ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
Received: 21 October 2024; Accepted: 23 August 2025
https://doi.org/10.17559/TV-20241021002080
Original scientific paper

Estimation of the Specific Charge in the Tunnel Excavation by Using the Drilling and Blasting Method

Tung Manh BUI, Hoang Hiep DO, Nghia Viet NGUYEN, Nhan Thi PHAM, Chi Thanh NGUYEN*

Abstract: The specific charge (q, kg/m^3) is one of the decisive technical parameters to the efficiency of tunnel construction using the drilling and blasting method. To accurately determine and calculate the specific charge (q, kg/m^3), thereby improving the efficiency of tunnel construction, currently, there are many methods to determine the specific charge (q, kg/m^3), such as: Pokrovsky's method, experimental method, and method of using numerical simulation software. In this paper, the authors used artificial neural network (ANN) and Random forest (RF) techniques to build artificial intelligence models capable of identifying and predicting the specific charge (q, kg/m^3) with high accuracy. By using data compiled during the construction of the Deo Ca tunnel, Phu Yen, Vietnam, artificial intelligence models with ANN and RF techniques were built. Based on the prediction results of artificial intelligence models with specific data compiled from the actual construction process of Deo Ca tunnel, the accuracy of the results of the artificial intelligence models was confirmed.

Keywords: ANN; blasting; estimation; random forest; the specific charge; tunnel

1 INTRODUCTION

The specific charge (q, kg/m^3) is a crucial technical parameter for the efficiency of tunnel construction using the drilling and blasting method. Two groups of parameters greatly impact the effectiveness of drilling and blasting methods when constructing tunnels. The first group consists of parameters that cannot be controlled, such as geological and hydrogeological conditions, as well as the physical and mechanical properties of the rock and soil surrounding the tunnel. The second group includes parameters that can be controlled, such as the properties of explosives used, the design and utilization of the tunnel's cross-sectional area, the shape of the tunnel cross-section, and the tunnel depth. The specific charge (q, kg/m^3) belongs to the second group of parameters.

Given the significance of the specific charge (q, kg/m^3) for the effectiveness of the tunnel construction method using drilling and blasting, accurately determining its value is essential. There are several methods available for determining the specific charge (q, kg/m^3), by experimental and theoretical methods, including: Pokrovsky., 1980; Lilly., 1986; Ghose., 1988; Hagan., 1992; Kahriman et al., 2001; Chakraborty et al., 2004., and numerical simulation software [1-6]. Currently, there have been a number of scientists who have researched and built a number of artificial intelligence models capable of determining the specific charge (q) with high accuracy, such as: Alipour et al., 2012; Alipour A. et al., 2021 [7, 8]. Artificial intelligence models have proven their advantages, such as: high accuracy, fast result generation speed, and low cost for model building. Alipour A. has constructed artificial intelligence models using two techniques: artificial neural networks (ANN) and support vector regression (SVR). These models accurately predict the specific charge (q, kg/m^3) during tunnel construction using drilling and blasting methods. Alipour A. employed specific input variables for each model. The ANN models utilized Rock-Quality Designation (RQD), maximum depth of the hole, hole diameter, cut angle, and tunnel area. On the other hand, the SVR models considered Uniaxial Compressive Strength (UCS), P-wave velocity, rock density, Rock-Quality Designation (RQD), Tunnel area, and Coupling Ratio as input variables. Gathering detailed measurements, statistics, and monitoring of these input variables is necessary during geological surveys and the actual tunnel construction. Consequently, applying these models to different tunnel construction projects becomes challenging.

In this study, the authors utilized artificial neural network techniques (ANN) and random forest techniques (RF) to develop accurate artificial intelligence models for identifying and predicting the specific charge (q, kg/m^3), which is: the average depth of holes drilled in the area of the tunnel face during the construction tunnel, l (m); the area of the tunnel face to design, S_{ds} (m^2); the rock mass index, RMR of rock mass surrounding the tunnel. By using 100 data points collected during the construction of the DeoCa tunnel in Phu Yen, Vietnam, the authors identified the simplest input variables with the greatest influence on the specific charge (q, kg/m^3). The artificial intelligence models were then built using the aforementioned techniques. By comparing the predictions of these models with the actual data from the construction process of the DeoCa tunnel, the accuracy of the artificial intelligence models was confirmed.

2 DATABASE FOR CASE STUDY

In this paper, data during the actual construction process of some sections of the DeoCa tunnel (Fig. 1), Phu Yen province, Vietnam, were synthesized to build artificial intelligence models capable of predicting the specific charge (q, kg/m^3) when using the drilling and blasting method for construction.

DeoCa Tunnel is located on National Highway 1A, which is a tunnel that connects the two provinces of Phu Yen and Da Nang. DeoCa tunnel is located in rocky areas with relatively complex conditions. During the construction of the Deo Ca traffic tunnel, rocks, and soil were broken up using the drilling and blasting method. The explosive employed for this purpose is the P113 explosive in emulsion form. For this study, 100 databases were compiled during the tunnel construction process. To serve the purpose of building artificial intelligence models capable of predicting and calculating the specific charge (q, kg/m^3) when using the drilling and blasting method to construct tunnels, 03 parameters have a great influence on the value of the specific charge (q, kg/m^3), which is: the average depth of holes drilled in the area of the tunnel face during the construction tunnel, l (m); the area of the tunnel face to design, S_{ds} (m^2); the rock mass index, RMR where the tunnel is located has been selected and used as input variables for the artificial intelligence models being built.

Figure 1 The DeoCa tunnel

The values of the above parameters are shown in Tab. 1.

The database used to build artificial intelligence models capable of predicting and calculating the specific charge (q, kg/m^3) when using the drilling and blasting method for construction is standardized according to Eq. (1). The normalization process brings the data within a range of −1 to 1. The remaining 20% of databases (20 data points) are used to verify the accuracy of these models [5, 7-9].

$$Y_n = \frac{Y - Y_{\min}}{Y_{\max} - Y_{\min}} \tag{1}$$

where Y and Y_n represent the measured and normalised values, respectively. $Y_{\min}$ is the minimum measured parameters and $Y_{\max}$ is the maximum measured parameters, respectively. Tab. 1 displays the narrow range of values associated with four parameters.

Table 1 The input and output parameters

The variables of models	Symbols	Unit	Role	Min	Max
The Rock Mass Rating	*RMR*	-	Input	5.0	72.0
The design area of tunnel face	S_{ds}	m^2	Input	48.6	64.0
The average boreholes length	l	m	Input	1.0	3.2
The specific charge	q	kg/m^3	Output	0.42	2.34

3 THE AREA OF THE TUNNEL FACE PREDICTION MODELS

3.1 Artificial Neural Network (ANN)

Artificial neural network (ANN) is a computer technique used to build artificial intelligence models capable of predicting the specific charge q when using drilling and blasting methods for construction tunnels. Artificial neural networks are based on the operating principles of the human brain. Artificial neural networks are composed of layers of neurons with neurons inside. Artificial neural networks are capable of finding underlying relationships in the set of data used to build and train artificial neural networks. The structure of an artificial neural network usually includes artificial neurons linked in 3 layers: Input layer: Information from the outside world enters the artificial neural network through the input layer. Input nodes process the data, analyze or classify it, and then pass the data to the next layer [10-14].

Hidden layer: The data that goes into the hidden layer comes from the input layer or other hidden layers. Artificial neural networks can have a large number of hidden layers. Each hidden layer analyzes the output data from the previous layer, processes that data further, and then passes the data to the next layer.

Output layer: The output layer gives the final result of all the data processed by the artificial neural network. This class can have one or more nodes.

In this paper, the artificial neural network uses the BP backpropagation algorithm. In the BP backpropagation algorithm, artificial neural networks continuously learn using a corrective feedback loop to improve their predictive analysis. Eq. (2) represents the learning and gives the results of the artificial neural network.

$$Z = \sum_{i=1}^{n} z_i \mathrm{w}_i - \theta \tag{2}$$

where z_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, Z: is the value the neuron outputs.

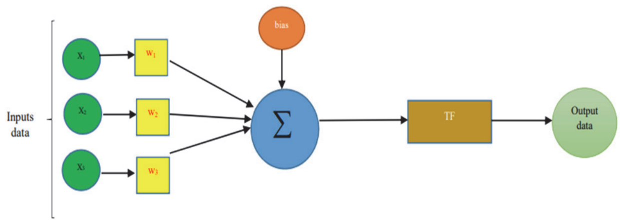

Figure 2 Structure of the ANN models

3.2 Random Forest (RF)

The Random Forest algorithm (RF) is a computer technique used to build artificial intelligence models capable of predicting the specific charge q when using drilling and blasting methods for construction. The Random Forest (RF) algorithm includes many decision trees, each of which has random elements, including:

- Randomly take data to build a decision tree;
- Randomly select attributes to build a decision tree.

RF is widely regarded as one of the top machine learning algorithms nowadays. Its effectiveness has been demonstrated across various research domains, both for regression analysis and classification tasks. When utilizing RF in artificial intelligence models, certain parameters of the algorithm must be defined. These parameters include the number of trees and the number of leaves within the algorithm.

Random Forest (RF) was initially introduced by Breiman in 2001 [17]. It is a supervised learning technique used for classification and regression tasks, achieved by combining multiple decision trees to make predictions. Each decision tree in this ensemble is built using a random subset of the original training data, generated through a process called sampling with replacement (Bootstrap method). This means that some samples may appear multiple times in a single tree. The decision trees are constructed using only a certain number of input variables at each split node, based on the newly created sample set. The final prediction is obtained by averaging the results from all the decision trees. By utilizing a large number of decision trees, the model effectively reduces estimation error.

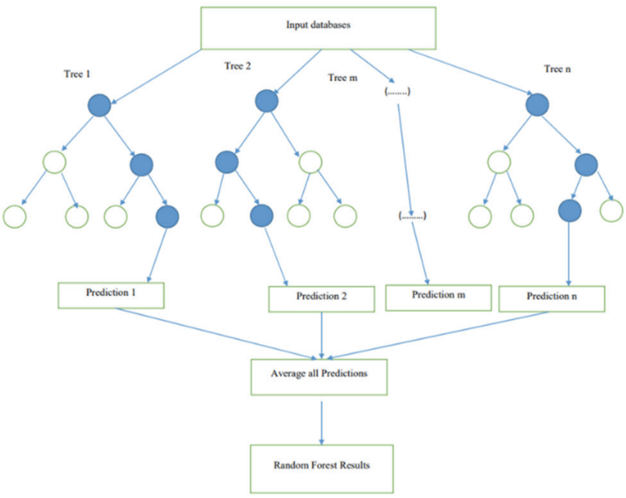

Figure 3 The Random Forest algorithm (RF) [17, 18]

In regression problems, prediction trees assign specific numerical values instead of using classification techniques for decision-making [17, 18]. When designing regression analysis decision trees, the prediction trees in Random Forest (RF) can grow to the maximum depth of the training data without undergoing any reduction or branching. This approach enhances the performance of the regression prediction model because the implementation of tree reduction significantly impacts the model's performance [18]. Breiman [17] also states that as the number of trees increases, the general error of the RF model will always converge, even without tree reduction. Dealing with the overfitting phenomenon in the model is based on the principle of the law of large numbers. Research indicates several crucial parameters that can affect the performance of random forest models: (1) number of decision trees used, (2) sampling technique (with or without the bootstrap technique), (3) number of variables used at each node, and (4) characteristics of the dataset, including input and output parameters of the model.

4 RESULTS AND DISCUSSION

In this paper, the authors utilized 100 databases gathered during the construction of the DeoCa traffic tunnel, which connects Phu Yen province with KhanhHoa province in Vietnam. This paper's goal was to develop intelligent models using artificial intelligence techniques such as RF and ANN. These models were designed to identify the key parameters for optimal performance. This paper employed a trial-and-error approach and obtained several significant outcomes.

Among these results, the authors found that three parameters greatly influenced the specific charge (q, kg/m^3) and were selected as input variables for the artificial intelligence models. These parameters include the average depth of holes drilled in the area of the tunnel face during the tunnel construction, denoted as l (m). Another influential factor is the area of the tunnel face used in the design, expressed as S_{ds} (m^2). Additionally, the rock mass index at the RMR tunnel location was also selected as an input variable for the artificial intelligence models being developed.

To test the accuracy of the paper's models, the authors allocated 20% of the data (20 data points) for testing, while the remaining 80% was utilized for model training. The authors employed the compiled datasets from the construction process of the Deo Ca traffic tunnel, which were normalized within the range of [−1; 1]. Using these datasets, this paper developed artificial intelligence models using artificial neural networks (ANNs) and the Random Forest (RF) method. These models showcased the capability to predict the specific charge (q, kg/m^3). The paper has yielded some promising results.

To compare the statistical data from the results of the ANN and RF models, this paper used the mean squared error (MSE), as indicated in Eq. (3), and the coefficient of determination (R^2), as described in Eq. (5).

4.1 Results of ANN Models

By using artificial neural network (ANN) technology, the authors have built an AI model that can predict and calculate the specific charge (q, kg/m^3) for tunnel construction using the drilling and blasting method. This paper has obtained highly accurate results in this prediction and calculation. To ensure the effectiveness of the ANN model in predicting and calculating the specific charge (q, kg/m^3), it was crucial to identify the optimal structure for the model.

To achieve this, the paper employed trial-and-error techniques and utilized the K-fold algorithm. The data set collected from the actual construction of the Deo Ca tunnel in Phu Yen was divided into different models using the K-fold algorithm. Each model underwent training and testing phases to assess the accuracy of the ANN models in predicting the specific charge (q, kg/m^3). Based on the results obtained from these models, the paper selected the most suitable structure that provided the best prediction results for the specific charge (q, kg/m^3) in tunnel construction using the drilling and blasting method.

Below, this paper presents the structure and important parameters of the ANN that have been found and selected for this purpose. In this study, the authors built an artificial intelligence model using the ANN (Artificial Neural Network) technique to predict the area of the tunnel face after blasting. The model utilized the BP (Backpropagation) algorithm. Based on the obtained results through the trial-and-error technique, the paper determined the following parameters for the ANN model:

- The ANN model consists of 1 hidden layer with 5 neurons (shown in Tab. 2).
- The activation function used in this model is the tangent function.
- The structure of the artificial neural network is 3 × 5 × 1, with 03 input variables: the average depth of holes drilled in the area of the tunnel face (l, m); Design area of the tunnel face (S_{ds}, m^2); Rock mass rating (RMR) for the tunnel's location. The model provides 01 output variable, which is the specific charge (q, kg/m^3).
- The dataset used for constructing the ANN models is Iteration 5 because it has the highest accuracy results (Tab. 3).

Based on the coefficient of determination R^2 and the mean squared error *MSE* to evaluate the accuracy of the ANN artificial intelligence model capable of predicting the specific charge (q, kg/m^3) (Figs. 4 and 5).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \overline{y}_i)^2 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y_i^{\,i})^2} \tag{4}$$

$$R^2 = \left[\frac{\sum_{i=1}^{N}(y-\overline{y})(y^{/}-\overline{y}^{/})}{\sum_{i=1}^{N}(y-\overline{y})^2\sum_{i=1}^{N}(y^{/}-\overline{y}^{/})^2}\right]^2 \tag{5}$$

where y_i are the observations, y'_i predicted values of a variable, $\overline{y}$ is the mean of the y values and $\overline{y}^{/}$ is the mean of the $y^{/}$ values, and n is the number of observations available for analysis.

Table 2 The number of neurons in the hidden layer of ANN models

Number neurons in hidden layer	Network result													
	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
8	0.7616	0.5927	0.7893	0.5618	0.7240	0.8048	0.7418	0.3644	0.6828	0.8806	0.7399	0.6409	7	9	16
9	0.8055	0.4504	0.7858	0.5600	0.7138	0.8185	0.8613	0.3421	0.7046	0.8556	0.7742	0.6053	9	5	14

Table 3 The *MSE* of ANN models with the difference neurons in the hidden layer

Number neurons in hidden layer	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	Rank Train	Rank Test	Sum Rank
1	$4.39E^{-05}$	$7.59E^{-05}$	$3.66E^{-05}$	$6.47E^{-05}$	$4.49E^{-05}$	$3.03E^{-05}$	$3.94E^{-05}$	$5.49E^{-05}$	$4.95E^{-05}$	$2.90E^{-05}$	$4.2853E^{-05}$	$5.096E^{-05}$	3	6	9
2	$4.96E^{-05}$	$1.31E^{-04}$	$5.24E^{-05}$	$7.18E^{-05}$	$4.05E^{-05}$	$4.14E^{-05}$	$3.59E^{-05}$	$6.91E^{-05}$	$4.64E^{-05}$	$3.39E^{-05}$	$4.4957E^{-05}$	$6.9421E^{-05}$	1	1	2
3	$3.96E^{-05}$	$8.56E^{-05}$	$3.67E^{-05}$	$5.26E^{-05}$	$8.34E^{-05}$	$8.26E^{-05}$	$3.00E^{-05}$	$5.99E^{-05}$	$4.06E^{-05}$	$1.68E^{-05}$	$4.6054E^{-05}$	$5.9519E^{-05}$	2	2	4
4	$3.39E^{-05}$	$5.48E^{-05}$	$3.91E^{-05}$	$6.71E^{-05}$	$4.43E^{-05}$	$4.40E^{-05}$	$3.04E^{-05}$	$4.26E^{-05}$	$5.52E^{-05}$	$3.25E^{-05}$	$4.0574E^{-05}$	$4.8204E^{-05}$	4	7	11
5	$3.63E^{-05}$	$6.10E^{-05}$	$2.83E^{-05}$	$7.05E^{-05}$	$2.84E^{-07}$	$3.43E^{-05}$	$3.50E^{-05}$	$4.79E^{-05}$	$3.76E^{-05}$	$1.40E^{-05}$	$2.7496E^{-05}$	$4.5546E^{-05}$	9	9	18
6	$2.45E^{-05}$	$7.87E^{-05}$	$2.87E^{-05}$	$5.91E^{-05}$	$4.03E^{-05}$	$4.15E^{-05}$	$2.98E^{-05}$	$6.77E^{-05}$	$3.67E^{-05}$	$3.55E^{-05}$	$3.1973E^{-05}$	$5.6501E^{-05}$	8	4	12
7	$4.44E^{-05}$	0.0001021	$3.59E^{-05}$	$5.47E^{-05}$	$4.41E^{-05}$	$4.41E^{-05}$	$3.14E^{-05}$	$6.70E^{-05}$	$4.44E^{-05}$	$2.35E^{-05}$	$4.0052E^{-05}$	$5.827E^{-05}$	5	3	8
8	$2.84E^{-05}$	$6.40E^{-05}$	$2.74E^{-05}$	$5.19E^{-05}$	$3.35E^{-05}$	$3.22E^{-05}$	$3.94E^{-05}$	$6.73E^{-05}$	$4.02E^{-05}$	$1.92E^{-05}$	$3.379E^{-05}$	$4.6927E^{-05}$	6	8	14
9	$2.34E^{-05}$	$8.68E^{-05}$	$2.87E^{-05}$	$5.36E^{-05}$	$3.42E^{-05}$	$2.94E^{-05}$	$4.13E^{-05}$	$6.25E^{-05}$	$4.02E^{-05}$	$3.28E^{-05}$	$3.3566E^{-05}$	$5.3008E^{-05}$	7	5	12

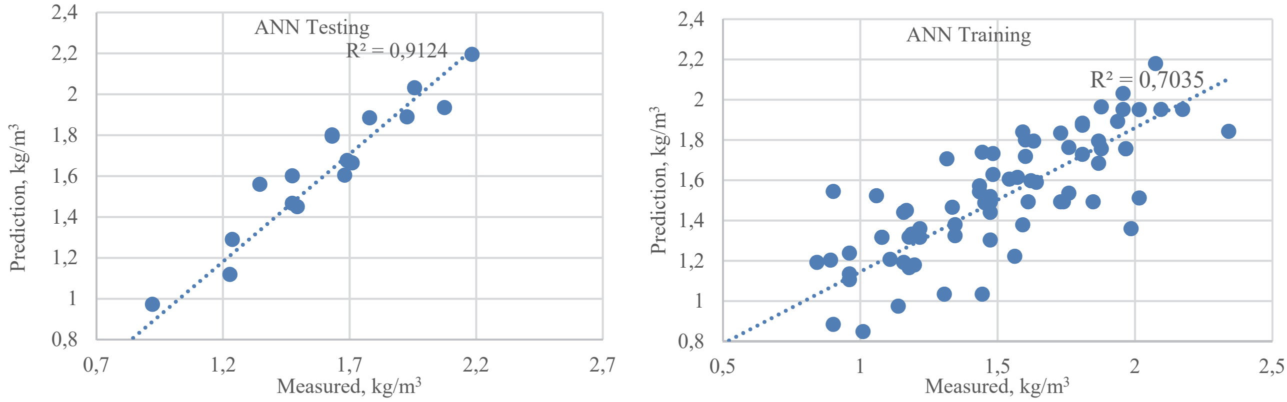

Figure 4 The coefficient of determination between measured values of specific charge and predicted values by optimal ANN models

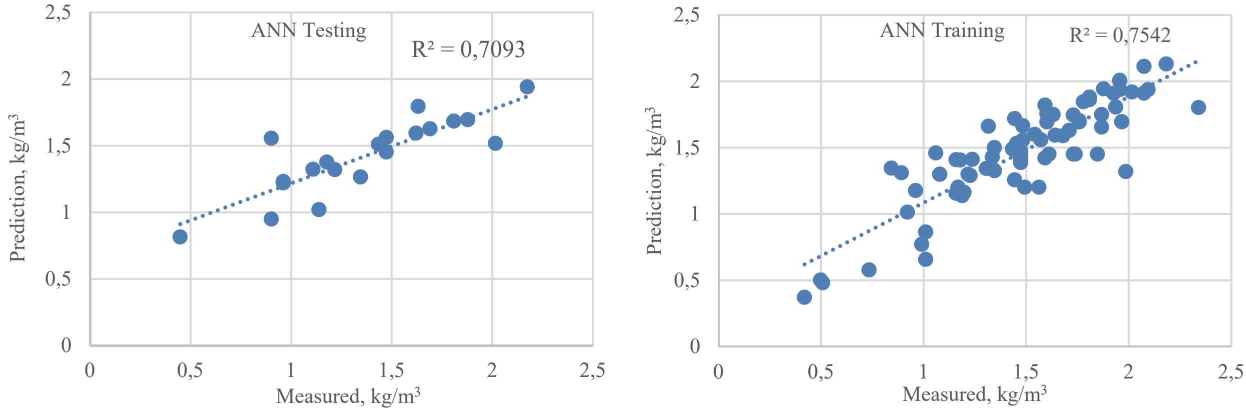

Figure 5 The coefficient of determination by ANN models using the databases of RF models

4.2 Results of Random Forest Models

Similar to artificial intelligence models that utilize artificial neural networks to predict and calculate the specific charge (q, kg/m^3) during tunnel construction using the drilling-blasting technique, the artificial intelligence models employing RF techniques also require determining parameters to optimize their effectiveness. This paper built RF models with various important parameter values using the trial-and-error techniques approach. Use the Iteration 5 dataset to construct the RF models. Iteration 5 is considered the most suitable dataset for achieving accurate q-prediction results with ANN models. Based on the corresponding mean squared error (*MSE*) parameter value of each model (Fig. 6), the paper proceeds to propose a model with the most optimal parameter values, prioritizing accuracy in predicting the specific charge (q, kg/m^3). The data set used to construct and train the RF model consists of 100 data points collected and synthesized at the Deo Ca tunnel construction site (the same dataset used for building ANN models).

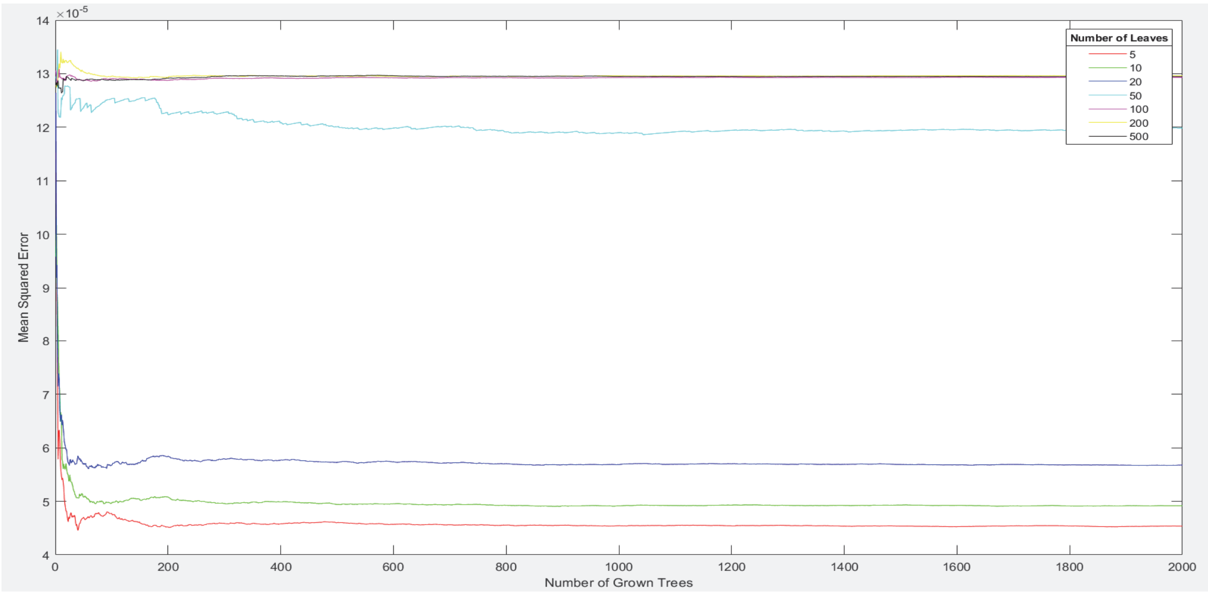

Figure 6 The number of trees and number of leaves in the algorithm RF

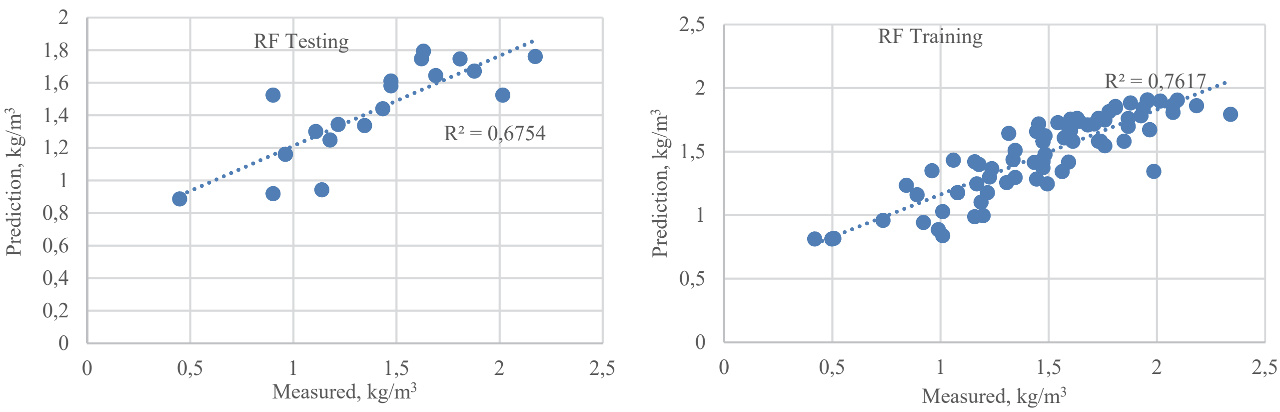

Figure 7 The coefficient of determination between measured values of specific charge and predicted values by RF models.

To assess the accuracy of the RF model, such as the ANN artificial neural network model, the authors can utilize two metrics: the coefficient of determination R^2 and the mean squared error *MSE* (or root mean square error *RMSE*). The findings from the RF model can be found in Fig. 7.

4.3 Discussion

From the results obtained using artificial intelligence models, specifically ANN and RF models, for predicting and calculating the specific charge (q, kg/m^3) in tunnel construction using the drilling and blasting methods, let's compare and contrast the prediction performance of these models. This paper could assess their performance through parameters such as the coefficient of determination (R^2) and the mean squared error (*MSE*). These parameters are crucial in evaluating the efficiency of the artificial intelligence models designed to predict the specific charge (q, kg/m^3) during tunnel construction. It should be noted that the dataset used to construct and predict the optimal specific charge (q, kg/m^3) in the RF models was also used to build and predict the specific charge (q, kg/m^3) in the ANN model (Fig. 5). This approach aims to ensure consistent forecast results between the ANN and RF models by employing the same dataset. The specific charge for measured and estimated data obtained from ANN models and RF models were shown in Figs. 6, 7, 8 and 9.

The results of applying these models are compared. The comparison shows that the predictive performance of the ANN model is better than that of the RF models for predicting the specific charge (q, kg/m^3). The training and testing data produced R^2 values of 0.7617 and 0.6754, respectively, in the RF model. In comparison, the ANN model had R^2 values of 0.7542 and 0.7093 in training data and testing data. For the training and testing data, the RF model had *MSE* values of 0.20065 and 0.25358, while the equivalent values for the ANN model were 0.20069 and 0.24675.

Based on the results obtained from the ANN and RF computer techniques, it is evident that these artificial intelligence models can accurately predict and calculate the specific charge (q, kg/m^3) with a high level of accuracy. This capability fulfills the practical requirements when constructing tunnels using the drilling and blasting method.

Among the three input variables used to predict the specific charge (q, kg/m^3) in the ANN and RF models, the rock mass index (*RMR*) parameter has the most significant influence on the analysis of the specific charge (q, kg/m^3) (Fig. 10). This has demonstrated the influence of the physical and mechanical properties of the soil and rock environment where the tunnel is located on the efficiency and corresponding values of the parameters during the process of drilling, blasting, and breaking soil and rock for tunnel construction.

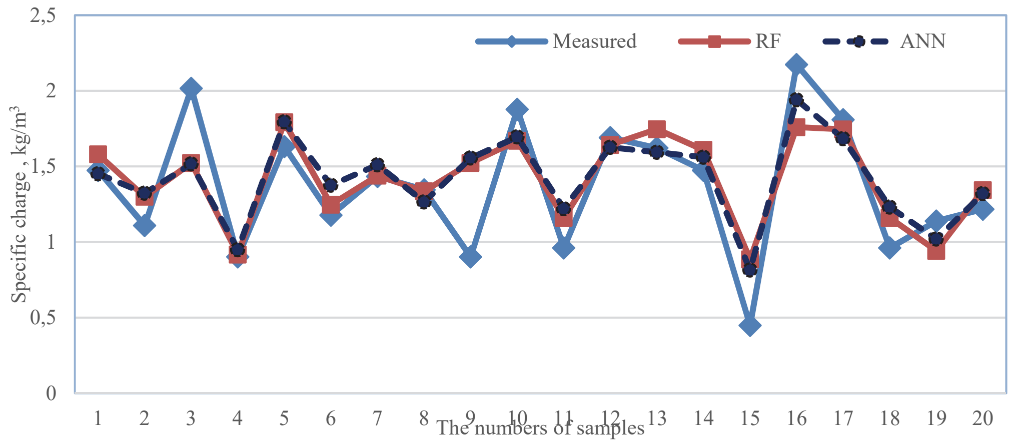

Figure 8 The specific charge values from the testing database were measured and predicted using ANN and RF models.

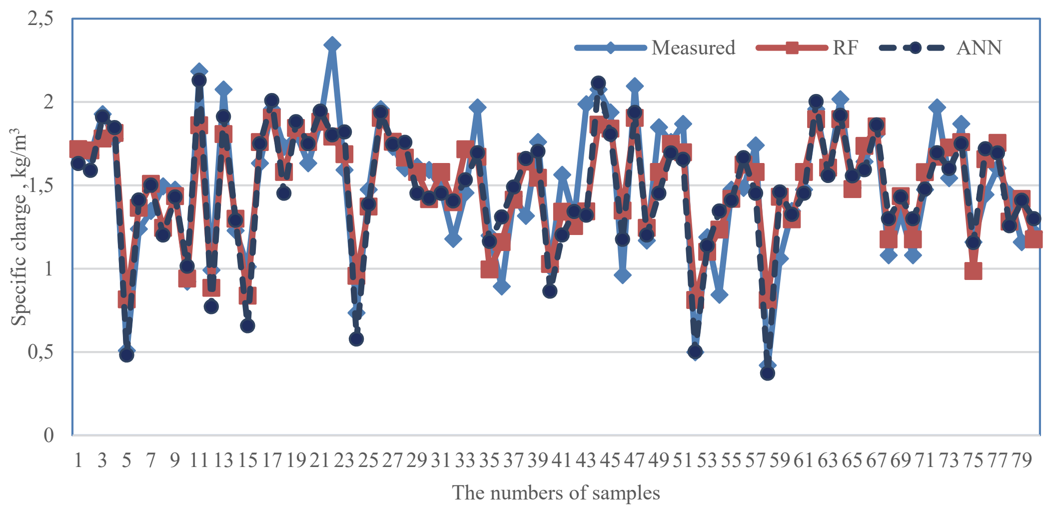

Figure 9 The specific charge values from the training database were measured and predicted using ANN and RF models

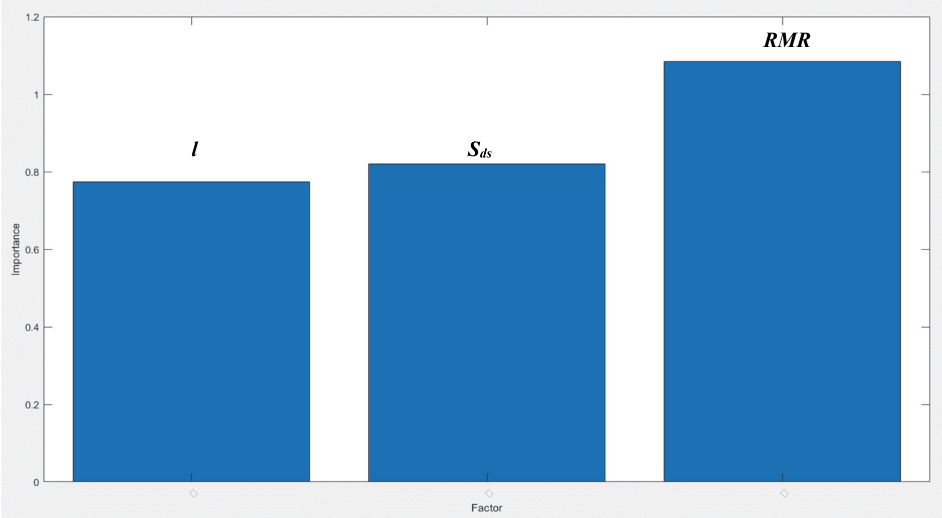

Figure 10 The impact of Input variables to output variables

5 CONCLUSION

The paper has developed and identified the most effective structure for Artificial Neural Network (ANN) and Random Forest (RF) models. These models were based on datasets obtained from the actual construction of the Deo Ca traffic tunnel in Phu Yen, Vietnam. The paper presented the results of the R^2 and *MSE* parameters for both ANN and RF models. The following conclusions were drawn:

- Artificial intelligence models, especially those using Artificial Neural Networks (ANNs) and Random Forests (RF), can accurately predict the specific charge (q, kg/m^3) required for blasting. This leads to improved tunnel design and construction when using the drill and blast method, enhancing both progress and safety. Accurate prediction of the specific charge value helps in calculating and establishing a more optimal drilling and blasting passport. Precise predictions of specific charge (q, kg/m^3) allow adjustments to the parameters and number of holes drilled on the tunnel face, maximizing blasting efficiency. This results in better control of overbreak and underbreak areas after blasting, and improved borehole utilization;
- The ANN models outperformed the RF models in this study. The training data set for the ANN models showed a slightly lower coefficient of determination (R^2) and a lower mean square error (*MSE*) compared to the RF models, however, the differences were negligible. In the testing data set, the ANN models achieved better results than the RF models in terms of both R^2 and *MSE*;
- It is crucial to accurately determine the significant parameters in ANN and RF models to optimize their performance. In ANN models, these parameters include the number of hidden layers, the number of neurons in the hidden layer, the activation function, and the processing algorithm. For RF models, the important parameters to consider are the number of trees and leaves in the RF computing technique;
- When using AI models in different situations, it is important to adapt them accordingly. Since each tunnel has unique requirements and characteristics, effectively using AI models to predict the specific charges in drill and blast methods for tunnel construction requires updating the input and output data used to build these models. The structure and performance of these models depend on the values of the corresponding input and output data;
- Adjusting and normalizing data to align with the algorithm models is essential. Calibrating and normalizing data will improve the model's performance by ensuring the transfer functions operate correctly within the specified data range.

Acknowledgements

This research is supported by Vietnam National Coal and Mineral Industries Holding Corporation Limited (Vinacomin) under grant number: KC.01.Đ06-25/21-25. We thank two anonymous reviewers for their comments that were very valuable for revising the manuscript.

6 REFERENCES

[1] Pokrovsky, N. M. (1980). *Driving horizontal workings and tunnels.* Mir Publishers, Moscow.
[2] Lilly, P. A. (1986).An empirical method of assessing rock mass blastability. *Large Open Pit Mining Conference*, 89-92.
[3] Ghose, A. K. (1998).Design of drilling and blasting subsystems - a rock mass classification approach. *Proceedings of International Symposium on Mine Planning & Equipment Selection*, 335-340.
[4] Hagan, T. N. (1992). Safe and cost-efficient drilling and blasting for tunnels, caverns, shafts and raises in India. *Proceedings of a Workshop on Blasting Technology for Civil Engineering Projects*, 16-18.
[5] Kahriman, A., Özkan, Ş. G., Sül, Ö. L., Demirci, A. (2001). Estimation of the powder factor in bench blasting from the Bond work index. *Mining Technology*, *110*(2), 114-118. https://doi.org/10.1179/mnt.2001.110.2.114
[6] Chakraborty, A. K., Jethwa, J. L., & Dhar, B. B. (1997). Predicting powder factor in mixed-face condition: development of a correlation based on investigations in a tunnel through basaltic flows.*Engineering Geology*, *47*(1-2), 31-41. https://doi.org/10.1016/S0013-7952(96)00117-2
[7] Alipour, A., Jafari, A., & Hossaini, S. M. F. (2012). Application of ANNs and MVLRA for Estimation of Specific Charge in Small Tunnel. *International Journal of Geomechanics*, *12*(2), 189-192. https://doi.org/10.1061/(ASCE)GM.1943-5622.0000125

[8] Alipour, A., Mokhtarian, M., & Abdollahei Sharif, J. (2012). Artificial neural network or empirical criteria? A comparative approach in evaluate maximum charge per delay in surface mining - Sungun copper mine. *Journal of the Geological Society of India*, *79*(6), 652-658. https://doi.org/10.1007/s12594-012-0102-3

[9] Alipour, A., Mokhtarian-Asl, M., & Asadizadeh, M. (2021). Support Vector Machines for the Estimation of Specific Charge in Tunnel Blasting. *Periodica Polytechnica Civil Engineering*, *65*(3), 967-976. https://doi.org/10.3311/PPci.17790

[10] Monjezi, M. & Dehghani, H. (2008). Evaluation of effect of blasting pattern parameters on back break using neural networks. *International Journal of Rock Mechanics and Mining Sciences*, *45*(8), 1446-1453. https://doi.org/10.1016/j.ijrmms.2008.02.007

[11] Jang, H. & Topal, E. (2013). Optimizing over break prediction based on geological parameters comparing multiple regression analysis and artificial neural network. *Tunnelling and Underground Space Technology*, *38*, 161-169. https://doi.org/10.1016/j.tust.2013.06.003

[12] Armaghani, D. J., Hajihassani, M., Mohamad, E. T., Marto, A., & Noorani, S. A. (2014). Blasting-induced flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization. *Arabian Journal of Geosciences*, *7*(12), 5383-5396. https://doi.org/10.1007/s12517-013-1174-0

[13] Mohammad, E., Morteza, O., Rashidinejad, F., Aghajani, B. A., & Mohammad, T. (2014). Multiple regression, ANN and ANFIS models for prediction of backbreak in the open pit blasting. *Engineering with Computers*, *30*, 549-558. https://doi.org/10.1007/s00366-012-0298-2

[14] Sonmez, H., Gokceoglu, C., Nefeslioglu, H. A., & Kayabasi, A. (2016). Estimation of rock modulus: for intact rocks with an artificial neural network and for rock masses with a new empirical equation. *International Journal of Rock Mechanics and Mining Sciences*, *43*(2), 224-235. https://doi.org/10.1016/j.ijrmms.2005.06.007

[15] Chi, T. N., Do, N. A, Pham, V. V., Nguyen, P. T., & Gospodarikov, A. (2022). Prediction of blast-induced the area of the tunnel face in underground excavations using fuzzy set theory ANFIS and artificial neural network ANN. *International Journal of GEOMATE*, *23*(95), 136-143. https://doi.org/10.21660/2022.95.3327

[16] Chi,T.N., Nghia,V.N. (2023). Prediction of Tunnel Cross-Sectional Area after Blasting. *Inżynieria Mineralna*, *2*(52), 39-49. https://doi.org/10.29227/IM-2023-02-11

[17] Breiman, L. (2001). Random Forests. *Machine Learning*, *45*, 5-32. https://doi.org/10.1023/A:1010933404324

[18] Aldrich, C. (2020). Process Variable Importance Analysis by Use of Random Forests in a Shapley Regression Framework. *Minerals*, *10*(5), 420. https://doi.org/10.3390/min10050420

Contact information:

Tung Manh BUI, PhD
Department of Underground Mining,
Hanoi University of Mining and Geology,
18 Vien Stress, Duc Thang, Bac Tu Liem, Hanoi, Vietnam
E-mail: buimanhtung@humg.edu.vn

Hiep Hoang DO, PhD Student
Department of Underground Mining,
Hanoi University of Mining and Geology,
18 Vien Stress, Duc Thang, Bac Tu Liem, Hanoi, Vietnam
E-mail: hiepdo2709@gmail.com

Nhan Thi Pham, PhD
Faculty of Civil Engineering, Hanoi University of Mining and Geology,
18 Vien Stress, Duc Thang, Bac Tu Liem, Hanoi, Vietnam
E-mail: phamthinhan@humg.edu.vn

Nghia Viet NGUYEN, PhD, Associate Professor
Department of Mine Surveying,
Hanoi University of Mining and Geology,
18 Vien Stress, Duc Thang, Bac Tu Liem, Hanoi, Vietnam
E-mail: nguyenvietnghia@humg.edu.vn

Chi Thanh NGUYEN, PhD, Associate Professor
(Corresponding author)
Department of Underground and Mining Construction,
Hanoi University of Mining and Geology,
18 Vien Stress, Duc Thang, Bac Tu Liem, Hanoi, Vietnam
Tunnelling and Underground Space Technology (TUST), Hanoi, Vietnam
E-mail: nguyenthanh.xdctn47@gmail.com; nguyenchithanh@humg.edu.vn