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APPLICATION OF THE ANN AND RANDOM FOREST MODELS FOR PREDICTING THE AREA OF THE TUNNEL FACE AFTER THE BLASTING

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ABSTRACT: To evaluate the effectiveness of underground construction methods using drilling and blasting, the area of the tunnel face after blasting has been used for the following reason: it is the main determining factor in the amount of work needed when constructing tunnels. Therefore, determining and predicting the area of the tunnel face after blasting in advance will greatly affect the completion of underground works, construction progress, and safety. This paper utilizes ANN (Artificial Neural Network) and RF (Random Forest) algorithms to predict the area of the tunnel face after blasting based on four input parameters (input variables): average borehole depth on the tunnel face (l, m), area of the tunnel face after the blasting when designed (D, m^2), specific charge used during the tunnel construction (q, kg/m^3), and the rock mass rating (RMR) where the tunnel is located. Based on comparisons of the obtained results from these artificial intelligence models with the actual results from the construction process of the Deo Ca tunnel, Phu Yen, Vietnam (the RF model achieved R^2 values of 0.9058 and 0.891 for training and testing data, respectively. On the other hand, the ANN model had R^2 values of 0.8818 and 0.894. In the RF model, with RMSE values of 0.15975 and 0.1774 for training and testing data, respectively, with equivalent RMSE values of 0.1634 and 0.1683 for the ANN model), the paper confirms the ability to predict the area of the tunnel face after the blasting during construction with high accuracy using artificial neural networks ANN and Random Forest models.

Keywords: Tunnel face, Blasting, Predict, ANN, Random Forest, Models

1. INTRODUCTION

Tunnels and underground constructions are essential components of a complete infrastructure system. Currently, various construction methods are available for building tunnels. Each method has its own advantages and disadvantages. The drilling and blasting method is a commonly used and well-established approach due to its simplicity and cost-effectiveness compared to other methods. However, other construction methods can also be employed based on specific requirements [1, 2].

During the design and construction process of tunnels using the drilling and blasting method, the area of the tunnel face after blasting plays a crucial role. Evaluating the effectiveness of construction methods heavily relies on this factor, as it determines the volume of work required for tunnel construction. Several studies have been conducted to accurately determine the extent of the tunnel face after blasting [3]. Currently, two main research methods are employed for this purpose: experimental and numerical simulation approaches [4, 5]. Lately, scientists have successfully developed artificial intelligence models capable of predicting the tunnel face area after blasting with high accuracy. These models offer advantages such as high accuracy and quick forecast, meeting the requirements of tunnel design and construction [6, 7].

According to Adel Mottahedi et al., 2018 [4], there exist multiple parameters that influence the value of the tunnel face area after blasting. These parameters can be categorized into two groups. The first group comprises parameters that can be controlled and adjusted to achieve a highly accurate value of the tunnel face area after an explosion compared to the designed area. These parameters include the depth and diameter of the borehole, properties of the explosives used, and tunnel design features such as the shape of the tunnel face area. The second group consists of uncontrollable parameters, such as geological conditions (particularly rock properties and fracture systems) and hydrogeological conditions. These parameters significantly impact the tunnel face area after blasting, depending on their specific characteristics [8].

In this paper, the authors conducted research to identify parameters that have the greatest influence on tunnel mirrors after blasting when using the drilling and blasting method for tunnel construction, including average borehole depth on the tunnel face (l, m), area of the tunnel face after the blasting when designed (D, m^2), specific charge used during the tunnel construction (q, kg/m^3), and the rock mass rating (RMR) where the tunnel is located. The study utilized 110 databases obtained from the construction process of the DeoCa tunnel in Phu

Yen, Vietnam. The author applied the ANN (Artificial Neural Network) and RF (Random Forest) techniques, successfully developing artificial intelligence models. These models accurately predict the area of the tunnel face after blasting. By comparing the predicted results from ANN (Artificial Neural Network) and RF (Random Forest) models with the corresponding actual measurements, the study demonstrates the ability to use these models for highly accurate predictions for the area of the tunnel face after blasting. This has the potential to improve the efficiency of tunnel construction when employing the drilling and blasting method.

2. DATABASE FOR CASE STUDY

To predict the area of the tunnel face after blasting, this paper used 110 datasets obtained during the construction process to develop artificial intelligence models to predict the area of the tunnel face after blasting A (m^2). After conducting an analysis, the paper identified four parameters that significantly impact the tunnel's mirror area. These parameters are: the average length of the boreholes (l, m); the design area of the tunnel face (D, m^2); the specific charge used during tunnel construction (q, kg/m^3); the rock mass rating (RMR) for the tunnel's location.

During the construction of the DeoCa traffic tunnel, a total of 110 datasets were collected. Out of these, 80% of datasets (88 data points) are used to train artificial intelligence models that can predict the area of the tunnel's mirrors after blasting. The remaining 20% of datasets (22 data points) are used to verify the accuracy of these models.

Fig. 1 The DeoCa tunnel.

To ensure the accuracy of the results presented in the paper, it is important to normalize both the input and output data. In this study, the data was normalized using the following Eq. (1). The normalization of data in models depends on the transfer functions used in models. The normalization process brings the data within a range of -1 to 1 [8, 11].

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

Where Y and Y_n represent the measured and normalized values, respectively. Y_{min} is the minimum measured parameters and Y_{max} is the maximum measured parameters, respectively. Table 1 presents the limited range of values associated with these parameters.

Table 1. The input and output parameters

The parameters	Min	Max	Mean	Std. Deviation
A (The area of tunnel face after blasting, m^2) – Output	50.27	71.05	58.23	6.38
l (the average boreholes length, m) – Input	1.0	3.2	1.95	0.64
D (The design area of tunnel face, m^2) – Input	49.26	64.85	54.55	6.16
q (specifc charge, kg/m^3) – Input	0.37	2.32	1.434	0.41
RMR (rock mass rating) – Input	5.0	73.0	51.33	14.53

3. THE AREA OF THE TUNNEL FACE PREDICTION MODELS

3.1 Artificial Neural Network (ANN)

Artificial neural networks are one of the earliest computer techniques used to apply artificial intelligence in various engineering fields. They are capable of building and developing prediction models by finding relationships within a set of data. Similar to the human brain, artificial neural networks consist of layers of neurons. There are two main types of artificial neural networks. The first type is a simple form with three layers: input layer, hidden layer, and output layer. The input layer receives information from the outside world, and the input nodes process, analyze, and classify the data before passing it to the next layer. The hidden layer receives data from the input layer or other hidden layers, processes it further, and transfers it to the next layer. Finally, the output layer produces the final result based on the data processed by the network.

The second type, called a deep neural network or deep learning network, is more complex. It consists of multiple hidden layers with interconnected artificial neurons, often totaling millions. The connections between nodes are represented by weights, which can be positive or negative. Positive weights indicate stimulation between nodes, while negative weights represent inhibition. Nodes with higher weights have a greater influence on other nodes. In theory, deep neural networks can map any type of input data to any type of output data. However, they require much more training compared to simpler networks. While a simpler network may need hundreds or thousands of training examples, deep neural networks typically require millions.

In artificial neural networks ANN, several algorithms have been suggested for training models. Out of the mentioned algorithms, the most widely used one is BP, short for backpropagation. This algorithm is commonly employed in MLP feedforward artificial neural networks. Backpropagation calculates the gradient of neural network parameters. To put it simply, it traverses the network in reverse, going from the output to the input, following the chain rule in calculus [5, 6].

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

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.

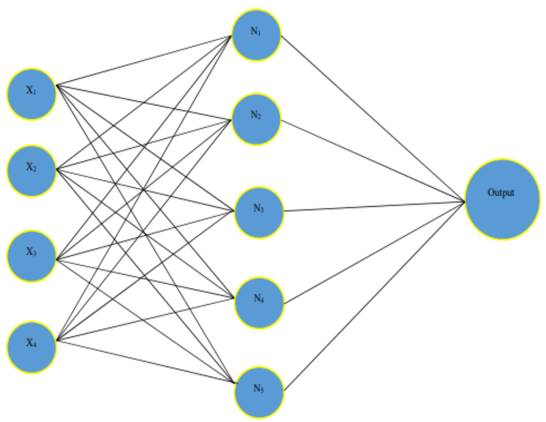

Fig.2 Structure of the ANN models

By using BP algorithm, artificial neural networks learn continuously by using a feedback loop to improve their predictive analysis. To put it simply, data flows from input nodes to output nodes through various paths in the neural network. Among these paths, there is only one correct path that maps the input node to the appropriate output node. The neural network employs a feedback loop to discover this path, which operates as follows:

1, Each node predicts the next node in the path.

2, The accuracy of the prediction is evaluated. Nodes assign higher weight values to paths with more accurate predictions and lower weight values to paths with incorrect predictions.

3, When encountering the next data point, the nodes make new predictions using the paths with higher weights and then repeat step 1 [8, 9].

3.2. Random Forest (RF)

Random forest (RF) is a statistical machine learning method that serves the purposes of classification, regression, and other tasks by creating multiple decision trees. The Random Forest algorithm constructs numerous decision trees through the Decision Tree algorithm, with each tree containing a random element, resulting in different trees. The prediction results are then compiled from these decision trees. Random forests are highly effective in machine learning as they can address overtraining problems encountered by single decision trees. During training, RF builds multiple decision trees to perform tasks such as classification, regression, and others.

In artificial intelligence models that use RF techniques, two parameters play a significant role and must be determined: the number of trees and the number of leaves.

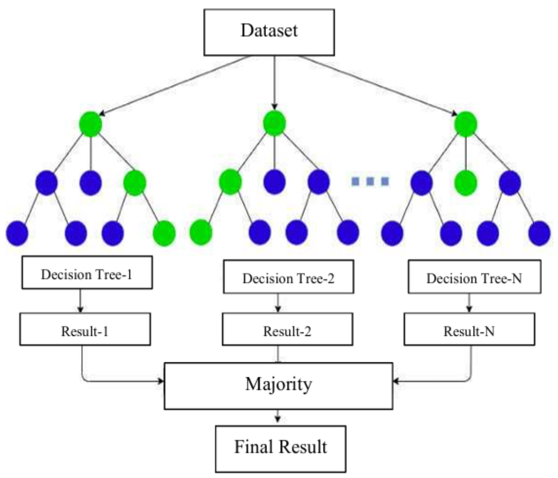

Fig. 3 Structure of RF Regression models [12]

4. RESULTS AND DISCUSSION

In the paper, four parameters are considered to have the greatest influence on the area of the tunnel face after blasting, including: the average length of the boreholes (l, m); the design area of the tunnel face (D, m^2); the specific charge used during tunnel construction (q, kg/m^3); the rock mass rating (RMR) for the tunnel's location, listed and used in datasets to build and develop artificial intelligence models to predict the area of the tunnel face after blasting. The coefficient of determination R^2 and the root mean square error RMSE are the known statistical indexes to be evaluated the network performance. Using data sets compiled during the construction process of the DeoCa traffic tunnel that were normalized in the range [-1; 1] to build artificial intelligence models using artificial neural networks ANN and the Random forest RF technique capable of predicting the area of the tunnel face after blasting, the paper has obtained some results.

4.1 Results of ANN models

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 trial-and-error technique, the paper determined the following optimal parameters for the ANN model:

- The structure of the artificial neural network is 4x5x1. The ANN model consists of 1 hidden layer with 5 neurons (based on these values: 4, 5, 6, 7, 8, and 9 is the number of neurons in the hidden layer, six ANN models were built, as presented in Table 2 and Table 3) that is the best ANN configuration;

-The activation function used in this model is the tang function.

-The ANN model has 4 input variables: Average length of the boreholes (l, m); Design area of the tunnel face (D, m^2); Specific charge used during tunnel construction (q, kg/m^3); Rock mass rating (RMR) for the tunnel's location. The model provides 1 output variable, which is the area of the tunnel face after blasting S, m^2.

Based on the coefficient of determination R^2 and the root mean square error RMSE to evaluate the accuracy of the ANN artificial intelligence model capable of predicting the area of the tunnel face after blasting (Figs 3, 4, 5, 6, 7, 8).

4.2. Results of Random forest models

The corresponding results are shown in Figure 6. Based on the results obtained from the built and run cases of the RF model, it is found that the optimal RF model is the model with 200 trees, and the number of leaves is 5.

Table 2. Determine the optimal number of neurons in the hidden layer of the ANN model through R^2

Number of neurons in hidden layer	Model 1		Model 2		Model 3		Model 4		Model 5		Average R^2	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing		
	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	Training	Testing
4	0.9001	0.8371	0.8457	0.7855	0.9012	0.8466	0.9005	0.8658	0.9063	0.8782	0.890766	0.842634
5	**0.9267**	**0.7740**	**0.8955**	**0.8819**	**0.9030**	**0.9107**	**0.9301**	**0.8726**	**0.8903**	**0.9170**	**0.909122**	**0.871239**
6	0.9128	0.5749	0.9035	0.7643	0.9695	0.9163	0.9090	0.8658	0.8850	0.9137	0.915949	0.806986
7	0.9065	0.7088	0.9094	0.6581	0.8915	0.8722	0.9090	0.8751	0.8952	0.9191	0.902315	0.806689
8	0.8910	0.6123	0.8873	0.6147	0.8480	0.8935	0.9026	0.8079	0.8726	0.8538	0.880296	0.756452

Table 3. Determine the optimal number of neurons in the hidden layer of the ANN model through RMSE

Number of neurons in hidden layer	Model 1		Model 2		Model 3		Model 4		Model 5		Average R^2	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing		
	RMSE	RMSE	RMSE	RMSE	RMSE	RMSE	RMSE	RMSE	RMSE	RMSE	Training	Testing
4	0.1646	0.2261	0.1895	0.2163	0.1543	0.1972	0.1449	0.2078	0.1411	0.1895	0.158869	0.207387
5	**0.1378**	**0.1700**	**0.1606**	**0.1729**	**0.1473**	**0.1497**	**0.1225**	**0.2236**	**0.1526**	**0.1487**	**0.144178**	**0.17297**
6	0.1500	0.2202	0.1483	0.2300	0.1575	0.1559	0.1360	0.2078	0.1562	0.1565	0.149605	0.194097
7	0.1612	0.2522	0.1432	0.2683	0.1694	0.1786	0.1360	0.2128	0.1533	0.1616	0.152629	0.214703
8	0.1673	0.2522	0.1600	0.2985	0.1852	0.1587	0.1510	0.2236	0.1676	0.2177	0.166232	0.230151

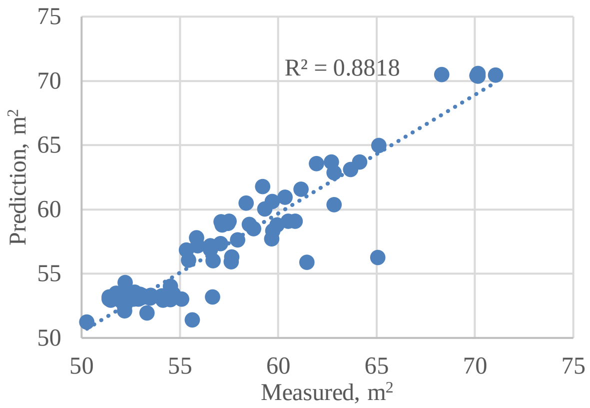

Fig. 4 R^2 values of the ANN model for training datasets

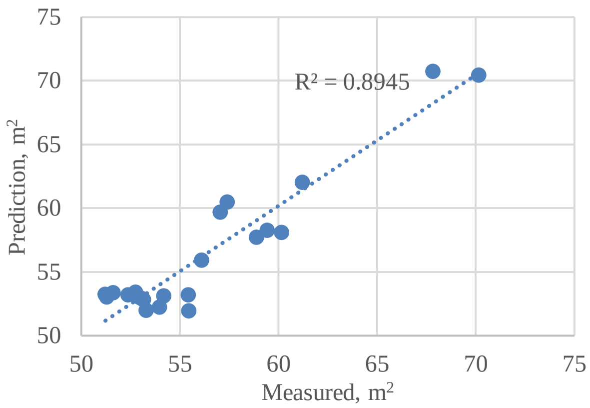

Fig. 5 R^2 values of the ANN model for testing datasets

Use the coefficient of determination R^2 and the root mean square error RMSE to evaluate the accuracy of the RF model, similar to the ANN artificial neural network model. The results of the RF model are presented in Figure 6.

4.3. Dicussion

Based on the results obtained by the ANN models and RF models when using these models to predict the area of area of the tunnel face after blasting, compared the prediction performance of these models with each other. Statistical indexes such as coefficient of determination R^2, and root mean square error (RMSE) are statistical indexes of the models used for comparison. The results of the ANN models and RF models were shown and compared in Figs 8, 9. The area of the tunnel face after blasting for measured and estimated data obtained from ANN models and RF models were shown in Figs. 4, 5, 7, 8, and 9. According to these figures, the RF model showed better prediction performance compared to the ANN model. It achieved R^2 values of 0.9058 and 0.891 for training and testing data, respectively. On the other hand, the ANN model had slightly lower R^2 values of 0.8818 and 0.894. The RF model, with RMSE values of 0.15975 and 0.1774 for training and testing data, respectively, with equivalent RMSE values of 0.1634 and 0.1683 for the ANN model. This indicates that the RF technique is superior to the ANN technique in predicting the area of the tunnel face after blasting.

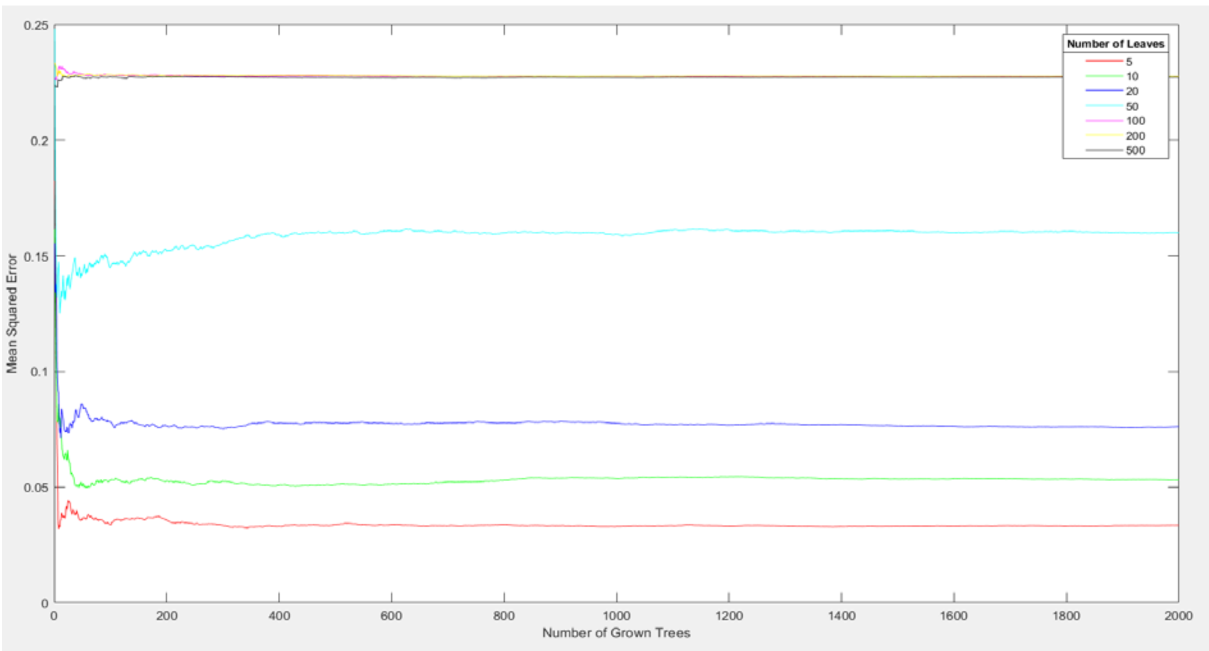

Fig. 6 Determine the optimal number of trees and leaves in the RF models

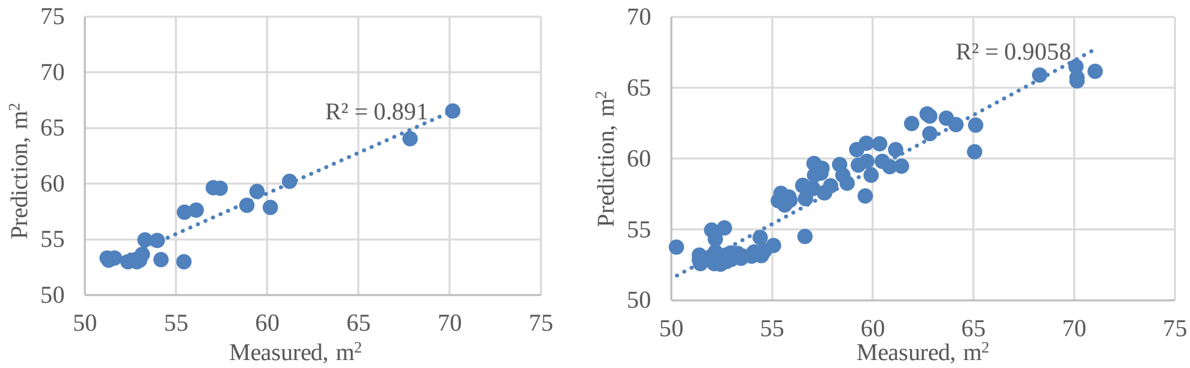

Fig. 7 Measured and predicted values of the tunnel face area after blasting obtained via the RF model for testing datasets and training datasets

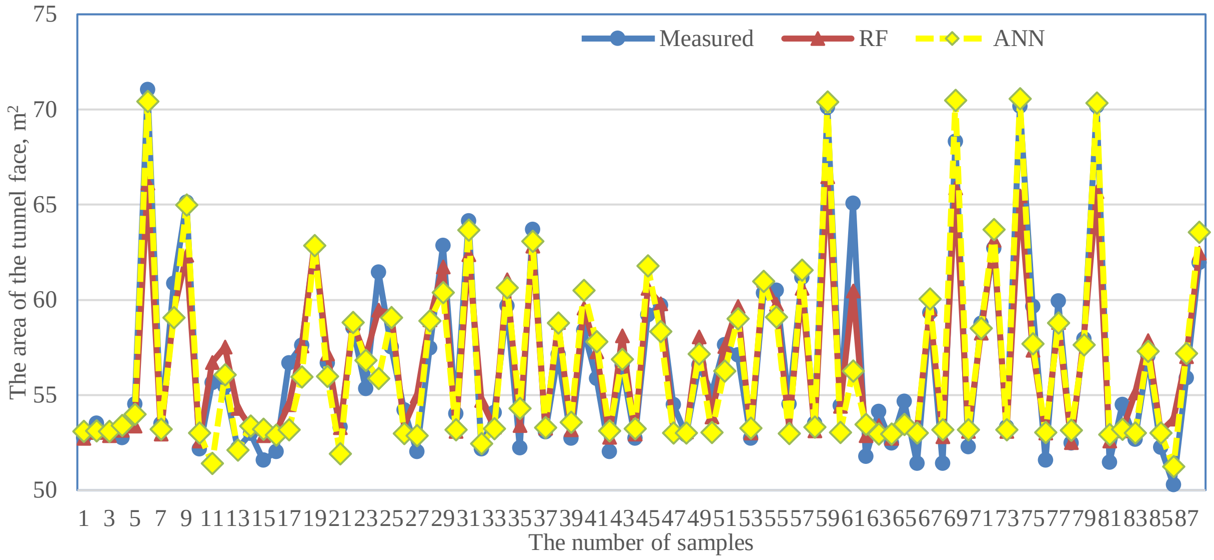

Fig. 8 Comparison of measured and predicted the tunnel face area after blasting for RF and the optimal ANN models in training databases

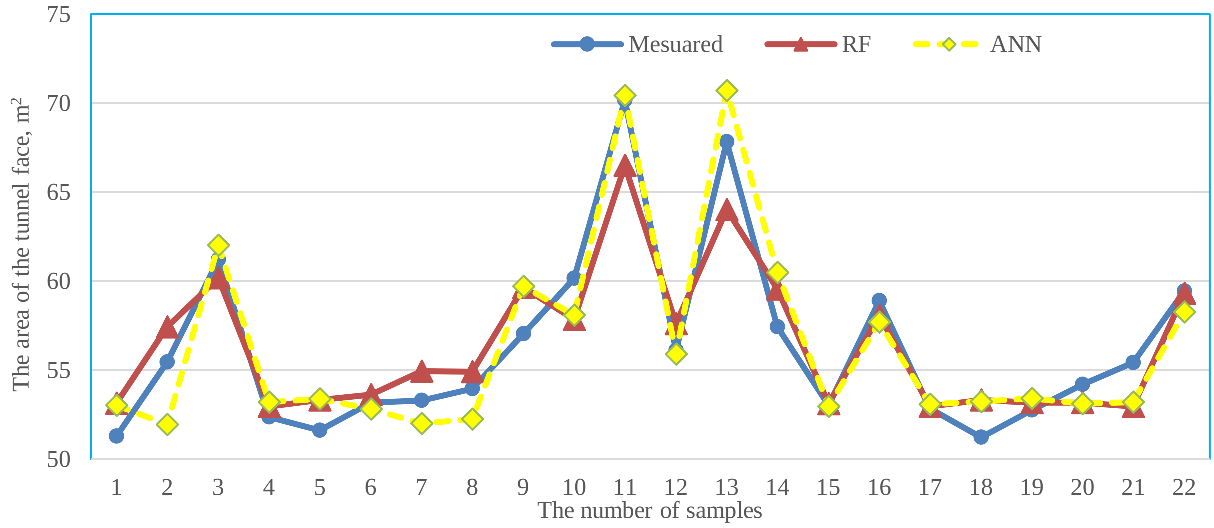

Fig. 9 Comparison of measured and predicted the tunnel face area after blasting for RF and the optimal ANN models in testing databases

5. CONCLUSION

The area of the tunnel face after blasting is a crucial factor that significantly impacts the quality and progress of tunnel construction when using the drilling and blasting method. In this paper, the authors utilized 110 databases collected and synthesized during the construction of the Deo Ca tunnel in Phu Yen, Vietnam. The paper employed artificial intelligence models, specifically the Artificial Neural Network (ANN) and Random Forest (RF) techniques, to accurately predict the tunnel face area after blasting. Through trial and error techniques, the paper determined the necessary parameters to achieve the highest performance in forecasting models.

For the ANN models, the paper constructed models with different structures. Based on the results, the paper confirmed that the optimal structure is 4x5x1, consisting of 4 input variables, 1 hidden layer with 5 neurons, and 1 output variable. The ANN model utilizes the backpropagation BP algorithm. In the models using the RF technique, we determined the optimal number of trees and leaves by analyzing the model results. Our findings established that using 200 trees (n) and 5 leaves (m) as parameters yields the highest performance for the RF model.

Based on the results of predicting the area of the tunnel face after blasting, some conclusions have been drawn:

- The ANN and RF techniques can be employed with high accuracy to predict the tunnel face area after blasting. By accurately forecasting this area, the drilling and blasting method can be more effective and contribute to faster construction progress, while ensuring safety.
- The RF model outperformed the ANN model in this case study.
- It is crucial to precisely determine the parameters for optimal ANN and RF models.
- Both ANN and RF models heavily rely on real data, necessitating adjustments when applied to objects with different characteristics.
- During the data collection, synthesis, and model-building process, it is important to carefully evaluate the influence of input variables on output variables. It is necessary to adjust the data to suit the algorithm models. Among the four input parameters used to build the ANN and RF models for predicting the tunnel face area after blasting, the area of the designed tunnel face has the greatest impact on the resulting area after blasting;
- To enhance the accuracy of the artificial intelligence models predicting the tunnel face area after blasting, future studies could utilize hybrid algorithms or optimization techniques to refine these prediction models.

6. ACKNOWLEDGMENTS

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