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DIGITAL TRANSFORMATION AND TECHNOLOGY IN EARTH, MINING AND ENVIRONMENTAL SCIENCES (Big Data, ML, and AI)

PREDICTION OF SPECIFIC CHARGE IN TUNNEL BLASTING

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Abstract: Currently, tunnel construction extensively utilizes the drilling and blasting method. It is important to calculate the specific charge accurately for this method. The specific charge significantly affects the advancement of tunnel construction, the involved workload, and the stability of the tunnel both during construction and its subsequent operation. In practice, establishing the value of a given charge is intricately tied to rock properties at the explosion site. Empirical formulas are employed to calculate this value. However, accurately determining a specific charge is difficult and requires adjustments based on the prevailing characteristics of the tunnel construction site. This study has developed two AI models that use ANN and ANFIS techniques. These models are designed to predict the specific charge for the Deo Ca tunnel in Phu Yen, Vietnam. The paper employs 100 databases to construct these AI models, enabling accurate prediction of the specific charge required in the construction of the Deo Ca tunnel.

1. INTRODUCTION

The drilling and blasting method is a traditional method, widely used in underground construction, because of its advantages, including: low cost, does not require a high technical level, and low investment cost, the method can be used for tunnels with different features and in different geological conditions... By calculations and results obtained in practice, it can be given it was commented that the effectiveness of blasting for tunneling depends on the rock mass characteristics that surrounding the tunnels and the properties of the explosives used in the blasting method as well as the interactions between them. A number of important parameters can greatly affect the efficiency of the blasting process, including the specific charge, the area of the tunnel face, the mechanical properties of the rock mass where it is stored tunnels, properties of boreholes used in tunnel construction... Among these important parameters, the specific charge is considered one of the most important criteria that can greatly affect the advancement of tunnel construction, the amount of work that needs to be completed during the process of tunnel construction, and also greatly affects the stability of the tunnel during construction and use. Thus, on the basis of the above analysis, it can be seen that it is necessary to accurately determine the value of the specific charge when tunneling by the drilling and blasting method. In fact, at present, to determine the value of the specific charge during the construction of tunnels by drilling and blasting method, empirical formulas [1] are often used. These empirical formulations consider the properties of the explosives and the parameters of the rock mass surrounding the tunnel. In some models studied by authors such as Ryu, C.H et al., 2006 [2]; Han J. et al., 2000 [3]... mentioned the influence of a number of other parameters on the specific charge index value, including the static and dynamic elastic modulus of the rock mass that surrounding the tunnel. However, the value of the specific charge obtained when using empirical formulas for calculation is often not very accurate and needs to be adjusted in accordance with the actual construction of the tunnel.

Currently, there have been a number of studies using artificial intelligence to determine and predict the amount of the specific charge when using drilling and blasting methods for tunnel construction [4], [5], [6]. Initially, the results obtained from these studies have proved the accuracy of the artificial intelligence models when these models are used to predict the value of the specific charge indicator in the process construction of tunnels using the drilling and blasting method.

In this study, two AI models, specifically the artificial neural network (ANN) and artificial neuro-fuzzy (ANFIS) models, were developed to forecast the precise charge during the construction of tunnels using the drilling and blasting technique. A dataset of 100 variables, gathered from the actual construction of the Deo Ca traffic tunnel in Phu Yen, Vietnam, was utilized to train these AI models. By assessing the determination coefficients R^2 and the root mean square error (*RMSE*) deviation of the predicted values against the actual specific charge values employed in the construction of Deo Ca traffic tunnels, it's clear that utilizing AI models to predict the specific charge of tunnel construction using the drilling and blasting method is practical and essential.

2. CASE STUDY AND DATA PROCESSING

Figure 1. *Deo Ca tunnel project.*

Deo Ca traffic tunnel is located between the two provinces, Phu Yen and Khanh Hoa. The total length of the Deo Ca traffic tunnel is 4.2 km and the tunnel is located in a rocky area with relatively complex geological conditions with mainly igneous and metamorphic rocks. According to geological surveys of the rock mass that surrounds the tunnel, the rock mass rating (*RMR*) has a large amplitude of fluctuations, receiving values from 0 to 73. This tunnel has a constant cross-sectional shape, a vertical-wall arched.

In this study, a database of 100 variables obtained from the actual construction of the Deo Ca tunnel was used to train and test for artificial intelligence models, these capable of predicting the specific charge q for tunnel construction by the drilling and blasting method. In there, which uses 80% of datasets to train the models, and 20% of datasets were used in testing models' performance. By the evaluation and comments, this study used 3 parameters as input variables for artificial intelligence models built to predict the specific charge (*Q*), including rock mass rating RMR; the design area of the tunnel face (S_d); the average boreholes length (*L*). The output variable of the built artificial intelligence models is the specific charge *Q*. The data in this study were normalized using the following equation, resulting in a range of [-1÷1] [7], [8], [9]:

$$Y_n = \frac{Y - Y_{\min}}{Y_{\max} - Y_{\min}} \quad (1)$$

Where Y and Y_n: the measured and normalized values, respectively. Y_{min}: the minimum measured variable, Y_{max} is the maximum measured variable, respectively.

Table 1 represents the value regions of the input and output variables of the artificial intelligence models. In this paper, all datasets used to build artificial intelligence models are divided to conduct the 5-fold cross-validation, random datasets. Build AI models using these datasets to predict the specific charge (*Q*). Compare models' prediction results to select optimal models.

Table 1. The input and output variables.

The variables	Symbols	Unit	Role	Min	Max
Rock Mass Rating	*RMR*	-	Input	4.9833	72.0142
The design area of tunnel face	S_d	m^2	Input	48.6126	63.9853
The average boreholes length	*L*	m	Input	1.0403	3.2089
Specifc Charge	*Q*	kg/m^3	Output	0.4193	2.3415

3. MODELING

2.1. ANN modeling

Artificial neural networks (ANNs) are built and developed by McCulloch and Pitts, 1943 [10]. ANNs operate similarly to human neurons. The multi-layer perceptron (MLP), designed by Haykin, 1999 [11] is a widely utilized and advanced artificial neural network. Consisting of input layer, hidden layers, and output layer, MLP's neurons are interconnected via weights. Typically, number of hidden layers and number of neurons in these hidden layers are determined through trial and error [12], [13]. In an ANN, each input parameter is initially assigned a weight between 0 and 1. The input is multiplied by the weight, and the sum of these values is given to the hidden layer(s). This result is then added to the bias (neuron weight), typically set as one.

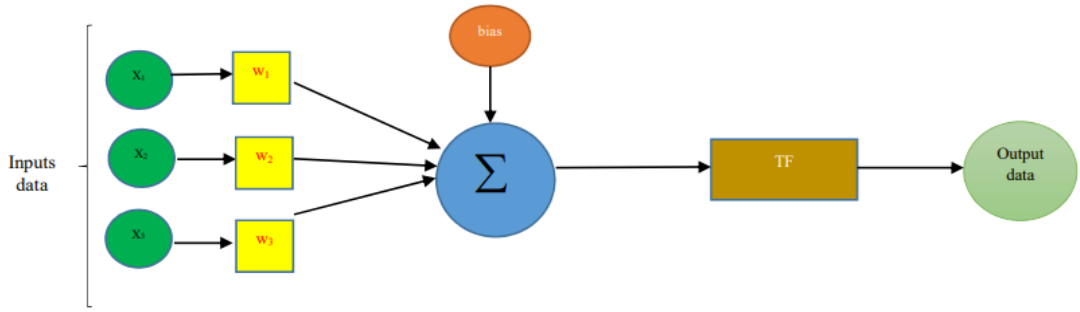

Figure 2. *The architecture of the ANN model.*

The process continues with a new weight assigned to the obtained value, moving to the next layer (output layer). The sum of all values obtained from each layer represents the final step of ANN modeling. In a feed-forward-backpropagation (FF-BP) algorithm, signals pass from the input layer to the output layer during the forward pass. The system's results are then compared to the actual values to calculate the error [7], [8]. This error is then sent backward through the network to update the weights during the backward pass. This procedure helps reduce errors for both the training and testing datasets. The feed-forward-backpropagation process repeats until the error converges to a defined level determined by a cost function like mean square error (*MSE*) or root mean squared error (*RMSE*) [14], [15]. However, constructing a suitable ANN model requires a database with an adequate number of datasets.

In this paper, MLP has been used in the ANN model to predict the specific charge in tunnel construction by the drilling and blasting method. In this study, a hidden layer of neurons is utilized. As per certain authors, the hidden layer's neuron count significantly affects the model's predictions. Typically, the hidden layer's neuron count should not exceed "2*N+1", with N representing the input variables' count [16]. To assess the quality of AI models, 5-fold cross-validation is employed. The 5 sub-datasets, each of equal size, are divided to conduct the 5-fold cross-validation. Using 5 models for 5 randomly generated datasets derived from the original dataset. Tables 2 and 3 present the results obtained for models with varying hidden layer neuron counts. This study examined ANN models with 1 to 9 neurons in the hidden layer and identified an optimal architecture: the ANN (3x5x1) model with N=5 neurons in the hidden layer. The activation function is tangent sigmoid function. This model yields the best results (highest R^2 and lowest *RMSE*) among the surveyed ANN models. The results of the respective models are shown in Tables 2 and 3.

Table 2. Selecting the number of optimal neurons for the hidden layer of the ANN model based on R^2.

Number nerouns in hidden layer	Network result														
	The determination coefficients R^2														
	Iteration 1		Iteration 2		Iteration 3		Iteration 4		Iteration 5		Average		Rank		
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Rank Train	Rank Test	Sum Rank
1	0.6419	0.5327	0.7178	0.4871	0.6221	0.8411	0.7216	0.4539	0.6243	0.7919	0.6656	0.6213	3	7	10
2	0.5854	0.2301	0.6174	0.0415	0.6703	0.8347	0.7572	0.3005	0.6516	0.7924	0.6564	0.4398	2	1	3
3	0.6802	0.4352	0.7235	0.5765	0.3023	0.6521	0.7872	0.2638	0.6786	0.8765	0.6344	0.5608	1	3	4
4	0.7135	0.6649	0.7067	0.4308	0.6365	0.7792	0.7904	0.3968	0.5872	0.7922	0.6869	0.6128	4	6	10
5	0.6962	0.6352	0.7920	0.4513	0.6820	0.7992	0.7675	0.3374	0.7035	0.9124	0.7282	0.6271	6	8	14
6	0.7949	0.5240	0.7918	0.4513	0.6743	0.7678	0.8007	0.2993	0.7113	0.8842	0.7546	0.5853	8	4	12
7	0.6416	0.3800	0.7305	0.5570	0.6358	0.7520	0.7812	0.1920	0.6562	0.8233	0.6891	0.5409	5	2	7

According to Tables 2 and 3, following Chi Thanh Nguyen et al., 2022 [9] ranking principle, the chosen ANN model for predicting specific charge (Q) during the construction of the Deo Ca tunnel using drilling and blasting is 5th model, there are 5 neurons in the hidden layer of this model.

Table 3. Selecting the number of optimal neurons for the hidden layer of the ANN model based on RMSE

Number nerouns in hidden layer	Network result														
	The root mean square error *RMSE*														
	Iteration 1		Iteration 2		Iteration 3		Iteration 4		Iteration 5		Average		Rank		
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Sum Rank
1	0.0066	0.0087	0.0061	0.0080	0.0067	0.0055	0.0063	0.0074	0.0070	0.0054	0.0065	0.0070	3	6	9
2	0.0070	0.0114	0.0072	0.0085	0.0064	0.0064	0.0060	0.0083	0.0068	0.0058	0.0067	0.0081	1	1	2
3	0.0063	0.0093	0.0061	0.0073	0.0091	0.0091	0.0055	0.0077	0.0064	0.0041	0.0067	0.0075	2	2	4
4	0.0058	0.0074	0.0063	0.0082	0.0067	0.0066	0.0055	0.0065	0.0074	0.0057	0.0063	0.0069	4	7	11
5	0.0060	0.0078	0.0053	0.0084	0.0005	0.0059	0.0059	0.0069	0.0061	0.0037	0.0048	0.0065	9	9	18
6	0.0049	0.0089	0.0054	0.0077	0.0063	0.0064	0.0055	0.0082	0.0061	0.0060	0.0056	0.0074	8	3	11
7	0.0067	0.0101	0.0060	0.0074	0.0066	0.0066	0.0056	0.0082	0.0067	0.0048	0.0063	0.0074	5	4	9

3.2. ANFIS modeling

ANFIS is a hybrid intelligent system that combines fuzzy logic and artificial neural networks to process data and make predictions, integrating their learning and reasoning capabilities to enhance prediction compared to using either method alone. Its objective is to establish a mapping that accurately associates input values with target values. ANFIS employs a fuzzy inference system (FIS) where each fuzzy rule defines a local system behavior. The ANFIS model consists of 5 layers: input, rule, normalization, defuzzification, and output. The ANFIS model used the BP back-propagation algorithm with least square estimation to adjust the nonlinear parameters of the MFs. [17].

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

$$\textit{Rule 1: If } (x \textit{ is } A_1) \textit{ and } (y \textit{ is } B_1) \textit{ then } (f_1=p_1x+q_1y+r_1) \quad (2)$$

$$\textit{Rule 2: If } (x \textit{ is } A_2) \textit{ and } (y \textit{ is } B_2) \textit{ then } (f_2=p_2x+q_2y+r_2) \quad (3)$$

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 the consequent part (the design parameters); x and y is the inputs.

In the first Layer: The initial layer fuzzifies the input signal via adaptive nodes:

$$i=1,2 \quad O_{1,i}=m_{Ai(x)}; \quad (4)$$

$$i=3,4 \quad O_{2,i}=m_{Bi(y)}. \quad (5)$$

Every node in this layer is an adaptive node. Parameters in this layer are called premise parameters.

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.

The Layer 2. Fixed nodes labeled Π multiply incoming signals, representing rule firing strength. In the 2nd layer: Layer 1's output becomes input to IF-THEN rule in Layer 2.

$$w_i = m_{Ai}(y)*m_{Bj}(y)\ i=1, 2 \tag{6}$$

The third Layer layer normalizes Layer 2's output as input to Layer 3.

$$\boldsymbol{w_i} = \frac{\boldsymbol{w_i}}{\boldsymbol{w_1+w_2}} i=1, 2 \tag{7}$$

Fourth layer: The fourth layer defuzzification of Layer 3's output occurs.

Fifth layer: In the fifth layer, Final model output is determined by summing results from previous layer computations (4th layer).

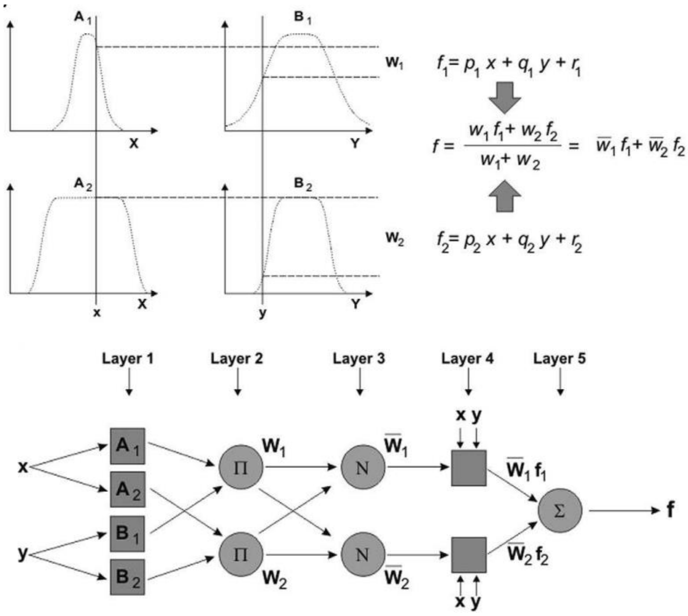

Figure 3. *The ANFIS model has got two fuzzy if-then rules of Takagi-Sugeno's type. [18]*

In this paper, several models were built and trained, each having three input parameters and one output parameter. To evaluate ANFIS models, cross-validation is used with 5-fold cross-validation. The 5 sub-datasets, of equal size, are split to perform the cross-validation. The models were assessed based on their structures (FIS division), with R^2 and *RMSE* used to determine the best model. During the development of an ANFIS model for estimating the specific charge, three membership functions were incorporated for each input parameter along with three rules. Table 4 outlines the additional parameter types and corresponding values used in the artificial neuro-fuzzy (ANFIS). The correlation between measured and predicted values derived from the artificial neuro-fuzzy (ANFIS) model during the testing phase is illustrated in Figure 4.

Table 4. The ANFIS parameters.

ANFIS parameter type	Value
Membership function (MF) type	Gaussia
Number membership function MFs	3
Type of Output function	Linear
Number of nodes	78
Number of linear parameters	27
Total number of parameters	54
Number of training data pairs	80
Number of fuzzy rules	27

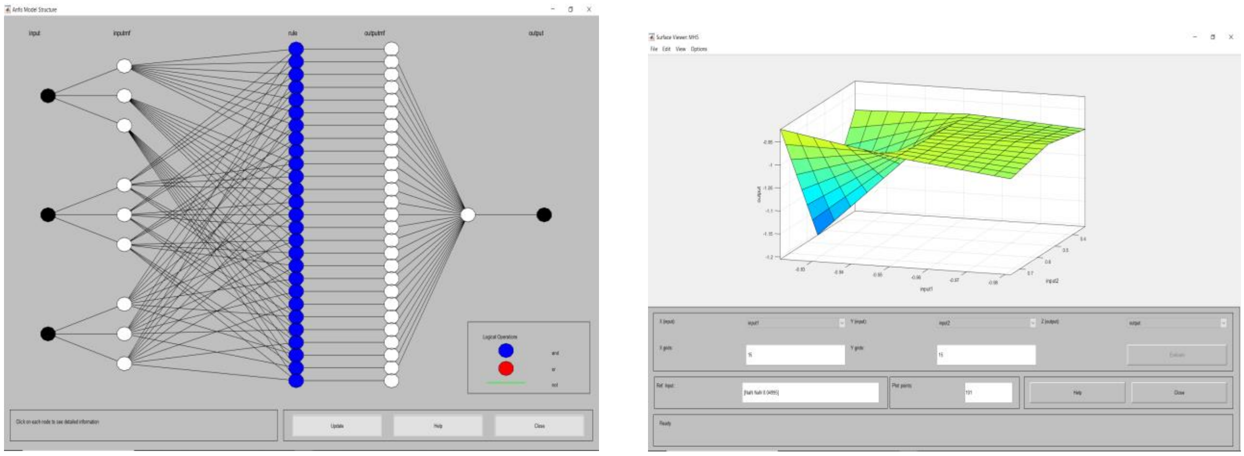

Figure 4. ANFIS model structures.

Based on the trial-and-error method and employing the simple ranking technique, the authors selected the optimal ANFIS model with its architecture and parameters (fuzzy rule count and input membership function type) [19], [20]. It can be concluded that the ANFIS structure with 3 MFs per input yields superior performance when comparing the models' *RMSE*. In the final step, ANFIS models were constructed to forecast the specific charge values. The predictive performances of these ANFIS models are displayed in Tables 5, 6 and 7. Table 5, 6 and 7 demonstrates that the specific charge *Q* values were repeated five times using the same randomly chosen datasets employed in the ANN model. Based on the table's results, 5th model was selected as it outperformed the other models.

4. RESULTS AND DISCUSSION

This paper describes and compares the use of artificial neural network (ANN) and artificial neuro-fuzzy inference system (ANFIS) models for predicting the specific charge. In this study, the authors discussed and compared the utilization of ANN and ANFIS models for predicting the specific charge. The modelling process involved randomly selecting 100 datasets and dividing them into five sets to build models in case of Deo Ca tunnel. To assess the prediction performance, the authors calculated various performance indices such as R^2 and root mean square error (*RMSE*).

Table 5. R^2 of ANFIS models to predict specific charge.

ANFIS Model	Network result									
	The determination coefficients R^2									
	ANFIS Model 1		ANFIS Model 2		ANFIS Model 3		ANFIS Model 4		ANFIS Model 5	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
ANFIS Sugen 3x3x3	0.8141	0.5801	0.8228	0.5264	0.7654	0.8358	0.829	0.3446	0.7702	0.8577
Rank	3	3	4	2	1	4	5	1	2	5
SumRank of R^2	6		6		5		6		7	

Table 6. RMSE of ANFIS models to predict specific charge.

ANFIS Model	Model's result									
	The root mean square error *RMSE*									
	Model 1		Model 2		Model 3		Model 4		Model 5	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
ANFIS Sugen 3x3x3	0.0046	0.0081	0.0048	0.0081	0.0052	0.0053	0.0049	0.0075	0.0053	0.0068
Rank	1	4	2	5	4	1	3	3	5	2
SumRank of *RMSE*	5		7		5		6		7	

Table 7. SumRank ANFIS models

ANFIS Sugen Model 3x3x3	ANFIS Model 1	ANFIS Model 2	ANFIS Model 3	ANFIS Model 4	ANFIS Model 5
SumRank models	11	13	10	12	14

The graphs in Figures 5, 6, and 7 show the predicted specific charge Q using ANN, and ANFIS techniques compared to the measured specific charge for training and testing datasets. From these figures, it is evident that the ANFIS model outperforms other predictive models in predicting the specific charge *Q*. The $R^2_{testing}$ value of 0.8577 for the testing dataset further confirms the superiority of the artificial neuro-fuzzy inference system (ANFIS) model, while the corresponding values for artificial neural networks (ANN) model is $R^2_{testing}$=0.9124, respectively. For the training dataset, $R^2_{training}$value of 0.7702 of the ANFIS model and 0.7035 of the ANN model. With *RMSE*, for the training dataset, $RMSE_{training}$= 0.0053 with the ANFIS model and $RMSE_{training}$= 0.0061 with the ANN model. For the testing dataset, the $RMSE_{testing}$ of the ANFIS model has the value $RMSE_{testing}$= 0.0068; ANN model has $RMSE_{testing}$= 0.0037. It is evident that the ANFIS and ANN models have the higher performance capacity compared to other techniques previously implemented (Table 2, 3, 5, 6 and 7).

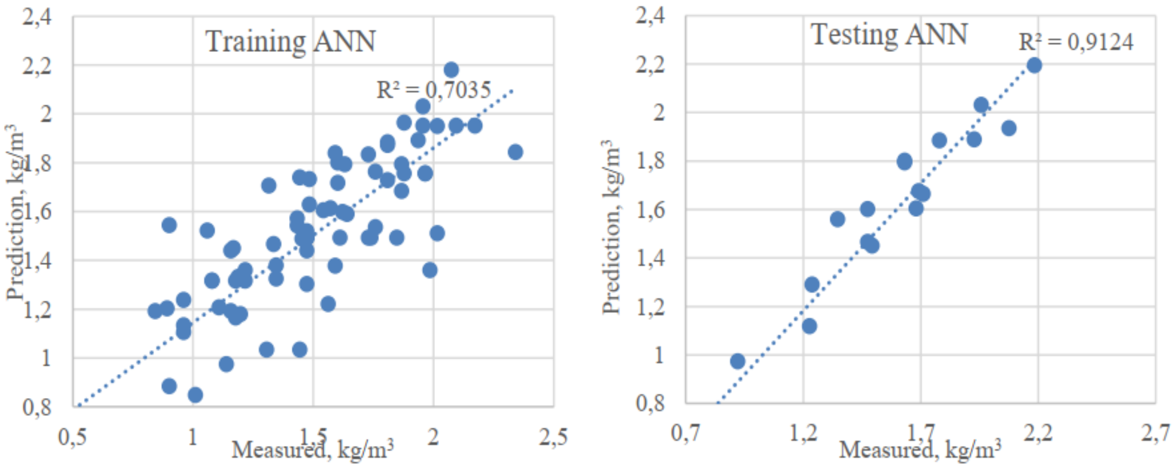

Figure 5. *Correlation coefficient for the ANN model.*

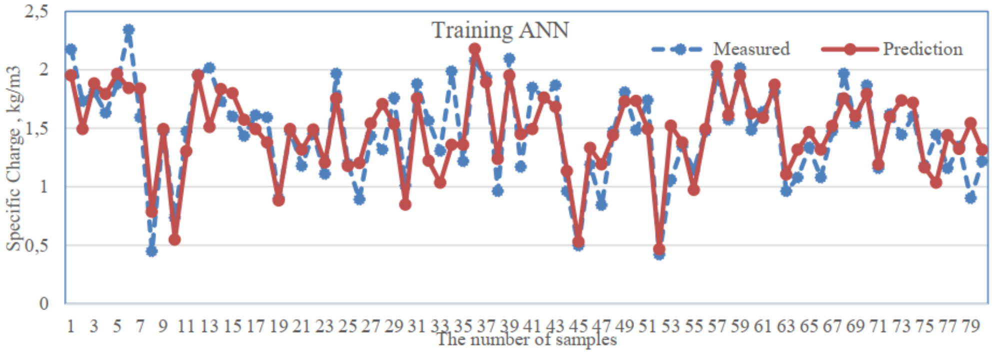

Figure 6. *The simile of measured and predicted specific charge in the training database of Artificial neural network (ANN) model.*

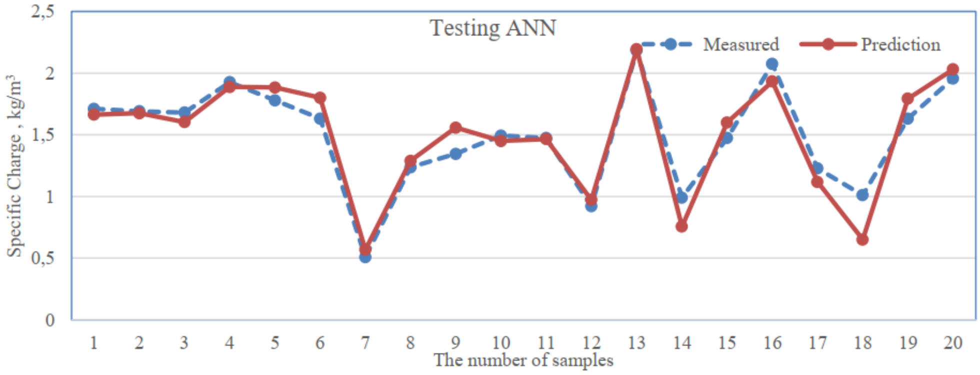

Figure 7. *The simile of measured and predicted specific charge in the testing database of Artificial neural network (ANN) model.*

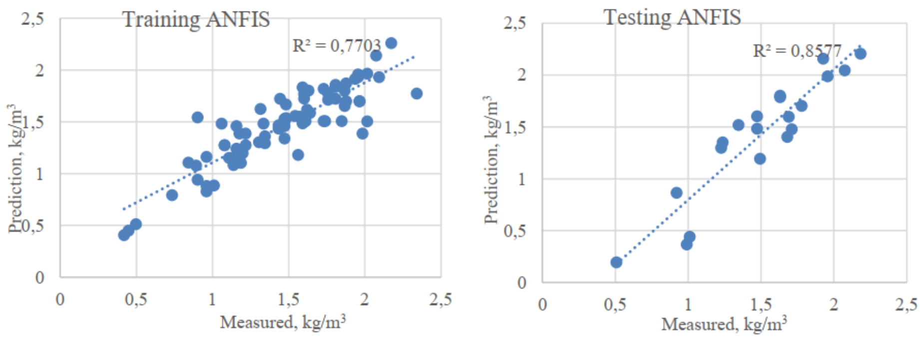

Figure 8. *Correlation coefficient for the ANFIS model.*

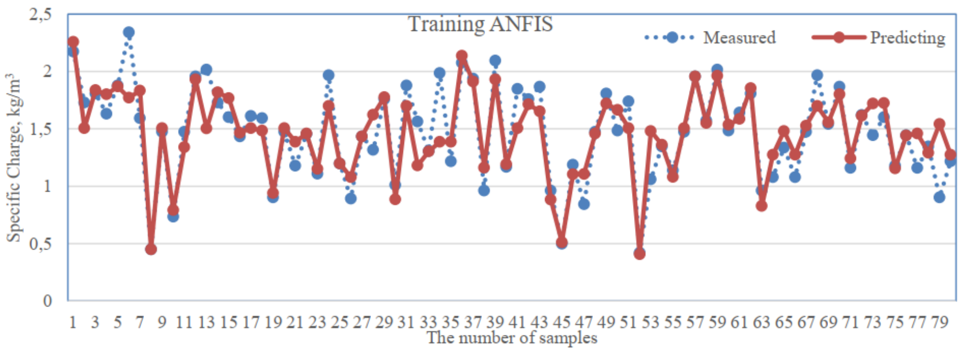

Figure 9. *The simile of measured and predicted specific charge in the training database of Artificial neuro-fuzzy inference system (ANFIS) model.*

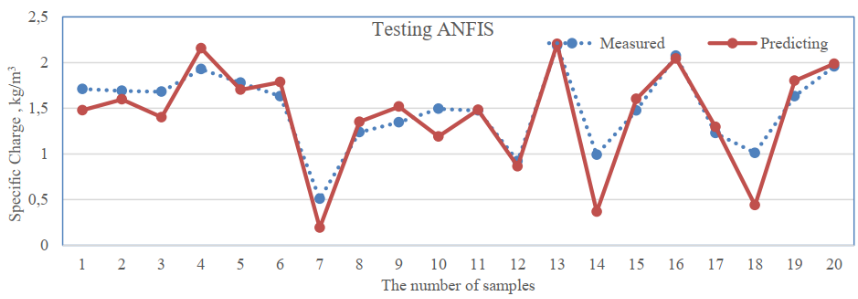

Figure 10. *The simile of measured and predicted specific charge in the testing database of Artificial neuro-fuzzy inference system (ANFIS) model.*

5. CONCLUSIONS

This paper presented how to predict the specific charge in tunneling blasting. Data collected from the Deo Ca tunnel project were used to build the ANN and ANFIS models for the prediction of specific charges in tunnel blasting. Different artificial intelligence models were tested, and three parameters, including rock mass rating *RMR*; the design area of the tunnel face S_d; the average boreholes length *L*, were identified as influential in achieving accurate estimations for specific charges *Q*. These parameters were selected as input variables for the final artificial intelligence models. ANFIS and ANN techniques demonstrate their efficacy in establishing the correlation between rock and tunnel specifications for specific charges. The ANFIS model's results were evaluated and compared with the ANN model's simulation results. Based on the results obtained from the AI models developed in this study, the following conclusions can be drawn:

- The ANFIS and ANN models can be used to predict the specific charge (*Q*) when constructing tunnels by drilling and blasting method with acceptable accuracy;

- It is necessary to study and add some parameters of the rock mass where the tunnel is located, including Young's modulus (*E*), uniaxial compressive strength (*UCS*), Rock Quality Designation (*RQD*) index, exact consumed explosive materials, and applying the details of holes arrangement in drilling and blasting method pattern as input variables of artificial intelligence models, with the aim of improving the accuracy of specific charge prediction results of artificial intelligence models ANN and ANFIS. Adding parameters like *E*, *UCS*, *RQD*, explosive materials, and hole arrangement can improve the accuracy of specific charge prediction;

- Selecting a suitable architecture for ANN and ANFIS models with different research objects is important.

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