RESEARCH ON THE APPLICABILITY OF ARTIFICIAL NEURAL NETWORK MODEL TO PREDICT THE AVERAGE DIMENSION OF FRAGMENTATION AND THE VOLUME OF EXCAVATION FOR THE ELECTRICAL EXPLOSION MODEL

Vu Van Tuan[1,*]

[1]*Le Quy Don Technical University*

Abstract

Artificial neural network (ANN) has been applied successfully to many engineering problems. In this paper, an ANN model is developed in predicting the average dimension of fragmentation and the volume of excavation for the electrical explosion model in two cases of explosion: one free surface and two free surfaces. The criterions to evaluate the accuracy of the models are the R squared (RS) and the mean square error (MSE). Comparing the predicted data with the tested data, the result indicates that ANNs should be used in predicting the average dimension of fragmentation and the volume of excavation for the electrical explosion model at once.

***Keywords**: Artificial neural network (ANN); prediction; degree of fragmentated rock; electrical explosion model.*

1. Introduction

At present, artificial intelligence is being successfully applied and continues to be focused on research and development in many fields. However, in general constructions as well as in the field of underground works and mining in particular, the research and application of artificial intelligence have not really stood out, especially in our country. The biggest reason is probably that full-scale data sets (including real data, observational data, experimental data, etc.) have not been available and the big data and the data science have just started to build.

ANN is a part of artificial intelligence (AI). The advantages of ANN model are clear, easy to implement, accurate and effective. Therefore, ANN has been widely used in various fields. Rankine and Sivakugan [6] applied the artificial neural networks (ANNs) to predict fill strengths based on the input parameters of cement content, solids content, curing time and grain size distribution; Kim [5] used the artificial neural network model for prediction of relative crest settlement of concrete-faced rockfill dams; Yoo and Kim [11] using an integrated GIS and neural network for tunneling

[*] Email: vutuan2601@yahoo.com
https://doi.org/10.56651/lqdtu.jst.v3.n01.69.sce

performance prediction; Goh and Kulhawy [3] had research on the neural network approach to model the limit state surface for reliability analysis. The studies of Shahin in the field of geotechnical engineering are outstanding examples. Those were about using B-spline neurofuzzy models to predict the settlement of shallow foundations on granular soils [8] and using the intelligent computing for modeling axial capacity of pile foundations [9].

It can be seen that there are almost no studies on the application of ANN to predict the average dimension of fragmentation and the volume of excavation for the electrical explosion model. In this paper, an ANN model was developed in predicting the average dimension of fragmentation and the volume of excavation for the electrical explosion model in two cases of explosion: one free surface and two free surfaces based on the input parameters of the specific energy to blast a unit volume of rock. The testing data is from a previous study of Dam Trong Thang [1]. The criterions to evaluate the accuracy of the models are the R squared (RS) and the mean square error (MSE). The relative conclusions would be drawn by comparing the predicted data with the tested data.

2. Overview of artificial neural networks

Artificial neural networks (ANNs) are numerical modeling techniques inspired by the functioning of the human brain and nervous system. The purpose of ANNs is similar to conventional statistical models, which is to determine the relationship between the model inputs and corresponding outputs. However, ANNs only use the data and do not require predefined mathematical equations of the relationship between the inputs data and outputs data. This allows ANNs to overcome the limitations of the conventional models.

A Multi-layer feed-forward with the back-propagation algorithm training which was introduced by Rumelhart [7] is used in this study. The multi-layer feed-forward neural network is composed of several processing elements (called nodes or neurons). The processing elements are fully or partially connected via connection weights (w_{ji}), and they are often classified into layers: an input layer; an output layer; and hidden layers (layers in between).

Many authors already described the structure and operation of ANNs. Figure 1 shows the structure and operation of an ANN depicted by Shahin [9]. At each processing element, the input from the processing element of the previous layer (x_i) is multiplied by an adjustable connection weight (w_{ji}), and weighted inputs are summed and a bias (θ_j) is added or subtracted. The combined input (I_j) is then passed through a non-linear transfer function ($f(.)$) (e.g. sigmoidal function or tanh function) to produce the output of the processing element (y_j). In this structure, the neurons of the input layer do not perform any calculations of the input data, it only receives the input data and transmits it to the next layer. The neurons of the output layers and hidden layers perform calculations of data.

The training of the multi-layer feed-forward neural network starts at the input layer, after that, a learning rule is used to obtain the network output (Figure 1). The weights (w_{ji}) and the bias (θ_j) will be generated randomly to obtain the output value. In the next step, the weights (w_{ji}) and the bias (θ_j) are adjusted in order to get the smallest possible error between the desired output and the output which is obtained from the preview step. As soon as the training phase is accomplished, the trained model would be validated by an independent testing set.

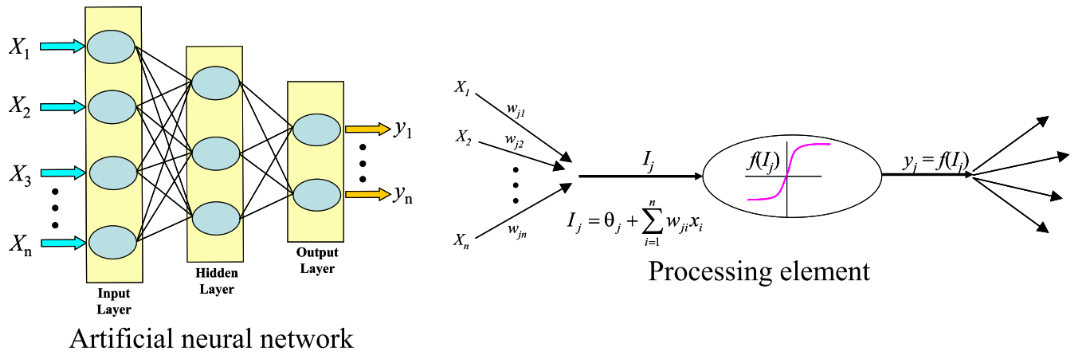

Figure 1. Structure and operation of an ANN (Shahin [9])

3. Development of the ANN model

The ANN model in this study has been developed with the aid of the software package PYTHON Version 3.6, which is a very powerful software about deep learning and artificial intelligence (AI).

An ANN model has been developed for the estimation of the average dimension of fragmentation and the volume of excavation based on the specific energy to destroy a unit volume of rock. The testing data is from a previous study of Dam Trong Thang [1]. This experiment inherits the electric explosion testing method of Moscow State Mining University. The main test instruments include: an electric blasting machine (providing burst power up to 500 J) and gypsum test samples of categories 1 and 2 (corresponding to the one free surface and two free surfaces). During the experiment, the explosive energy levels will be assigned from low to high. The fragmentation degree will be classified after that by using a standard sieve [1].

Table 1 lists the database of electric explosion testing that used to develop ANN model. The specific energy to destroy a unit volume of rock (*q*) was chosen as input variables; the average dimension of fragmentation (D_{tb}) and the volume of excavation were chosen as output variables.

3.1. Data division and preprocessing

As the rules, the testing data have been divided into two subsets, training set for model calibration and validation set for model verification. Depending on the size of the laboratory testing data, the ratio of validation data to the laboratory data stands at 20% to 30% [10]. However, since the laboratory testing data here is quite small, only three arbitrary values (italicized and underlined values in Table 1) would be taken for model verification (equivalent to 15%).

Table 1. Database of electric explosion test [1]

No	One free surface			Two free surfaces		
	Specific energy to destroy a unit volume of rock, *q* (J/cm^3)	D_{tb} (cm)	Volume of excavation (cm^3)	Specific energy to destroy a unit volume of rock, *q* (J/cm^3)	D_{tb} (cm)	Volume of excavation (cm^3)
1	4,71	3,41	12,75	4,74	3,42	12,67
2	5	3,33	14	4,77	3,37	14,67
3	5,19	3,22	15,42	4,87	3,35	20,55
4	5,43	3,02	18,42	*<u>4,91</u>*	*<u>2,92</u>*	*<u>26,5</u>*
5	*<u>5,58</u>*	*<u>2,8</u>*	*<u>25,08</u>*	5,36	2,53	29,83
6	6,24	2,4	27,25	5,74	2,23	34,83
7	6,44	2,31	29,5	6,08	2,02	36,17
8	6,81	2,27	30,83	7,07	1,83	36,75
9	7,11	2,11	32,33	*<u>7,57</u>*	*<u>1,79</u>*	*<u>37</u>*
10	*<u>7,92</u>*	*<u>1,92</u>*	*<u>32,83</u>*	8,02	1,74	37,42
11	8,78	1,75	34,17	8,18	1,68	37,92
12	9,47	1,68	34,83	8,68	1,65	38
13	10,16	1,59	35,42	8,94	1,61	39,17
14	10,71	1,52	37,33	9,37	1,57	39,5
15	*<u>11,15</u>*	*<u>1,45</u>*	*<u>37,67</u>*	10,68	1,53	40,25
16	11,52	1,42	39,92	*<u>11,2</u>*	*<u>1,48</u>*	*<u>41,08</u>*
17	11,56	1,42	40,67	11,46	1,48	41
18	11,93	1,42	40,25	11,66	1,48	41,17
19	12,15	1,42	40,33	11,95	1,48	41
20	12,35	1,42	40,5	12,22	1,48	40,92

In order to minimize the dimension of the variables and to make sure that all variables get equal attention during the training process, the preprocessing is conducted by scaling the input and output variables between 0 and 1. The scaled value of each variable x is calculated as follows:

$$x_n = x / x_{\max} \tag{1}$$

where x_{max} is maximum values of each variable x; x_n is the values after scaling the input and output variables.

3.2. Model architecture, weight optimization and stopping criterion

The model geometry (i.e. the number of hidden layers, the number of hidden nodes in each layer) and weight optimization (i.e. learning rate and momentum term) play a major role in the development of the ANN models.

Hornik [4] noted that a network with one hidden layer can approximate any continuous function provided that sufficient connection weights (w_{ji}) are used. Thus, one hidden layer is used in this ANN model.

ReLU and *tanh* are selected as transfer functions in the hidden and output layers. As the rule, the more training cycles (epochs) the more accuracy of the model. However, if the training cycles (epochs) is too much, it does not mean that the model is more accuracy but only time consumption. The 3000 of training cycles (epochs) are used to terminate the training process. Figure 2 shows the variation of loss (the difference between the experimental values and the predicted values) against epoch. It can be seen that the training loss at the end of the training process does not fluctuate and does not increase.

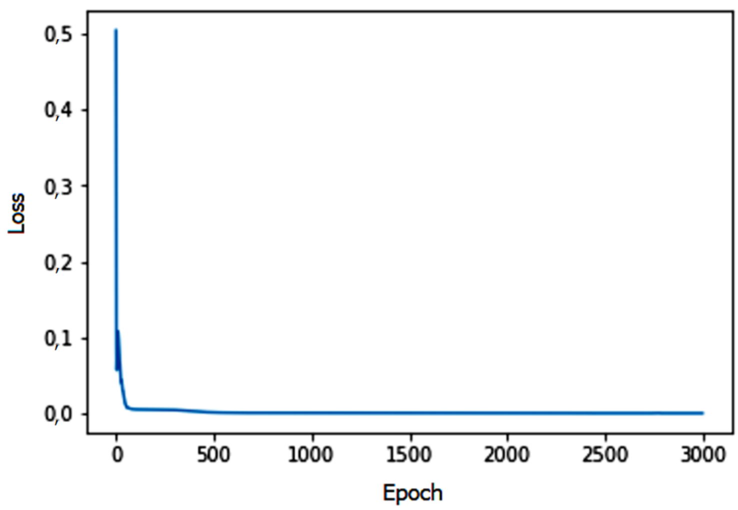

Figure 2. Variation of loss against epoch

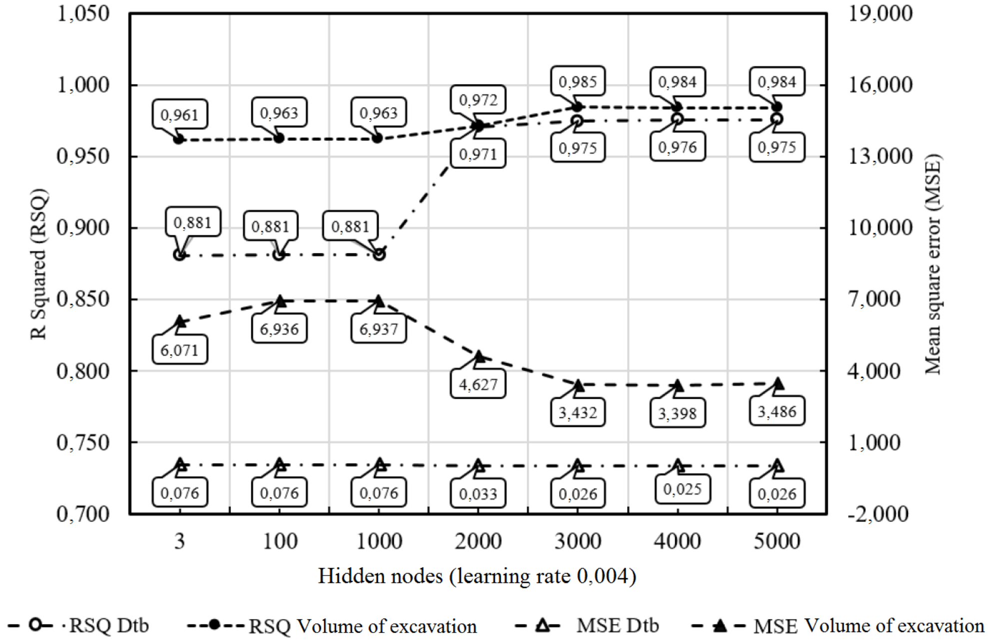

Figure 3. Effect of number of hidden layer nodes on performance of ANN model (one free surface)

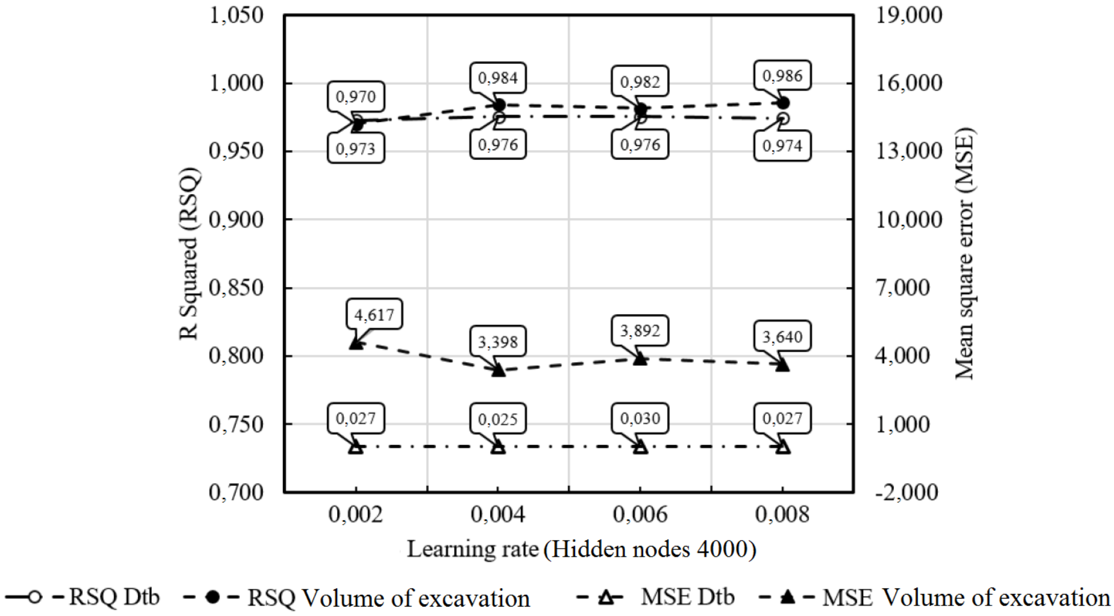

Figure 4. Effect of learning rate on performance of ANN model (one free surface)

Caudill Maureen (1988) [2] noted that 2I+1 hidden layer nodes are the upper limit needed to map any continuous function for a network with I number of inputs. However, based on the effect of the number of hidden nodes on the performance of ANN model (Figure 3), the ANN model with 4000 hidden nodes has the lowest prediction error (the highest of the R squared and the lowest of the Mean square error). The number of hidden nodes using for ANN model in this paper is much more than the number of hidden nodes recommended and used by authors Caudill Maureen [2] before.

The smaller the learning rate is, the more time for the model converges. The larger the learning rate is, the faster the model converges but the accuracy would not be high. Figure 4 shows the effect of learning rate on the performance of ANN models. It can be seen that the ANN model with the learning rate 0,004 has the lowest prediction error. The gradient descent optimization algorithm is Adam optimizer. It already incorporates something like momentum, thus, the momentum term is not examined.

It can be seen that the ANN with 4000 neurons in one hidden layer (not including the nodes or neurons in the input layer and output layer), 3000 training cycles (epochs), learning rate of 0,004, and the transfer functions in the hidden and output layers are *ReLU* and *tanh* has the highest accuracy. Thus, it will be chosen for model calibration and model verification in the next steps.

The model architecture, weight optimization and stopping criterion of the ANN model, which is developed in predicting the average dimension of fragmentation and the volume of excavation for the electrical explosion model, in the case of two free surfaces are similar to those in the case of one free surface.

4. Model validation

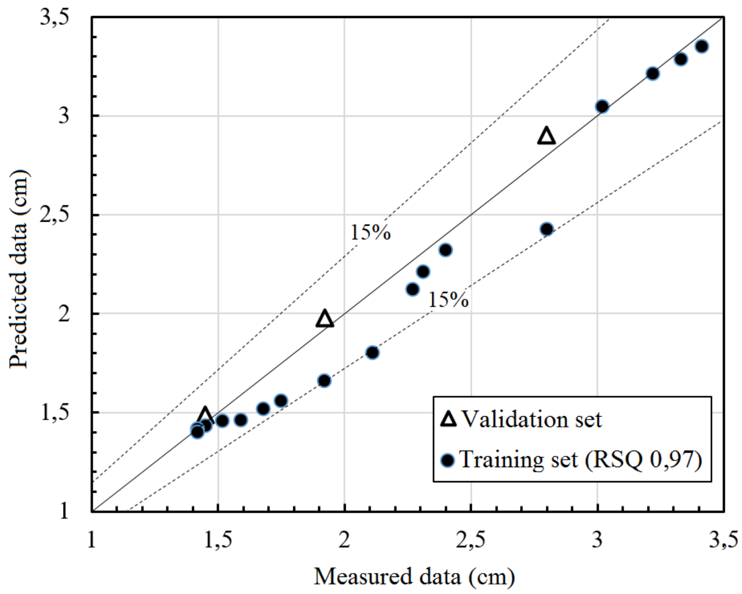

Figure 5. Scatter plots of predicted versus measured data for the average dimension of fragmentation D_{tb} (one free surface)

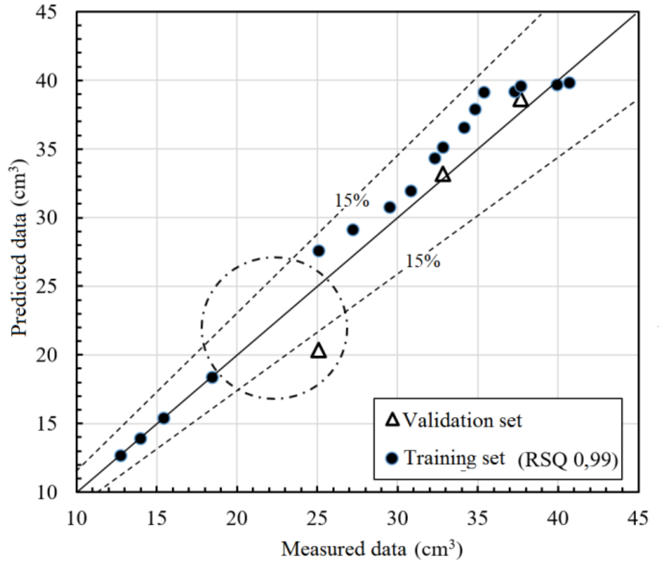

Figure 6. Scatter plots of predicted versus measured data for volume of excavation (one free surface)

After training, ANN model will be verified by the validation set (3 values for each explode test case) as well as by the training set. The performance of the ANN model in the training and validation sets for the case of one free surface is shown in Figure 5 and Figure 6. It may be seen that the predicted values of ANN model have minimum scatter around the best fit line, which is representing the agreement between the measured and predicted data. However, one of the predicted value of the ANN model, is still beyond and above the deviation-line 15% (dotted lines).

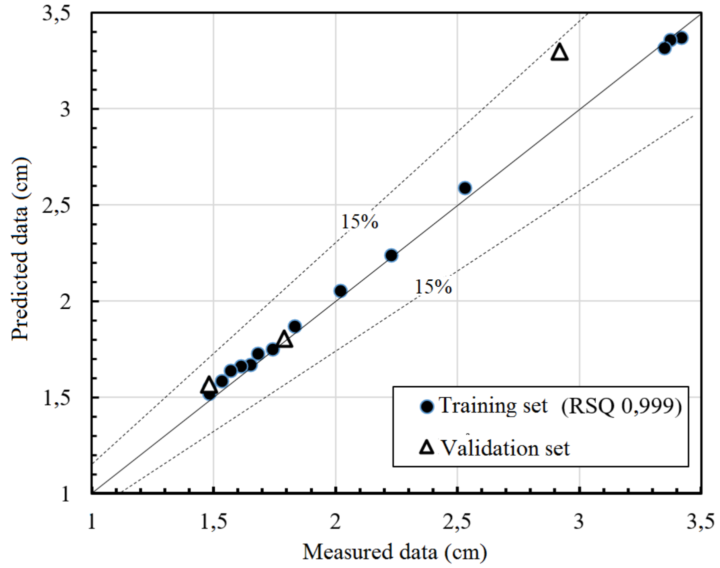

Figure 7. Scatter plots of predicted versus measured data for the average dimension of fragmentation D_{tb} (two free surfaces)

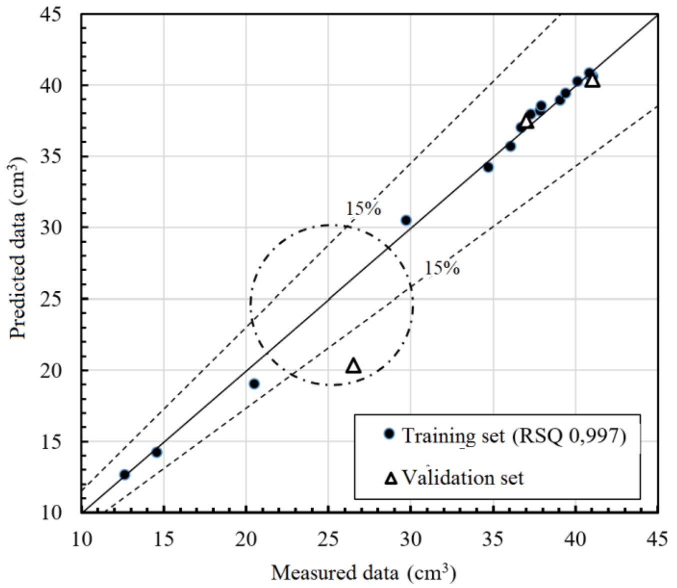

Figure 8. Scatter plots of predicted versus measured data for volume of excavation (two free surfaces)

Table 2 shows the accuracy of ANN model for the case of one free surface (validation set). The deviation bettwen the measured value and the predicted value is quite small. The biggest deviation (-18,83%) is the predicted value of the volume of excavation, which is corresponding to the specific energy to destroy a unit volume of 5,58 (J/cm^3). In Figure 6, the values around this point also have relatively high dispersion and sparse values. Therefore, in order to increase the accuracy of the model and make the training data set better, it really needs more experimental values around this point.

These phenomena are also happened to the case of two free surfaces. Even though the predicted values of ANN model are more accurate (the predicted values of the ANN model are highly concentrated around the best fit line), but the predicted value corresponding to the specific energy to destroy a unit volume of 4,91 (J/cm^3) also has a deviation of up to 23,19% (Figure 7, Figure 8 and Table 3). It once again confirms that it really needs more experimental values around this point.

Table 2. Accuracy of ANN model for the case of one free surface (validation set)

Specific energy to destroy a unit volume of rock, q (J/cm^3)	D_{tb} (cm)			Volume of excavation (cm^3)		
	Predicted value	Measured value	Deviation %	Predicted value	Measured value	Deviation %
5,58	2,91	2,80	3,80	20,36	25,08	-18,83
7,92	1,98	1,92	2,87	33,16	32,83	1,01
11,15	1,49	1,45	2,68	38,66	37,67	2,63

Table 3. Accuracy of ANN model for the case of two free surfaces (validation set)

Specific energy to destroy a unit volume of rock, q (J/cm^3)	D_{tb} (cm)			Volume of excavation (cm^3)		
	Predicted value	Measured value	Deviation %	Predicted value	Measured value	Deviation %
4,91	3,30	2,92	12,88	20,36	26,5	-23,19
7,57	1,81	1,79	0,93	37,45	37	1,21
11,2	1,56	1,48	5,62	40,38	41,08	-1,71

5. Conclusion

After developing the ANN model to predict the average dimension of fragmentation and the volume of excavation for the electrical explosion model based on the specific energy to destroy a unit volume of rock, the following conclusions can be drawn:

- It is totally possible to apply ANN to predict the average dimension of fragmentation and the volume of excavation for the electrical explosion model at once with a quite high accuracy (RSQ of D_{tb} is greater than 0,976 and RSQ of the volume of excavation is greater than 0,991 for two cases: one free surface and two free surfaces).

- The ANN models with 4000 hidden nodes have the lowest prediction error in predicting the average dimension of fragmentation and the volume of excavation for the electrical explosion. The number of hidden nodes in this study (4000 hidden nodes) is much more than the hidden nodes discussed by Caudill Maureen [2] (2I+1 hidden layer nodes for a network with I number of inputs).

- Although the ANN models have high accuracy, there are two predicted values were still quite different from the measured values (-18,83% and -23,19%). It is pretty obvious that: like all empirical models, ANNs perform well in the interpolation. Thus, in order to improve the performance of the ANN model, the training data set should have more value.

References

1. Đàm Trọng Thắng, Vũ Trọng Hiếu (2015). *Xây dựng quan hệ giữa tiêu tốn năng lượng nổ và mức độ đập vỡ đất đá khi nổ mìn trong thi công khoan nổ đường hầm trên mô hình nổ điện.* Tạp chí Khoa học và Kỹ thuật - Học viện KTQS, 170 (8-2015), pp. 170-179.

2. Caudill Maureen (1988). Neural networks primer, Part III. *AI Expert, 3*(6), pp. 53-59.

3. Goh ATC, Kulhawy FH (2003). Neural network approach to model the limit state surface for reliability analysis. *Can Geotech Jounal, 40*(6), pp. 1235-1244.

4. Hornik Kurt, Stinchcombe Maxwell, White Halbert (1989). Multilayer feedforward networks are universal approximators. *Neural networks, 2*(5), pp. 359-366.

5. Kim Y, Kim B (2008). Prediction of relative crest settlement of concrete-faced rockfill dams analyzed using an artificial neural network model. *Comput Geotech, 35*(3), pp. 313-322.
6. Rankine R, Sivakugan N (2005). *Prediction of paste backfill performance using artificial neural networks*. in *Proceedings of 16th international society for soil mechanics and foundation engineering*. Osaka.
7. Rumelhart David E, Hinton Geoffrey E, Williams Ronald J (1985). *Learning internal representations by error propagation*. California Univ San Diego La Jolla Inst for Cognitive Science.
8. Shahin MA, Maier HR, Jaksa MB (2003). Settlement prediction of shallow foundations on granular soils using B-spline neurofuzzy models. *Computers and Geotechnics, 30*(8), pp. 637-647.
9. Shahin Mohamed A (2010). Intelligent computing for modeling axial capacity of pile foundations. *Canadian Geotechnical Journal, 47*(2), pp. 230-243.
10. Shahin Mohamed A, Jaksa Mark B, Maier Holger R (2002). Artificial neural network based settlement prediction formula for shallow foundations on granular soils. *Australian Geomechanics: Journal and News of the Australian Geomechanics Society, 37*(4), p. 45.
11. Yoo C, Kim J (2007). Tunneling performance prediction using an integrated GIS and neural network. *Comput Geotech, 34*(1), pp. 19-30.

NGHIÊN CỨU KHẢ NĂNG ỨNG DỤNG MẠNG NƠRON NHÂN TẠO TRONG DỰ BÁO KÍCH THƯỚC TRUNG BÌNH CỦA CỤC ĐÁ VÀ THỂ TÍCH PHÁ MẪU SAU NỔ TRÊN MÔ HÌNH NỔ ĐIỆN

Tóm tắt: *Mạng nơron nhân tạo (artificial neural network - ANN) đã được áp dụng thành công trong hầu hết mọi vấn đề của khoa học - kỹ thuật. Bài báo này sẽ phát triển và ứng dụng một mạng nơron nhân tạo (ANN) để dự đoán đường kính đập vỡ đất đá trung bình và thể tích phá vỡ đất đá trong trường hợp một mặt thoáng và hai mặt thoáng khi nổ mìn trên mô hình điện. Độ chính xác kết quả dự báo của mạng ANN (so với giá trị thí nghiệm) sẽ được đánh giá qua hai chỉ số: hệ số tương quan bội R squared (RS) và sai số toàn phương trung bình (mean square error - MSE). So sánh kết quả dự đoán và kết quả thí nghiệm cho thấy mạng nơron nhân tạo (ANN) có thể sử dụng để dự báo một lúc đồng thời các tham số đường kính đập vỡ đất đá trung bình và thể tích phá vỡ đất đá khi nổ mìn trên mô hình điện.*

Từ khóa: Mạng nơron nhân tạo ANN; mô hình dự báo; độ đập vỡ của đất đá; nổ điện.

Received: 26/3/2020; *Revised:* 18/5/2020; *Accepted for publication:* 17/6/2020

❑