

Slope Stability Analysis Using Machine Learning Tools

6.1 General

In recent years, various machine learning tools have been implemented successfully in several slope stability projects, whether it was for natural or artificial slopes. The artificial neural network (ANN) being one of them, has been considerably used in solving various slope stability cases (Alimohammadlou et al., 2014; Verma et al., 2016; Erzin and Cetin, 2013; Pradhan and Buchroithner, 2010; Ray et al., 2020; Rahul et al., 2015). Also, there are several documented cases of the use of multiple regression analysis (MRA) for slope stability analysis (Erzin and Cetin, 2013; Chakraborty and Goswami, 2017; Tien et al., 2019). The multiple regression analysis (MRA) is a statistical technique that mainly derives a relationship between the output variable and the input variables. This technique has also been found to be useful for solving slope stability problems. In this chapter, machine learning tools have been used to solve the dragline dump slope stability problems. Therefore, ANN and MRA models have been designed using statistical software, which has also been used by the several previous researchers. The predicted results of the ANN and MRA models have also been compared with the calculated results of the numerical simulation.

6.2 Artificial Neural Network

Artificial neural network is a modern computing technique used to simulate data in a manner the human brain analyzes and processes any information. It comprises an interconnected assembly of artificial neurons that pass on the information through the tendons, which exist in the neuron. ANN is a powerful tool for the simulation of data used primarily when the relationship between the independent and target variables is unknown, and it can easily identify the existing correlation between both the variables (Khandelwal and Singh, 2011; Agatonovic and Beresford, 2000; Monjezi et al., 2013). The neural network architecture puts in the picture how it transforms its input variable into a target variable (Chakraborty and Goswami, 2017; Baziar and Ghorbani, 2005; Gupta et al., 2004). The ANN model comprises hundreds of single units, neurons, and respective weights combinedly formed neural structures. Since it processes the information, that's why it is also called processing elements (PE). The PE is an equation which forms a relationship between independent and dependent variables. There are numerous types of neural networks that have been designed so far and are still being designed, but all the models can be delineated by their neuron's transfer function, the training algorithm, and the connection formula (Khandelwal et al., 2018).

6.2.1 Development of artificial neural network models

The simulation data of the numerical models of dragline dump slope were utilized, which were analyzed using finite element method based RS2 V9.0 a Rocscience software, with different geometrical parameters by Bharati et al. (2020, 2021). The simulation results are used to construct artificial neural network architecture. ANN model is designed to predict the factor of safety of the homogeneous dragline dump slope by using its geometrical parameters as well as strength parameters as input variables. Bharati et al. 2020

considered the three crucial geometrical parameters affecting the FOS of dragline dump slopes and that has been included in the ANN model. Whereas, Bharati et al. 2021 has considered geometrical as well strength parameters. Statistica10 software has been used to develop the ANN model for both the dataset. This software consists of two types of neural network architecture viz. Multilayer perceptron (MLP) and Radial basis function (RBF) (StatSoft, 2011). In this study, MLP is used, as it is the most popular feedforward neural network architecture (Ray et al., 2020). The neural network architecture comprises two important tools, training algorithm and activation function of neurons. The Broyden-Fletcher-Goldfarb-Shanno (BFGS) training algorithm is used, which requires a smaller number of iterations due to its fast convergence rate and smart search criteria. The activation function of the hidden and output layer neurons is very crucial in deciding the desired neural network architecture, and it transforms the transmitted information from the previous layer to the subsequent layers by applying its mathematical function. To devise the best ANN model, several networks can be trained simultaneously by opting a range of the number of neurons within the hidden layers and the desired transfer function to the hidden and output layer of the model. Each neural network includes three layers such as; the input layer, one or more hidden layers, and an output layer. To assess the performance of the neural network, a sum of square (SOS) error function is used, which is the sum of squares of differences between the actual and predicted outputs of the training data set. Two datasets have been analyzed differently and termed as ANN1 and ANN2. ANN1 comprised with the dataset of Bharati et al. 2020 and ANN2 comprising the dataset of Bharati et al. 2021.

6.2.1.1 Developing ANN1 model

The simulation data of 216 numerical models of dragline dump slope were utilized, which were analyzed using finite element method based RS2 V9.0 a Rocscience software, with different geometrical parameters by Bharati et al. (2020). The simulation results are used to construct artificial neural network architecture. ANN model is designed to predict the factor of safety of the homogeneous dragline dump slope by using its most crucial three geometrical parameters as input variables. Three geometrical parameters affecting the *FOS* of dragline dump slopes are included in the ANN model; namely, the coal-rib height (Cr-Height), dragline dump slope height (H1), and dragline dump slope angle (A1) as input variables and the *FOS* is opted as an output parameter.

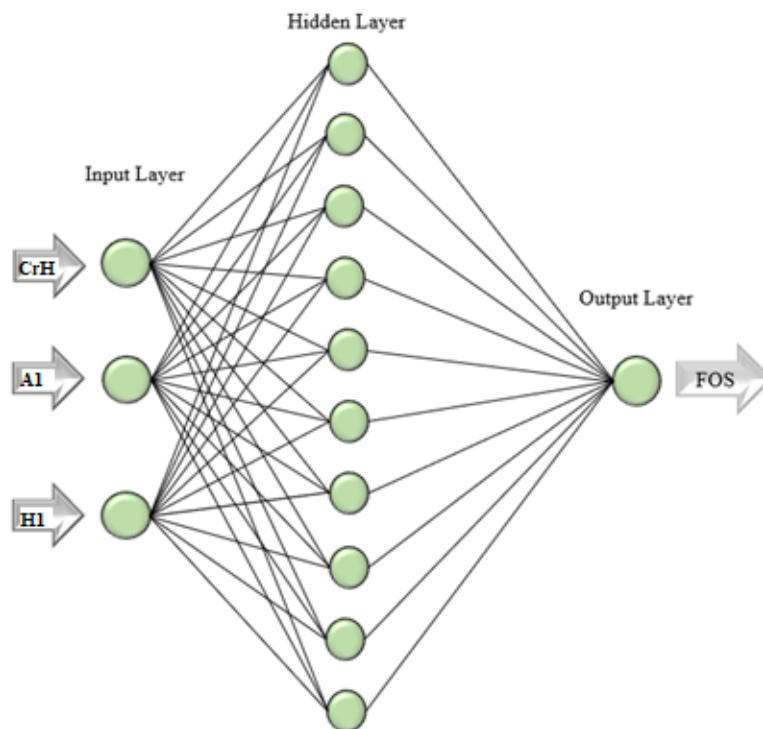


Figure 6. 1 Schematic diagram of the developed neural network.

The dragline dump simulation results data were divided into two parts, such as training and validation data sets, to build the ANN model and to determine the performance validity of the ANN1 model, respectively (Twomey and Smith, 1997). In this research,

out of 216 datasets, 78% (169 samples) were used as a training data set, and rest 22% (47 samples) were used as a validation data set to construct the ANN1 model (Baziar and Ghorbani, 2005). Since, several studies have been observed that the division of data has a considerable impact on the ANN1 model's outcome (Tokar and Johnson, 1999), and the ANNs are also incapable of providing accurate results if the data lies outside the range of training data. Therefore, the training and validation data set must characterize the same population. The statistical parameters of the applied training and validation data sets for ANN1 are shown in Table 6.1 In designing the neural network architecture, the selection of the number of hidden layers, and the number of neurons within the hidden layer is highly decisive in the performance of ANN models. It has been observed that a single hidden layer can approximate most of the functions in the network, that is why a single hidden layer was kept in the ANN1 model (Ripley, 2007). In this software, a range of 3–11 neurons have been opted to train the ANN1 model. There are two more layers, i.e. input and output layers other than the hidden layer. The number of neurons in these layers is constrained to the number of input and output variables, respectively (Ghiasi et al., 2016). A schematic diagram of the developed neural network architecture with three layers is depicted in Figure 6.1. The transfer function used for the hidden and output layer is sigmoidal, which is generally applicable in most of neural networks (Erzin and Cetin, 2013; McClelland et al., 1986; Demuth and Beale, 1998).

Table 6. 1 Statistical data of input and output variables of ANN1 model.

Input and Output Variables	Data Sets	Statistical Parameters				Range
		Mean	Std. D.	Min	Max	
Cr-Height (Coal rib height)	Training	15.101	3.415	10	20	10 to 20
	Validation	14.638	4.301	10	20	
H1 (Dragline dump slope height)	Training	34.799	6.830	25	45	25 to 45
	Validation	35.723	7.539	25	45	
	Training	40.272	6.897	30	50	

A1 (Dragline dump slope angle)	Validation	39.021	6.861	30	50	
FOS (Factor of safety)	Training	1.182	0.135	0.91	1.53	0.91 to 1.53
	Validation	1.202	0.157	0.89	1.48	0.89 to 1.48

6.2.1.2 Developing ANN2 model

The simulation results data of 506 models have been taken from Bharati et al. 2021 to design an ANN2 model and these data were also analyzed by using the RS2 V9.0 software which has considered the geometrical and strength parameters. Total nine geometrical and two strength parameters have been taken to develop model ANN2. In this model data is again divided into two parts training data and validation data. The parameters considered for the model has been mentioned in the Table 6.2. Total 506 data is available, out of which 76% (385 data) is used as training dataset and 24% (121) is used as validation dataset to design the ANN2 model. The data has been distributed as training and validation dataset in such a way that they must characterize the same population. Statistical parameters of the of the training and validation dataset for ANN2 is shown in Table 6.2.

In order to design the neural network architecture, one hidden layer and eight neurons within the hidden layer, has been opted. Other than hidden layer, one input and one output layer is present in the neural network architecture. Transfer function used for the output and hidden layer is sigmoidal, which is widely used in neural networks by most of the researchers.

Table 6. 2 Statistical data of input and output variables of ANN2 model.

Input and Output Variables		Statistical Parameters				Range
		Mean	Std. D.	Min.	Max.	
H1	Training	35.948	2.122	26	44	26-44
	Validation	35.834	3.072	26	44	
A1	Training	38.316	2.452	30	50	30-50
	Validation	38.595	3.241	30	50	
H2	Training	29.776	2.460	20	40	20-40
	Validation	30.330	3.207	20	40	
A2	Training	34.807	2.520	25	45	25-45
	Validation	35.082	3.124	25	45	
Cr-Height	Training	14.916	2.505	5	25	5-25
	Validation	15	2.851	5	25	
BW1	Training	9.940	1.265	5	15	5-15
	Validation	9.925	1.550	5	15	
BW2	Training	16.070	0.571	13	25	10-25
	Validation	16.074	1.003	10	23.5	
Cr-Width	Training	7.041	0.613	5	15	5-15
	Validation	7.024	0.272	7	10	
Dip	Training	4.005	0.180	2	6.5	2-6.5
	Validation	4.016	0.2321	3	6	
C	Training	64.306	12.574	10	80	10-80
	Validation	66.066	14.345	10	80	
f	Training	28.150	3.945	10	40	10-40
	Validation	27.958	4.610	10	40	
FOS	Training	1.2636	0.161	0.42	1.72	0.420-1.720
	Validation	1.2626	0.175	0.47	1.63	

6.3 Multiple Regression Analysis

Generally, the objective of regression analysis is to project the character of interconnections among the various input and output variables. In addition to this, multiple regression analysis (MRA) is applicable for more than one input variable. It also provides the most appropriate equation showing the relation between independent and

criterion variables (Yilmaz and Yuksek, 2008; Teymen and Menguc, 2020). The equation is further used to predict the output for particular values of the input variables and its validity is compared with the calculated or measured output values by using different performance indicators discussed earlier.

The analysis has been performed for the two dataset, one dataset has been taken from Bharati et al. (2020) and second dataset from Bharati et al. (2021). Multiple regression analysis conducted for former dataset is termed as MRA1 and for the later one is termed as MRA2.

In MRA1 model regression is performed by using only three critical geometrical parameters; coal-rib height, dragline dump slope height and dragline dump slope angle, whereas in MRA2 model nine geometrical as well as two strength parameters have been used. 216 data is used to perform MRA1 and 516 data is used to perform MRA2. Following relation has been found for both the models, respectively;

$$FOS = 2.37129 - 0.017579*Cr-Height - 0.008179*HI - 0.015881*A1 \quad (1)$$

$$FOS = 1.363576 - 0.00945*HI - 0.0166*A1 - 0.00494*H2 - 0.00634*A2 - 0.01514*Cr-Height + 0.008157*BW1 + 0.012441*BW2 + 0.000794*Dip + 0.002378*C + 0.032261*f \quad (2)$$

6.4 Results and Discussion

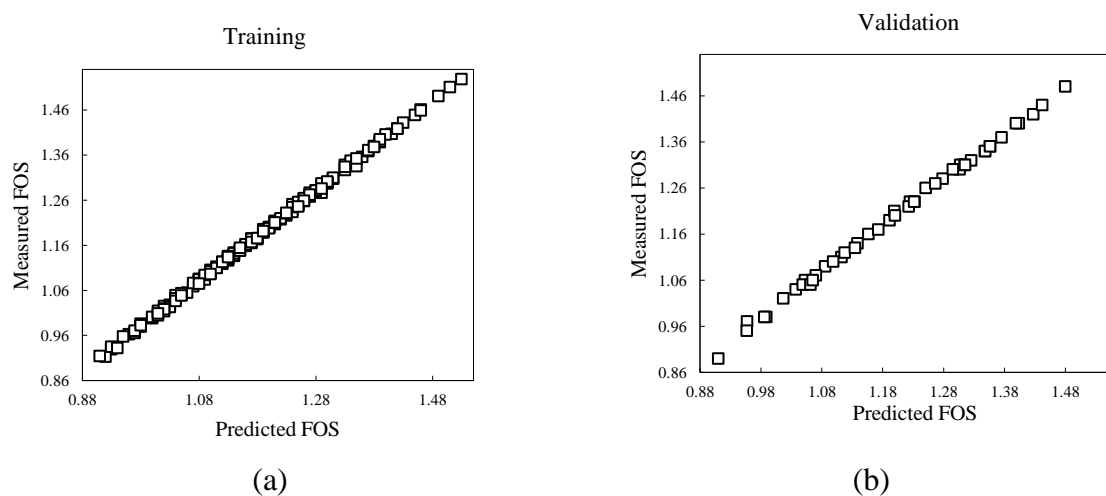
6.4.1 Artificial Neural Network Results

Based on multiple training results, both the models have been observed. ANN1 model with MLP 3-10-1 is found with the least training error 0.000007 and with maximum coefficient of determination (R^2) 99.96%. ANN1 model comprises three input, one output and one hidden layer of ten neurons, and sigmoidal activation function has proved to be

the best for hidden and output layer. ANN2 model with MLP 11-8-1 is found with the determination coefficient 99.72% with the training error 0.000172. This model has one hidden layer with eight neurons; therefore, it consists three layers. ANN1 model has considered three parameters whereas ANN2 has taken eleven parameters. The former has taken only the critical geometrical parameters, whereas later has considered geometrical as well as strength parameters and model ANN1 has negligible training error as compared to the ANN2. Summary of the trained MLP neural networks has been shown in Table 6.3 and Table 6.4 for ANN1 and ANN2, respectively. The R^2 value for both the model is very close to one, which says both the ANN models could be used for the prediction of FOS of the dragline dump slopes and graph comparing the predicted and measured FOS values have been shown in Figure 6.2 and Figure 6.3 for ANN1 and ANN2 models, respectively.

Table 6. 3 Summary of trained MLP neural networks for ANN1 model

Network name	Training Performance	Validation Performance	Training Error	Validation Error	Training Algorithm	Error Function	Hidden Activation Function	Output Activation Function
MLP 3-10-1	0.999585	0.999215	0.000008	0.000018	BFGS	SOS	Sigmoid	Sigmoid
MLP 3-6-1	0.999467	0.999161	0.000010	0.000018	BFGS	SOS	Sigmoid	Sigmoid
MLP 3-8-1	0.999569	0.999243	0.000008	0.000017	BFGS	SOS	Sigmoid	Sigmoid
MLP 3-10-1	0.999607	0.999173	0.000007	0.000019	BFGS	SOS	Sigmoid	Sigmoid
MLP 3-6-1	0.999248	0.999162	0.000014	0.000018	BFGS	SOS	Sigmoid	Sigmoid



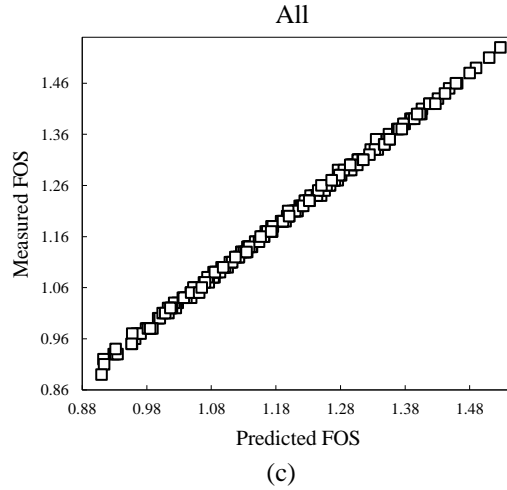


Figure 6. 2 Comparison of predicted and measured FOS values for ANN1 model (a) Training, (b) Validation, and (c) All datasets.

Table 6. 4 Summary of trained MLP neural networks for ANN2 model

Summary of active networks (ANN final)									
Index	Network Name	Training performance	Validation Perf.	Training Error	Testing Error	Training Algorithm	Error Function	Hidden Activation	Output Activation
1	MLP 11-8-1	0.983130	0.979419	0.001022	0.000736	BFGS 129	SOS	Sigmoid	Sigmoid
2	MLP 11-8-1	0.993117	0.988841	0.000486	0.000473	BFGS 134	SOS	Sigmoid	Sigmoid
3	MLP 11-8-1	0.997285	0.971429	0.000172	0.000881	BFGS 192	SOS	Sigmoid	Sigmoid
4	MLP 11-8-1	0.990011	0.987169	0.000636	0.000573	BFGS 72	SOS	Sigmoid	Sigmoid
5	MLP 11-8-1	0.995639	0.978486	0.000250	0.000697	BFGS 146	SOS	Sigmoid	Sigmoid
6	MLP 11-8-1	0.990232	0.984047	0.000609	0.000594	BFGS 72	SOS	Sigmoid	Sigmoid
7	MLP 11-8-1	0.986866	0.978903	0.000803	0.000605	BFGS 119	SOS	Sigmoid	Sigmoid
8	MLP 11-8-1	0.990278	0.985343	0.000678	0.000648	BFGS 83	SOS	Sigmoid	Sigmoid
9	MLP 11-8-1	0.992253	0.986882	0.000493	0.000519	BFGS 79	SOS	Sigmoid	Sigmoid
10	MLP 11-8-1	0.994988	0.977250	0.000329	0.000880	BFGS 54	SOS	Sigmoid	Sigmoid

for MRA2 is 0.9156. According to the model MRA1, slope angle is the most influential parameter among the chosen geometrical parameter, whereas friction angle is the most influential parameter among all the parameters in model MRA2.

Table 6. 5 Summary of the MRA1 for 206 dragline dump data

Summary of Multiple regression analysis						
Regression statistics						
Multiple R	0.988402933					
R ²	0.976940358					
Adjusted R ²	0.976614042					
Standard error	0.021090906					
Observations	216					
Geometrical parameters	Standardized Regression Coefficient (b*)	Standard Error of b*	Raw Regression Coefficient (b)	Standard Error of b	t-stat	P value
Intercept			2.371290	0.012901	183.8032	0.00
<i>Cr-Height</i>	-0.436382	0.010429	-0.017579	0.000420	-41.8416	0.00
<i>H1</i>	-0.406042	0.010429	-0.008179	0.000210	-38.9325	0.00
<i>A1</i>	-0.788442	0.010429	-0.015881	0.000210	-75.5982	0.00

Table 6. 6 Summary of the MRA2 for the 506 dragline dump data

Summary of Multiple regression analysis						
Regression statistics						
Multiple R	0.956915934					
Multiple R ²	0.915688104					
Adjusted R ²	0.913810713					
F (11,494)	487.7451721					
p	0					
Geometrical parameters	Standardized Regression Coefficient (b*)	Standard Error of b*	Raw Regression Coefficient (b)	Standard Error of b	t-stat	P value
Intercept			1.363576	0.101292	13.4619	0.0000
<i>H1</i>	-0.129656	0.013082	-0.009447	0.000953	-9.9110	0.0000
<i>A1</i>	-0.257401	0.013099	-0.016599	0.000845	-19.6501	0.0000

H2	-0.077409	0.013064	-0.004942	0.000834	-5.9253	0.0000
A2	-0.099350	0.013064	-0.006343	0.000834	-7.6048	0.0000
Cr-Height	-0.237080	0.013064	-0.015136	0.000834	-18.1474	0.0000
BW1	0.063881	0.013064	0.008157	0.001668	4.8898	0.000001
BW2	0.046170	0.013067	0.012441	0.003521	3.5334	0.000449
Cr-Width	0.058938	0.013079	0.018202	0.004039	4.5064	0.000008
Dip	0.000983	0.013067	0.000794	0.010563	0.0752	0.940081
C	0.186666	0.013519	0.002378	0.000172	13.8079	0.000000
f	0.807602	0.013485	0.032261	0.000539	59.8908	0.000000

6.5 Validation of performances of MRA and ANN models

To compare the prediction performance of the MRA and ANN models, the determination coefficient (R^2) between the predicted and the measured values could be used as a distinguishable indicator. In order to evaluate the performance of the prediction accuracy of the predictive models developed in this work, as implemented by Erzin, (2007); Erzin et al., (2008); and Erzin et al., (2010), additional performance parameters, such as variance accounted for (VAF) and root mean square error (RMSE), are also calculated. These two parameters have been defined by Equation 6.3 and Equation 6.4, respectively. If the VAF value is close to 100 percent and the RMSE value is close to 0, the suggested models are thought to be superior.

$$VAF = \left[1 - \frac{\text{var}(y-\hat{y})}{\text{var}(y)} \right] \times 100 \quad (6.3)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (6.4)$$

where y and \hat{y} are the quantities that have been calculated or measured and anticipated, respectively. Whereas N stands for the number of model samples and var stands for variance. Table 6.7 lists the determined VAF and RMSE values for the MRA and ANN models, which is calculated by using Equation 6.3 and Equation 6.4. Table 6.7 illustrates ANN model performs better than the MRA models because its VAF and RMSE values are, respectively, higher and lower with respect to MRA. Due to the presence of more processing neurons, each with a higher level of interconnection, the neural network model works better due to its higher degree of robustness and fault tolerance (Yilmaz and Yuksek, 2008). A residual error, which essentially displays the departure of predicted values from the measured or calculated values of FOS, wherein the distance between the predicted and measured values are computed, is another way to compare the MRA and ANN models. Figure 6.4 displays the variation in residual error for the MRA and ANN model. Then, a comparison of the MRA and ANN models was done, showing that the ANN1 model's deviation interval (- 0.020 to + 0.015) is substantially less than the MRA1 model's deviation interval (- 0.053 to + 0.054) for MRA2 and ANN2 models ranges from -0.133 to +0.219 and -0.065 to +0.136. As a result, it also demonstrates that the ANN model outperforms the MRA model.

Table 6. 7 Performance indicators of the developed ANN and MRA models

		R ²	VAF	RMSE
ANN1	Training	0.9996	99.92144	0.003784
	Validation	0.9991	99.83432	0.006112
ANN2	Training	0.997285	99.32887	0.014746
	Validation	0.971429	94.36247	0.041967
MRA1		0.9769	97.69405	0.020894
MRA2		0.915688	91.58543	0.057335

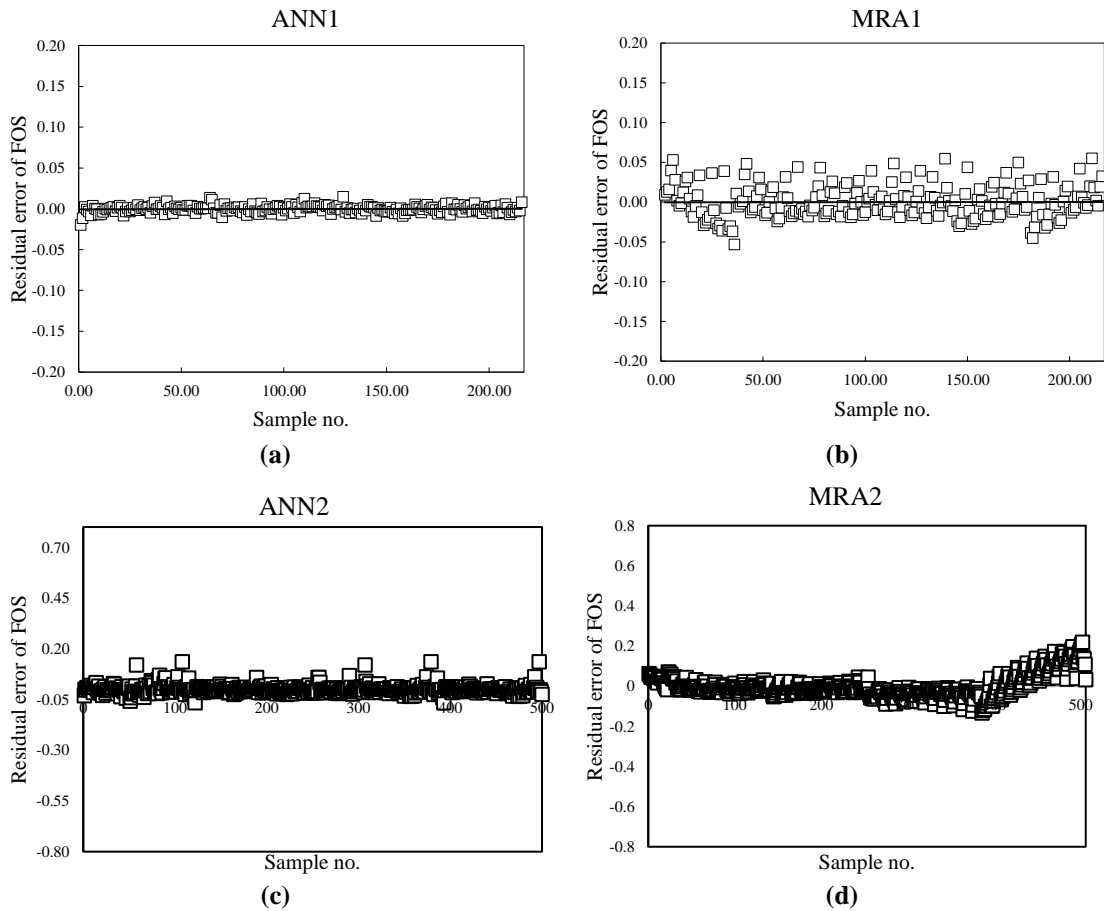


Figure 6. 4 Variation of residual error values predicted by (a) ANN1, (b) MRA1, (c) ANN2 and (d) MRA2 models

6.7 Summary

In this chapter, different ANN and MRA models have been developed for different dataset for the estimation of FOS of dragline dump slopes. Two MRA models have been devised MRA1 and MRA2, which were developed from three crucial geometrical parameters and nine geometrical as well as strength parameters, respectively, vis a vis two ANN models ANN1 and ANN2, respectively. It has been found that the ANN models have predicted much better results in comparison to MRA. The ANN models can be used in conjunction with the proposed safety chart and classification for analysing the overburden dragline dump slope behaviour. Various performance indices have been used to assess the efficacy

of ANN and MRA models, like; root mean square error, coefficient of determination, residual error and variance accounted for. The efficiency of both the developed models are high, which validates the accuracy of results obtained from the numerical analysis, which in turn confirms the accuracy of the safety chart as well as classification proposed for the dragline dump slopes.

The simplicity with which very heterogeneous non-linear datasets can be handled is one of the main advantages of employing ANN models. The model prediction is still close to 90% because the input dataset is derived from the stochastic geotechnical and geometrical parameters of the dragline dump slope. The findings obtained from the models, when considering the complexity of the dragline dump slope problem, are very positive and satisfactory, which provides a realistic expectation for the actual implementation of these models. The simplicity of updating the database is a significant advantage of employing ANN models. As seen in the example of the generated ANN model having stronger prediction ability than the MRA model, more datasets can be added in the future, which will further aid in boosting the predicting capacity of the models.

