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PREDICTION OF BLAST-INDUCED THE AREA OF THE TUNNEL FACE IN UNDERGROUND EXCAVATIONS USING FUZZY SET THEORY ANFIS AND ARTIFICIAL NEURAL NETWORK ANN

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ABSTRACT: The area of the tunnel face after the blasting determines the construction progress of the tunnel, the construction cost and the safety of the tunnel construction. Hence, it is a major concern to predict and subsequently control the area of the tunnel face after the blasting in tunnel excavations. This paper presented two artificial intelligence methods, the first method, the adaptive neuro-fuzzy inference system (ANFIS) and the second method, the artificial neural network (ANN) for the prediction of the area of the tunnel face after the blasting. 100 databases on blasting parameters and the area of the tunnel face after the blasting in practice at Deo Ca tunnel, Phu Yen, Viet Nam were used in this paper. On the basis of these data, models to predict the area of the tunnel face after the blasting using the ANN model and ANFIS model were built. The obtained results, including coefficient of determination (R^2), mean squared error (MSE) of the ANFIS model (with values $R^2_{training}$=0.9758; $R^2_{testing}$=0.9705; $MSE_{training}$=0.009816; $MSE_{testing}$=0.014676). Besides, in the training and testing data sets, R^2 values of (0.9503, 0.9722) and MSE values of (0.0208, 0.0136) were found in the optimal ANN model. The results obtained by these proposed models were compared with the measured values. The results indicate that the proposed ANFIS and ANN models are applicable and accurate tools to predict the area of the tunnel face after the blasting with high accuracy.

Keywords: Predict, Blast, The area of the tunnel face after the blasting, ANN, ANFIS.

1. INTRODUCTION

Drilling-blasting is a common technique for rock fragmentation in tunnels, underground constructions and mining operations. These operations in drilling-blasting when tunnel excavations cause several phenomena such as overbreak, underbreak... of the tunnel in the blasting environmental zone [1,2,3,4,5]. These phenomena make the area of tunnel face lose accuracy, from here, affecting other works in tunnel construction. These phenomena make the area of tunnel face lose accuracy, from here, affecting other works in tunnel construction and the phenomena (the area of tunnel face lose accuracy) has long been recognized as the principal cause of hazards and increasing costs in tunnelling management. The area of tunnel face after blasting includes overbreak and underbreak phenomenon. These phenomena such as overbreak, and underbreak... of the tunnel are often predicted and calculated through empirical methods in construction and give results that do not have high accuracy. Using artificial intelligence to predict and calculate the properties of the tunnel after blasting is one of the current popular research trends. Many studies have been devoted to clarifying the overbreak and underbreak phenomenon, but they are still unable to explain the exact occurrence process [1,3,6,7]. Currently, there are no published studies on the calculation and prediction of the area of tunnel face after blasting (SA) with height accuracy. According to many previous studies, it can be found that the area of the tunnel face after the blasting depends on many parameters [6,7]. Blasting parameters such as explosive properties, borehole depth, borehole diameter... can be easily changed. However, the parameters of the tunnel such as the shape of the tunnel, the design area of the tunnel or the geological parameters where the tunnel is located such as rock mass rating (*RMR*)... are parameters that are difficult to change or cannot be changed. From the predicted tunnel face after the blasting values with degree hight accuracy, it is possible to adjust some parameters affecting these values such as blasting parameters, tunnel parameters... to the area of the tunnel face after the blasting can achieve the designed value, thereby, improving the efficiency of the tunnel construction process. In this paper, the study focuses on the effects of geological parameters and the blast design of the tunnel to the area of the tunnel face after the blasting. Geological parameters (*RMR*) and tunnel parameters were collected through 100 blasting sections in Deo Ca tunnel, Viet Nam. Various methods have been applied in engineering for the prediction of the area of the tunnel face after the blasting. In this study, the application of the artificial neural network (ANN) and an adaptive neuro-fuzzy inference system (ANFIS) for prediction of the area of the tunnel face after the blasting, was described and then, compared the results of these models, respectively. In these modes, the geological datasets (*RMR*), tunnel and blast datasets (the average boreholes length *L*, design area of the tunnel face *S* and specifc charge *Q*) are put as input parameters and the area of the tunnel face after the blasting results are used as output parameters to ANFIS models and simultaneously to ANN models. Consequently, the optimum model that predicts the area of the tunnel face after the blasting is selected by comparing measured and predicted area of the tunnel face after the blasting and the coefficient of determination (R^2) with mean squared error (MSE) of each proposed model.

2. CASE STUDY AND DATA MONITORING

Fig.1 Deo Ca tunnel

The area of tunnel face after blasting is not exactly according to the design value, which is a phenomenon that causes great impacts on the construction cost and the construction progress of the tunnel. Therefore, it is necessary to build a model capable of accurately predicting the tunnel face area after blasting, from which it is possible to adjust the parameter values of explosives, tunnels... Based on this adjustment, could be received the tunnel face area after blasting exactly as the design value. Deo Ca tunnel project is a traffic tunnel project located on National Highway 1A, connecting the two provinces of Phu Yen and Khanh Hoa of Vietnam. Deo Ca traffic tunnel has a length of 4.1 km. The area where the tunnel is located has relatively complex geological conditions, mainly igneous and metamorphic rocks. This is an area that is considered to be greatly influenced by tectonic and dynamic geological phenomena. The rock mass rating (*RMR*) fluctuates in a large range, *RMR*=0÷73.

Database including 100 datasets were obtained from the blasting operation of this case study. There are 4 parameters used in this study to be able to establish a model to predict tunnel mirror area after blasting, including the average boreholes length *L*, design area of the tunnel face *S*, specific charge *Q* and rock mass rating *RMR*.

The input and output parameters values of these models (ANN and ANFIS) are shown in Table 1. The 80 sets of the datasets (80% of all datasets) were used in training the models and 20 sets (20% of all datasets) were used for testing models performance. To ensure the accuracy of the results of the models were built in the paper, the input and output data must be normalized. In this paper, the data were normalized into a range of [-1÷1] according to the following the formula [5,7,8,9,]:

$$\boldsymbol{X_n} = \frac{\boldsymbol{X - X_{min}}}{\boldsymbol{X_{max} - X_{min}}} \tag{1}$$

Where X and X_n represent the measured and normalised values, respectively. X_{min} is the minimum measured parameters and X_{max} is the maximum measured parameters, respectively.

Table 1 The input and output parameters

The parameters	Min	Max	Mean	Std. Deviation
SA (The area of tunnel face after blasting, m^2) – Output	51.221	71.049	58.878	6.476
L (the average boreholes length, m) – Input	1.0	3.2	1.953	0.644
S (The design area of tunnel face, m^2) – Input	49.26	64.855	54.55	6.163
Q (specifc charge, kg/m^3) – Input	0.37	2.32	1.434	0.416
RMR (rock mass rating) – Input	5.0	73	51.33	14.531

In this study, five different datasets were selected randomly from all datasets with the purpose of training and testing to develop the ANN models and ANFIS models. Based on the results and the comparison of the results obtained from these models, selected the best model.

3. METHODS OF MODELING

3.1 Artificial Neural Network

Artificial neural networks (ANN) have been focused on development and application in science and technology since 1991 [10,11].

In the ANN model, the multilayer perceptron neural network is one of the most used models because of its features and advantages. In the multilayer network model, the layers of neurons have different tasks. The input layer accepts input data from the outside and distributes them to the next layers in this model. The output layer exploits hidden features in the input patterns to determine the output patterns. Multilayer network has been applied together with the backpropagation algorithm and successfully solved some difficult problems in engineering. The content of the back-propagation algorithm is the error-correction learning rule. In the back-propagation algorithm, each input data travels through the network to produce a corresponding output. As input data passes through the neural network, each neuron determines its actual weighted input using the following equation:

$$\boldsymbol{Y = \sum_{i=1}^{n} y_i w_i - \theta}, \qquad (2)$$

where y_i and w_i denote the values of the i^{th} input and weight, respectively, n is the number of inputs in input layer, θ is the threshold applied to the neurons.

The input value passes in this model through an activation function. This procedure is the training procedure of the model. This model calculates the outputs, weights and a mathematical function model threshold, respectively. On the basis of the obtained results, the actual output is compared with the output of the model to calculate the output error. This error, respectively, is determined and propagated back through the network and updates the individual weights. This procedure is performed cyclically, iteratively until the error reaches a predetermined level [10,11,12].

In this paper, a hidden layer of neurons is used. According to some authors, the number of neurons in the hidden layer has a very important influence on the model's prediction results. Normally, the number of neurons in the hidden layer should not exceed "2**N*+1" where N is the number of input variables. In Table 2 and Table 3, the results obtained for the models corresponding to the number of neurons in the different hidden layers are presented. This study investigated the results of ANN models with the number of neurons in the hidden layer from 2 to 9 and selected an ANN model with the number of neurons in the hidden layer as *N*=8 and the architecture of the model ANN (4x8x1) was selected as the optimum architecture. This is the model that gives the most optimal results (including highest R^2 and lowest MSE) among the ANN models that was surveyed and investigated [2,13,14].

Table 2 Obtained results of R^2 for ANN models with different neurons in the hidden layer

Model no.	Nodes in hidden layers	Network result R^2											
		Iteration 1		Iteration 2		Iteration 3		Iteration 4		Iteration 5		Average	
		Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
1	1	0.9407	0.9361	0.9603	0.9010	0.9479	0.9586	0.942	0.9708	0.8875	0.8642	0.9357	0.9261
2	2	0.9421	0.9661	0.9637	0.8972	0.9515	0.9565	0.944	0.9669	0.944	0.9535	0.9491	0.948
3	3	0.9434	0.9566	0.9569	0.8782	0.9442	0.9516	0.9364	0.956	0.9464	0.9443	0.9455	0.9373
4	4	0.9627	0.9493	0.9532	0.8922	0.9415	0.9254	0.9241	0.9544	0.9383	0.9493	0.944	0.9341
5	5	0.9499	0.9145	0.9517	0.8526	0.9399	0.9687	0.9654	0.9649	0.949	0.9557	0.9512	0.9313
6	6	0.9062	0.8728	0.9351	0.7907	0.9226	0.9626	0.9175	0.9593	0.9484	0.9584	0.926	0.9088
7	7	0.9446	0.9314	0.9562	0.8888	0.9611	0.948	0.9492	0.9585	0.939	0.9546	0.95	0.9363
8	**8**	**0.9572**	**0.9409**	**0.9723**	**0.8842**	**0.9338**	**0.9208**	**0.9503**	**0.9722**	**0.9486**	**0.9693**	**0.9524**	**0.9375**
9	9	0.9650	0.9324	0.9544	0.7837	0.9327	0.8342	0.9538	0.9705	0.9262	0.9354	0.9464	0.8912

Table 3 Obtained results of MSE for ANN models with different neurons in the hidden layer

Model no.	Nodes in hidden layers	Network result MSE											
		Iteration 1		Iteration 2		Iteration 3		Iteration 4		Iteration 5		Average	
		Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
1	1	0.0255	0.0269	0.0166	0.0517	0.0238	0.0184	0.0243	0.0143	0.0485	0.0846	0.02774	0.03918
2	2	0.0259	0.0142	0.0153	0.0516	0.0226	0.0166	0.0230	0.0167	0.0230	0.0244	0.02196	0.0247
3	3	0.025	0.0205	0.0178	0.0591	0.0258	0.0180	0.0262	0.0219	0.0223	0.0332	0.02342	0.03054
4	4	0.0166	0.0247	0.0234	0.0643	0.0356	0.0354	0.0310	0.0233	0.026	0.0236	0.02652	0.03426

5	5	0.0214	0.0381	0.0207	0.0719	0.028	0.0223	0.0141	0.0209	0.0249	0.0214	0.02182	0.03492
6	6	0.0463	0.0551	0.0316	0.0952	0.0459	0.0139	0.0338	0.0218	0.0221	0.0206	0.03594	0.04132
7	7	0.0153	0.0302	0.0234	0.0576	0.0183	0.02	0.0217	0.0207	0.0251	0.0218	0.02076	0.03006
8	**8**	**0.0190**	**0.0276**	**0.0117**	**0.0557**	**0.0308**	**0.03**	**0.0208**	**0.0136**	**0.0211**	**0.0146**	**0.02068**	**0.0283**
9	9	0.0246	0.0336	0.0210	0.1032	0.0331	0.0867	0.0188	0.0159	0.0591	0.0464	0.03132	0.05716

Table 4 Total rank of average MSE values for predictive models obtained from five different datasets with different neurons in the hidden layer of the ANN model

Model no.	Nodes in hidden layers	Average of MSE				
		Train	Train Ranking	Test	Test Ranking	Sum Rank
1	1	0.02774	3	0.03918	3	6
2	2	0.02196	6	0.0247	9	15
3	3	0.02342	5	0.03054	6	11
4	4	0.02652	4	0.03426	5	9
5	5	0.02182	7	0.03492	4	11
6	6	0.03594	1	0.04132	2	3
7	7	0.02076	8	0.03006	7	15
8	**8**	**0.02068**	**9**	**0.0283**	**8**	**17**
9	9	0.03132	2	0.05716	1	3

Table 5 Total rank of average R^2 values for predictive models obtained from five different datasets with different neurons in the hidden layer of the ANN model

Model no.	Nodes in hidden layers	Average of R^2				
		Train	Train Ranking	Test	Test Ranking	Sum Rank
1	1	0.935721	2	0.926198	3	5
2	2	0.949132	6	0.948081	9	15
3	3	0.945503	4	0.93738	7	11
4	4	0.944022	3	0.93419	5	8
5	5	0.95123	8	0.931326	4	12
6	6	0.926019	1	0.908809	2	3
7	7	0.950056	7	0.936302	6	13
8	**8**	**0.952486**	**9**	**0.937526**	**8**	**17**
9	9	0.946472	5	0.891291	1	6

Table 6 The prediction performances and total rank values of these ANN models with the number hidden neurons equal to 8

Model no	R^2				MSE				Delta				Sum Rank
	Train	Rank	Test	Rank	Train	Rank	Test	Rank	R^2	Rank	MSE	Rank	
1	0.95726	4	0.940954	3	0.019	4	0.0276	3	0.016306	4	0.0086	2	20
2	0.972375	5	0.884261	1	0.0117	5	0.0557	1	0.088113	1	0.044	1	14
3	0.933845	1	0.920818	2	0.0308	1	0.03	2	0.013027	5	0.0008	5	16
4	**0.95032**	**3**	**0.972253**	**5**	**0.0208**	**3**	**0.0136**	**5**	**0.021932**	**2**	**0.0072**	**3**	**21**
5	0.948631	2	0.969342	4	0.0211	2	0.0146	4	0.020711	3	0.0065	4	19

3.2 ANFIS Model

ANFIS is a hybrid model of fuzzy logic and artificial neural network. In the ANFIS model, it is possible to adjust the MFs nonlinear parameters by using the BP back-propagation algorithm with least square estimation. ANFIS model is built and developed on the basis of Takagi and Sugeno. In an ANFIS model, there are 5 layers, including input layer, rule layer, normalization layer, defuzzification layer and output layer. The structure of an ANFIS model includes: input variables x, y; f is output [9, 15,16].

The ANFIS system contain two fuzzy if-then rules of Takagi-Sugeno's type:

Rule 1: If (x is A_1) and (y is B_1) then ($f_1=p_1x+q_1y+r_1$) (3)

Rule 2: If (x is A2) and (y is B_2) then ($f_2=p_2x+q_2y+r_2$) (4)

Where A_1 and B_1 are the fuzzy sets (nonlinear parameters of premise part); p_1, q_1 and r_1 are linear parameters of consequent part (the design parameters); x and y is the inputs.

In first layer: The first layer is the fuzzification layer and every node i in the first layer has a function to convert the input signal of this model to a fuzzy signal with an adaptive node:

i=1, 2 $O_{1,i}=m_{Ai}(x)$; (5)

i=3,4 $O_{2,i}=m_{Bi}(y)$. (6)

where x and y are the inputs to the first layer. A and B are the fuzzy sets. $O_{1,i}$ is the membership degree of the fuzzy set A according to the "x" input. $O_{2,i}$ is the membership degree of the fuzzy set B according to the "y" input, and m_{Ai} and m_{Bi} are the fuzzy membership function curve

In the second layer: This is a signal, an output signal from layer 1 becomes and this is input signal to layer 2 which is the IF-THEN rule.

$w_i = m_{Ai}(y)*m_{Bj}(y)$ i=1, 2 (7)

Third layer: In this layer, the normalization layer. In this layer, an output signal from layer 2 becomes an input signal to layer 3 and this signal is normalized using Eq.

$$\boldsymbol{w_i = \frac{w_i}{w_1+w_2}} \quad i=1, 2 \quad (8)$$

Fourth layer: This layer is the defuzzification process of the output signal from layer third. The output of this layer is received from a linear equation.

Fifth layer: This is the final output of ANFIS model. The final output was determined by summation of the outputs of the previous layer (fourth layer) computes.

In this study, grid partitioning (GP) was used in the ANFIS model. The hybrid learning algorithm, a combination of least squares and back-propagation gradient were implemented as an optimization method during the training process of the ANFIS model. They were applied to emulate FIS membership functions of training dataset. Next, the generalized Triangular membership function-shape fuzzy membership function was used in the ANFIS function with two numbers of membership functions is performed for this ANFIS model. All datasets were divided into two subsets randomly with 80% for all datasets (80 datasets) for training and 20% for all datasets (20 datasets) for testing in the ANFIS model (the same as ANN model).

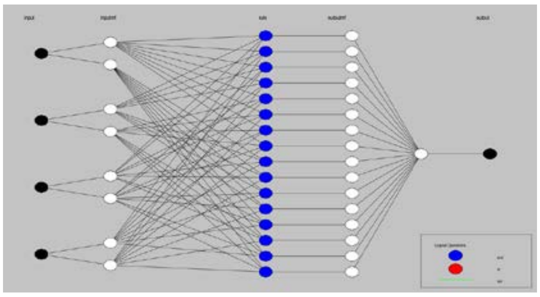

Fig.2 ANFIS structure for *SA* prediction

Based on the trial-and-error technique and and using the simple ranking method [2], the best ANFIS model with its architecture and its parameters were selected (the numbers of fuzzy rules, the type of MF utilized for each input). Then, it could be concluded that the ANFIS structure with 2 MFs for each input performs best when the MSE of models were compared. In the final step, ANFIS models were built to predict the area of the tunnel face after the blasting (*SA*) values. The prediction performances of these ANFIS models were shown in Table 7. Table 7 indicated that *SA* values were repeated five times using the same five randomly selected datasets employed in ANN modelling. Based on the results in this table, model number 4 was selected because model number 4 had results are better than other models.

4. RESULTS AND DISCUSSION

By previous studies when predicting overbreak value and underbreak of the tunnel face after blasting, it can be found that the parameters that have a great influence on the area of tunnel face after blasting including the average boreholes length *L*, design area of the tunnel face *S*, specific charge Q and rock mass rating *RMR* [6,15,16]. On the basis of the results obtained from the built models (ANN and ANFIS models), evaluate and compare the model's performance. For comparing the performance of models, the coefficient of determination (R^2) with mean squared error (MSE) as performance indices were used in this paper. The results of the ANN models and ANFIS models are shown and compared in Table 8. The area of tunnel face after blasting for measured and estimated data obtained from ANFIS models and ANN models is shown in Figs. 3, 4, 5, 6, 7. The results of analysis and comparison for all criteria of these models (R^2 and MSE) in Table 8 showed that the ANFIS model had the same efficiency in comparison with the ANN model.

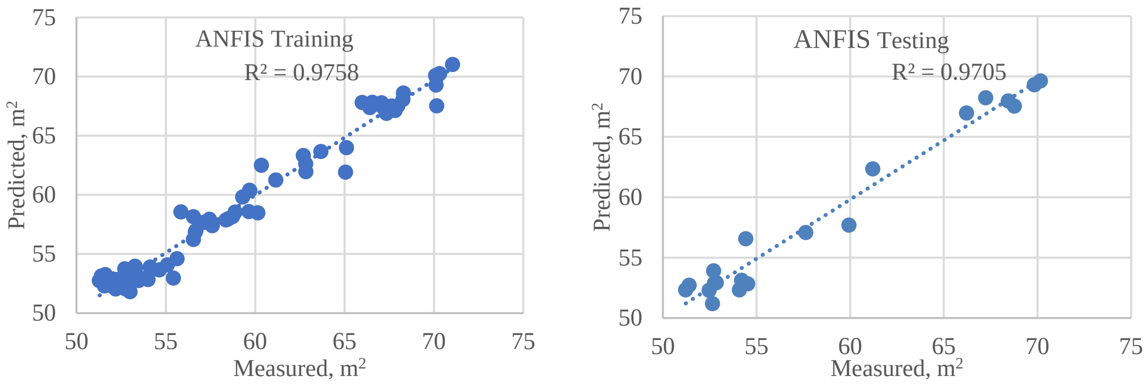

Fig. 3 R^2 of measured and predicted *SA* values using ANFIS model

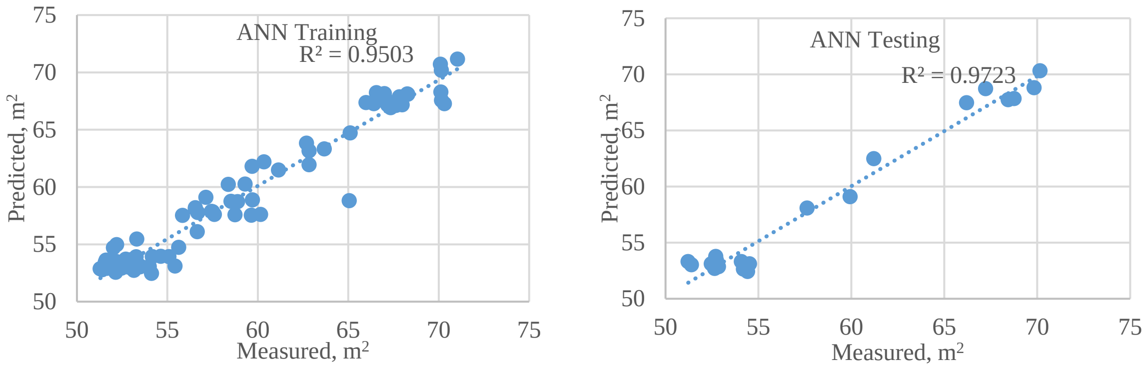

Fig.4 R^2 of measured and predicted *SA* values using ANN model

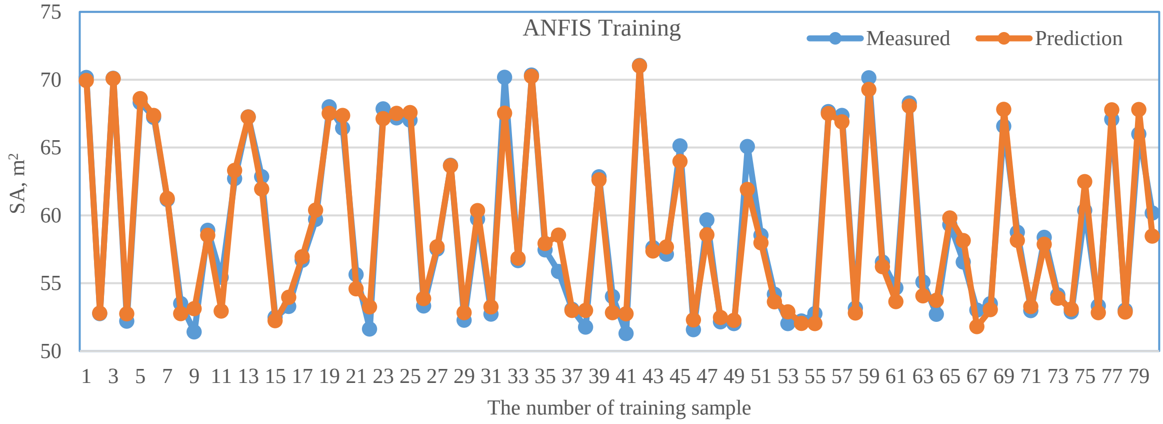

Fig.5 Comparison of measured and predicted *SA* of the optimum ANFIS model in training datasets

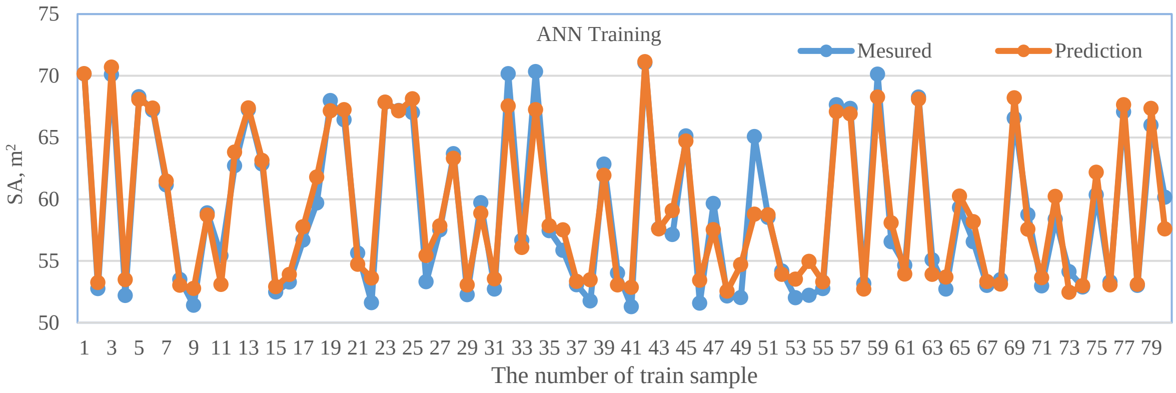

Fig.6 Comparison of measured and predicted *SA* of the optimum ANN model in training datasets

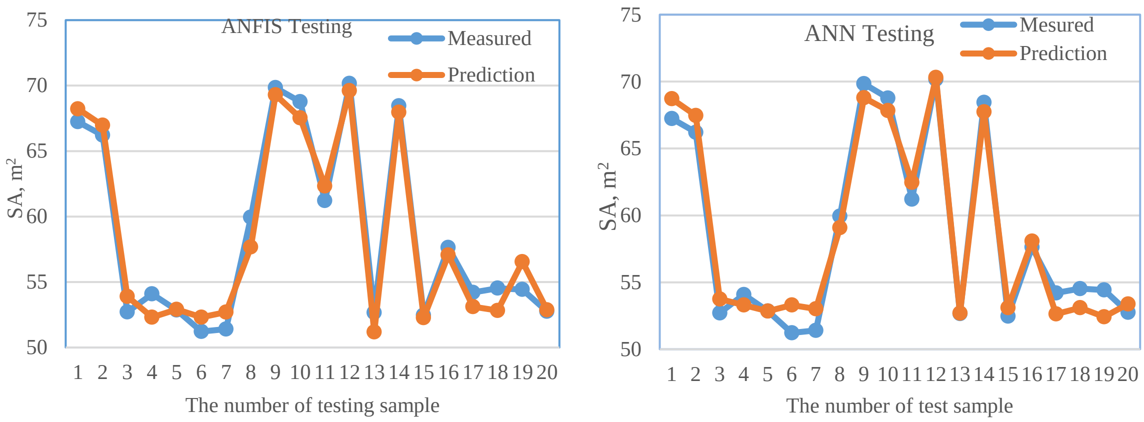

Fig. 7 Comparison of measured and predicted SA of ANN and ANFIS models in testing datasets

Table 7 The prediction performances and total rank values of these ANFIS models

Model no	R^2				MSE				Delta				Sum Rank
	Train	Rank	Test	Rank	Train	Rank	Test	Rank	R^2	Rank	MSE	Rank	
1	0.989684	5	0.879764	3	0.004379	5	0.050994	3	0.10992	1	0.046614	3	20
2	0.964653	1	0.86373	1	0.014623	1	0.064418	2	0.100922	3	0.049794	2	10
3	0.98731	4	0.922776	4	0.005777	4	0.03909	4	0.064534	4	0.033312	4	24
4	**0.982798**	**2**	**0.967716**	**5**	**0.00699**	**2**	**0.018596**	**5**	**0.015081**	**5**	**0.011606**	**5**	**24**
5	0.984129	3	0.874806	2	0.006511	3	0.095426	1	0.109323	2	0.088915	1	12

Table 8 Performance indices of models for prediction of the area of the tunnel after blasting SA

Model	R^2				MSE				Delta				Sum Rank
	Train	Rank	Test	Rank	Train	Rank	Test	Rank	R^2	Rank	MSE	Rank	
ANN	0.95032	1	0.972253	2	0.0208	1	0.0136	2	0.021933	1	0.0072	1	8
ANFIS	**0.975847**	**2**	**0.970458**	**1**	**0.009816**	**2**	**0.014676**	**1**	**0.005388**	**2**	**0.004859**	**2**	**10**

5. CONCLUSION

In this paper, ANN models and ANFIS models were studied and built to predict the area of tunnel face after blasting. In the process of building the above models, the 4 parameters that have the greatest influence on the area of tunnel face after blasting were used as the input variables of the models and there are 100 datasets in the Deo Ca tunnel, Phu Yen, Vietnam were collected and used. 80% of all dataset is used in training and 20% of all datasets is used in testing. This paper compared and investigated the results obtained from these models and some conclusions could be drawn:

- The optimum ANN architecture in this study was found (4x8x1) with 4 neurons in the input layer of this model, this model had one hidden layer with 8 neurons, and one neuron in the output layer;

- In the ANFIS model, the grid partitioning (GP) was used with the combination of least squares and back-propagation gradient. The generalized Triangular membership function-shape fuzzy membership function was applied in the ANFIS model with 2 MFs for each input;

- Investigation for the ANN model, the obtained results include the correlation coefficient (R^2) with mean squared error (MSE) had values 0,9503 and 0.0208, respectively with training datasets. With testing datasets, R^2=0.9723 and MSE=0.0136;

- The correlation coefficient (R^2) and mean squared error (MSE), indices had the values equal to 0.9758 and 0.0098 for the ANFIS model in training datasets. In testing datasets, R^2=0.97046 and MSE=0.01468. It was found that the constructed ANFIS model had a high performance for predicting the area of tunnel face after blasting;

- On the basis of the results obtained, the prediction performance of the ANFIS model was found to be higher than the ANN model in case of these models were used to predict the area of tunnel face after blasting;

- Both the ANN model and ANFIS model could be used to predict the area of Deo Ca tunnel face after blasting with highly accurate results. In the case of using for other tunnels, it is necessary to modify the above models to match the actual data of these tunnels, respectively.

6. ACKNOWLEDGMENTS

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