the annual mean precipitation is estimated 800 (mm). The area climate from Dommartan method is humid. From geological point of view, the most of geologic units are related to Senozoaek era that for reason of the existence of marl, shiel silty stone are susceptible to landslide occurrence.

Piezometer tubes were installed into the ground to measure changes in water level over a period of time. Ground investigations also include the in-situ and laboratory tests, area photographs, study of geological maps and memoirs to indicate probable soil conditions, visiting and observing the slope, previous instability which happened and plotting topography plan (Fig. 5) (Corominas et al., 2005).

3. ANN MODELING, ANALYSIS, RESULTS AND DISCUSSIONS

In problems dealing with different variables and with different ranges and dimensions, the application of several networks may be a good choice. Neural networks are efficient tools when used as pattern classifiers, it is important to properly select the input variables for training (learning) process of ANNs, as the way how to determine relationships between input and output variables (Riedmiller & Braun, 1993). A set of known input and output values is named as input-output pair. All such pairs are usually divided into three sets. The first and second are described as training and validation sets which are used to determine the connection weights or weighting coefficients (like in interpolation methods), usually marked as w_{ij},

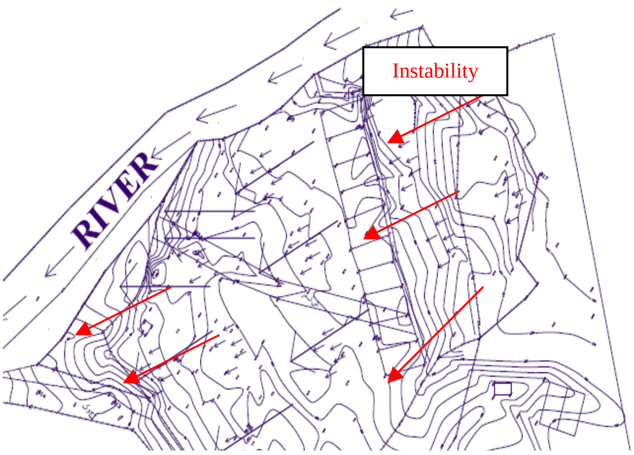
$$(y_i^k = f(y_i^{'}k) = f(\sum_{j=1}^{n_{k-1}} w_{ij}^k y_i^{k-1})).$$

Also the training and validation sets are used during the training process and the test set is used for obtaining the estimates (Rumelhart et al., 1986). All ANN models were trained using the automated regularization algorithm to improve generalization. The validation set served as a constraint on training, in order to minimize over fitting (Lee et al., 2007). The ANN models for this study were developed, trained, validated and tested within STATISTICA computational environment utilizing the neural network toolbox, and the accuracy of the ANN model was evaluated using Root Mean Squared Error (RMSE) between measured and predicted values and pressed as:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}(z_s - z_0)^2}{n}} \qquad (1)$$

Where z_s is observed value, z_0 is predicted value, n is number of samples.

The authors used two ANN models to apply landslide analysis. The first one was able to predict the landslide hazard probability or stability of slopes and the second one was used for prediction of safety factor in slopes. In the First ANN model, coefficient of cohesion (C), angle of slope (α), angle of internal friction (ϕ), distance from slope edge (x) (Figure 6), unit weight (γ) and slope elevation (H) are input variables.



(a) Topography map of Noabad.

(b) Extent of landslide damage.

Figure 5. A view of the active slide at the Noabad site.

In the second proposed ANN model for prediction of safety factor, several important parameters, including effective stress (σ'), coefficient of cohesion (C), angle of slope (α), angle of internal friction (ϕ), distance from slope edge, slope elevation (H) and length of slope (L) were used as the input parameters whilst the factor of safety was the output parameter. It should be noted that seismic parameters are one of the important parameters affecting on landslide hazard and in this research vertical and horizontal value of seismic parameters assumed constant. It is also important to note that, in fact, several ANN models using element tests data were constituted for generating the models. Among them, the model with better performance (greater coefficient of determination and smaller RMSE) for validation data set was then chosen. However, the ANN models were developed with the best performance concurrently for training and testing of data sets. For optimization of the developed ANN models, three different combinations of input parameters were considered as shown in tables 4 and 5.

It can be extracted from tables 4 and 5 that, regarding to RMSE value obtained by different models, first model is the best model chosen which was applied within current study.

These factors are based on exploration of typical, large scale slopes that have the potential to be failed and on statistical analyses throughout the central part of Mazandaran. In this study, all of these data had to be processed using standard adjustment as input variables in the ANN model. As for the qualitative indices, it is better to describe the state of a slope by means of values of 1 and 0, which express stable and unstable conditions, respectively.

In current research, regarding the available data and their quality, a neural network program written in back propagation algorithm, is used. Six and seven soil parameters are selected as input in different models, and these parameters are divided into data sets. Each data sets is introduced to the network individually, and performance of the network on the assessment of slope stability is investigated.

Back propagation is selected as the training algorithm of neural network (Table 6). It is the best known training algorithm for multilayer perceptrons neural networks, and still one of the most useful and later improved in some advanced forms like RProp. Back propagation algorithm means that network training includes determination of the difference between true and wanted network response, i.e. means calculation of error that is backed in the neural network for obtaining optimal training.

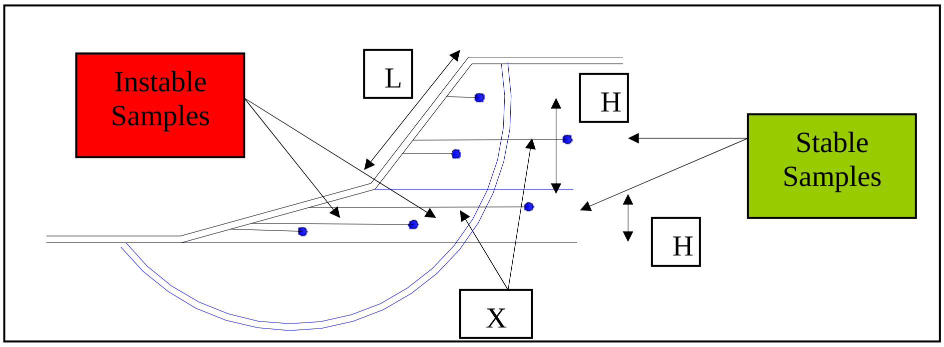


Figure 6. Sample selection and X distance from edge.

Table 4. Different combinations of input parameters for prediction of landslide hazard.

Model number	1	2	3
Input	C , α , ϕ , x , γ ,H	H , x , γ ,σ' ,σ	C , α , σ' ,σ , ϕ
RMSE	9%	12%	13%

Table . 5. Different combinations of input parameters for prediction of safety factor.

Model number	1	2	3
Input	σ' ,C , α , ϕ , x , H,L	H , x , γ ,σ' ,σ , α	C , α , σ' ,σ , ϕ , H
RMSE	11%	16%	14%

It has lower memory requirements than most algorithms, and usually reaches an acceptable estimation error quite quickly (in relative low number of iterations or epochs).

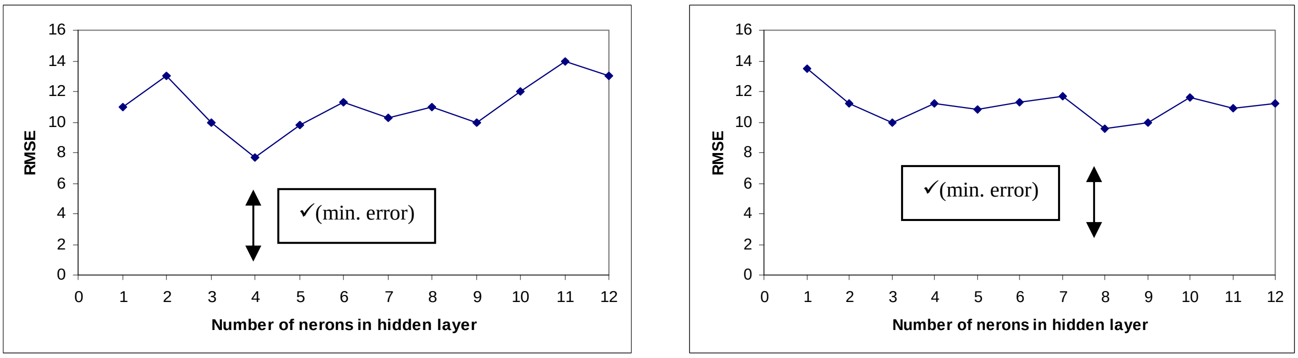
In the selection of learning / training algorithm number of neurons in different layers (input, hidden, output), number of epochs, learning rate and the momentum have been applied instant (Choobbasti et al., 2009b). The RMSE of the different neurons in hidden layer is plotted in Fig. 7.

As shown in table 6, the available data set is divided into three sets, namely training, validation, and test sets, based on random selection. This way we can examine the validity of the model in a more comprehensive manner. In ANN forecasting models, 60% of the records are selected as training, 30% are taken for test in final evaluation, and the remaining 10% used for validation or monitoring the performance of the model during the training phase (Table 7).

In each epoch, the entire training set is fed through the network, and used to adjust the network weights. Numbers of epochs are specified at the start, but also alternative stopping criterion may also be specified, and if over-trained network occurs the best network discovered during training can be retrieved. In this analysis, the number of epochs varied between 300 and 500.

Table. 6. Results of research in order to Learning / training algorithm selection for prediction of landslide hazard.

Supervised Learning/ training algorithms	Back propagation	Conjugate Gradient Descent	Levenberg-Marquardt	Quick Propagation	Delta -bar-Delta
RMSE (%)	7.2	10.6	11.3	9.9	8.6
	✓(min. error)				



(a) For prediction of landslide hazard. (b) For prediction of safety factor.

Figure 7. The RMSE of the different neurons in hidden layer.

Table 7. Performance of different sets of data used in ANN.

Case study	Number of data (I/O data pairs)	ANN used for	Training set	Validation set	Testing set
Flourd	883	Prediction of landslide hazard	503	95	285
Flourd	883	Prediction of Safety factor	503	95	285
Hollar	762	Prediction of landslide hazard	488	79	195
Hollar	762	Prediction of Safety factor	488	79	195
Noabad	1037	Prediction of landslide hazard	600	122	315
Noabad	1037	Prediction of Safety factor	600	122	315

A batch mode feed-forward Multilayer Perceptron (MLP) with back-propagation learning rules was used to create the desired ANN model an adaptive learning rate was employed to keep the learning step size as large as possible while the training is stable. According to a universal approximation theorem, demonstrated concurrently by several researchers for traditional MLP, a single hidden layer network is sufficient to uniformly approximate any continuous and nonlinear function. The model architecture was built with one hidden layer, a learning rate of 0.95 and a momentum term of 0.9 updated with a coefficient of 0.95 after each epoch. The studies performed here, were started with one hidden neurons to reach the optimum number of hidden neurons and desired precision. Input vector contains soil initial parameters and output (the target vector) is stability and safety factor of slope. In order to obtain a more efficient training process, the input and target were standardized to have zero mean and unity standard deviation. Cross-validation or employing another set of data for more testing can be used to increase the generality of the models for future predictions.

After determination of the factors affecting slope stability, a three-layer ANN with six input nodes, four neuron in hidden layer, one output node (stability of slope) and another three-layer ANN with seven input nodes, eight neuron in hidden layer and one output node (factor of safety) were constructed in this research.

The predictive capability of the proposed neural network has been assessed by comparing the calculated probability of failure with the actual slope conditions. Table 8 tabulated some random selected samples, showing the actual modes of failure and prediction of ANN. The system uses the slope characteristics and material property data and calculates the landslide hazard probability and the factor of safety for each slip.

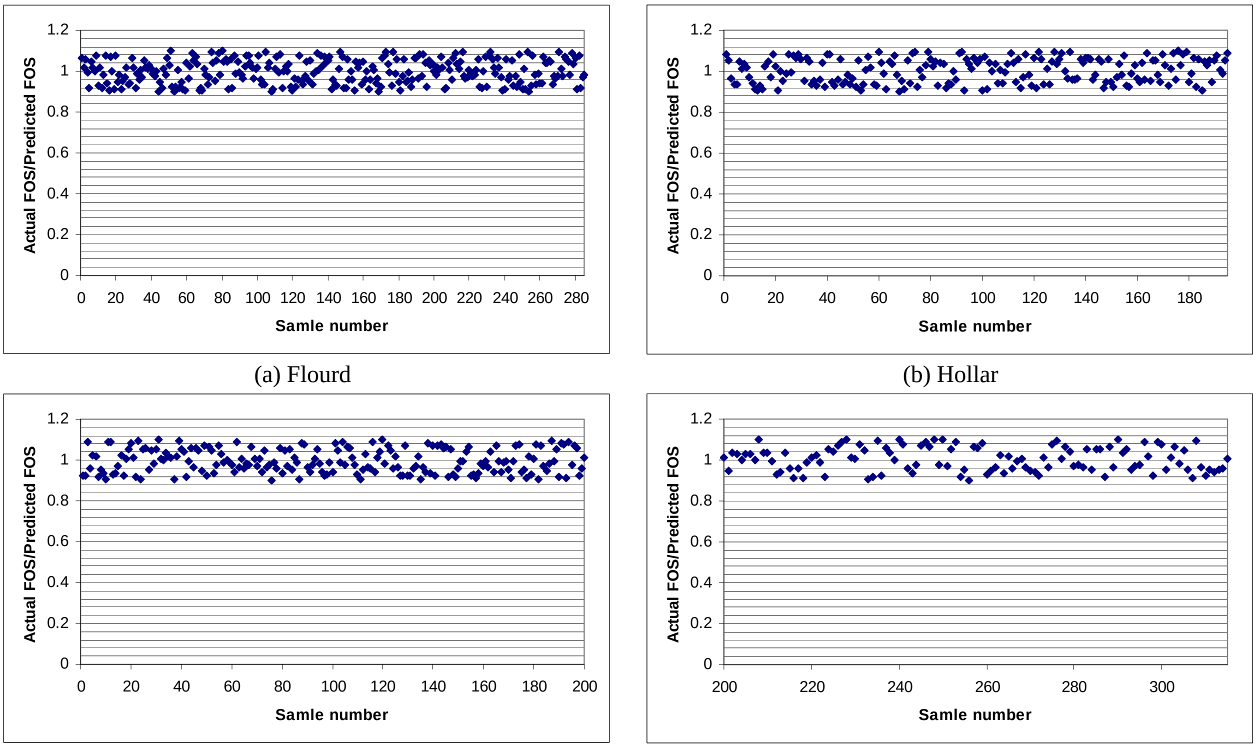
For the above discussion, it is clear that, first the learning or training dataset is used to determine the weights. Then a second validation set is used to monitor the performance of the model during the training phase and to minimize over fitting, and finally the test sets was used to evaluate the trained neural network. It is evident from test data sets that the developed ANN model can be applied successfully to predict the stability and factor of safety value of slope.

The samples are divided in to 3 groups (training, validation and testing). As shown in Figure8 samples of testing group are correlated in terms of sample number and the accuracy (comparison between prediction and real data) of each sample is shown.

In these figures, terms of the ratio of actual data per predicted value (in Y-axis) versus sample number (in X-axis) for different test samples are presented. It is clear that if the predicted and the true values were the same, such point lie on line y=1. It is clear that the average correlation of the ANN model and true data in all cases is over 90%. So it can be concluded, that the prediction of slope stability and its factor of safety agrees with actual landslide data obtained from bishop's method or finite element method.

Table. 8. Selected case studies showing the actual modes of failure and prediction of ANN.

Sample	C (kpa)	L (m)	α (□)	ϕ	X (m)	γ $(\frac{KN}{m^3})$	σ' $(\frac{KN}{m^2})$	H (m)	Stability (Actual condition)	FOS (Actual condition)	Stability (Prediction of ANN)	FOS (Prediction of ANN)
1-Flourd	14	83	31	23	1	19.2	5.46	27	0	0.78	0	0.72
2-Flourd	14	83	31	23	3	19.2	16.94	27	0	0.81	0	0.78
3-Flourd	14	83	31	23	5	19.2	28.24	27	0	0.97	0	0.89
4-Flourd	14	83	31	23	7	19.2	39.53	27	1	1.04	1	1.13
5-Flourd	14	83	31	23	9	19.2	50.83	27	1	1.10	1	1.06
6-Hollar	27.3	75	29	31	1	18.7	4.93	32	0	0.88	0	0.94
7-Hollar	27.3	75	29	31	3	18.7	14.80	32	1	1.07	1	1.13
8-Hollar	27.3	75	29	31	5	18.7	24.66	32	1	1.12	1	1.17
9-Hollar	27.3	75	29	31	7	18.7	34.53	32	1	1.20	1	1.12
10-Hollar	27.3	75	29	31	9	18.7	44.40	32	1	1.25	1	1.31
11-Noabad	10	96	32	28	1	20.1	6.43	24	0	0.66	0	0.72
12-Noabad	10	96	32	28	3	20.1	19.30	24	0	0.71	0	0.73
13-Noabad	10	96	32	28	5	20.1	32.18	24	0	0.90	0	0.97
14-Noabad	10	96	32	28	7	20.1	45.05	24	0	0.97	0	0.89
15-Noabad	10	96	32	28	9	20.1	57.92	24	1	1.02	1	1.09



(a) Flourd (b) Hollar

(c-1) Noabad (c-2) Noabad

Figure 8. Errors involved in ANN for prediction of landslide hazard.

4. CONCLUSION

In this paper, three cases of slope failures leading to landslide in northern part of Iran have been investigated. This investigation revealed the complexity involved in the analysis of landslide phenomenon.

To this end, first a complementary study involving field and laboratory tests, detailed geological survey of the site and its surroundings, using available geological maps, air photos and published literature has been performed. Then, an artificial neural network model has been developed to analyze these three cases of landslide, taking into account the complexity involved. In this ANN model, a back-propagation learning algorithm was used for the training process. The input data for stability estimation consist of values of geotechnical and geometrical input parameters. Finally, the results produced by the proposed artificial neural network model compared well with the determined factor of safety decision obtained by simplified methods. The ANN model developed in this study is believed to provide a viable landslide assessment tool that assist geotechnical engineers in making an accurate and realistic predictions. So it can be concluded, that the prediction of slope stability and its factor of safety agrees with actual landslide data obtained from bishop's method or finite element method.

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