Prediction of Tunnel Cross-Sectional Area After Blastin

Chi Thanh NGUYEN[1)], Nghia Viet NGUYEN[1)]*

[1)] Faculty of Civil Engineering, Hanoi University of Mining and Geology, 18 Vien Stress, Hanoi, VietNam
*Corresponding author: nguyenthanh.xdctn47@gmail.com, nguyenchithanh@humg.edu.vn

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Abstract

In this paper, two methods to predict and calculate the area of the tunnel face after the blasting were used. The first one is an artificial intelligence method using an artificial neural network system (ANN) model, and the second one – the support vector regression (SVR). After building predictive models for the area of the tunnel face after blasting by both methods, on the basis of comparing the results obtained in both methods, the performance of these models was assessed through the root mean square error RMSE and the coefficient of determination R^2. RMSE and R^2 values of the artificial neural network system (ANN) model were obtained as 0.1473 and 0.903 in training datasets, respectively. These values are 0.1497 and 0.9107 in testing datasets. In the SRV model, RMSE and R^2 were equaled to 0.1228 and 0.9331 in training datasets, respectively. These values are 0.1708 and 0.9055, respectively in testing datasets. It can be concluded that artificial intelligence using ANN and SVM models can be used to predict the area of the tunnel face after blasting with high accuracy.

Keywords: *ANN, SVR, tunnel, the drilling-blasting method, the cross-sectional area of tunnel, prediction*

1. Introduction

The method of drilling-blasting to break up rocks during the construction of tunnels is one commonly applied method in Vietnam due to its advantages, including cost effectiveness, simplicity, and fast progress. Several parameters affect the quality of the drilling and blasting method, with the cross-sectional area of the tunnel after blasting being crucial. Currently, there are few analytical methods available to predict and calculate the post-blasting tunnel area. Typically, the post-blasting tunnel area is taken within the range of (1÷1.25) times the design area of the tunnel face. Some scientists have statistically analyzed key parameters affecting the post-blasting tunnel area. However, accurately predicting the post-blasting tunnel area remains challenging using analytical methods. Some studies have successfully utilized artificial intelligence, specifically ANN and ANFIS models, to accurately predict and calculate the post-blasting tunnel area compared to actual values. In this study, the authors applied artificial intelligence, employing ANN and support vector regression (SVR) models, to build accurate prediction models for the post-blasting tunnel area. The study utilized a dataset of 110 regression data points obtained during the construction of the Deo Ca traffic tunnel. For the ANN models, the data in the dataset were randomly shuffled to create different models, each with training and testing datasets in a 4:1 ratio. The training dataset accounted for 80% of the total database, while the testing dataset accounted for 20%. Both the ANN and SVR models used the cross-validation algorithm (K-fold cross-validation) with the total database divided into k equal parts. The model was trained using (k-1) parts, and the remaining part was used to check model accuracy. The study compared the predicted post-blasting tunnel area from the models with measured data obtained during tunnel construction using the drilling and blasting method. The results revealed that the SVR model demonstrated high applicability in accurately predicting the post-blasting tunnel area. These findings serve as a foundation for applying ANN and SVR to build artificial intelligence models capable of accurately calculating and predicting other drilling and blasting parameters.

2. The ANN model and SVM model

2.1. Support Vector Machine SVM

Support Vector Machine (SVM) are supervised learning models. In the SVM, associated learning algorithms that analyze data for classification or regression analysis (in case of used to analyze data for regression, SVM as SVR- Support Vector Regression). According Aref A., et al., 2021, Support Vector Regression could use the training dataset to build the predicting model.

In regression, the SVM maps the input vectors to a multidimensional feature space. Next, the SVM creates a hyper plane that separates the input vectors with the maximum possible distance.

With the database $\{x_k, y_k\}$, k = 1,2, ... s, $x_k \in R^m$ is the input vector, $y_k \in R^n$ is the corresponding value of the desired model output, s is the number of samples. SVM is simulated using the following function:

$$f(x)=<w, x> +b \tag{1}$$

where: $w, x \in R^m$, $<w, x>$ is the input data mapping function of the model, b is estimate bios, w is weight vector values.

The optimal hyperplane was elicited to maximize the distance between the data layers in terms of w and b, satisfying the equation:

$$\min\left(\frac{1}{2}\|w\|^2 + C\sum_{k=1}^{s}\varepsilon_i + \varepsilon_k^*\right) \tag{2}$$

With the following conditions to be satisfied:

$$\begin{cases} y_k - (w.\varphi(x) + b \leq \in +\varepsilon_k \\ (w.\varphi(x) + b) - y_i \leq \in +\varepsilon_k^* \\ \varepsilon_k, \varepsilon_k^* \geq 0, k = 1, 2, \ldots s \end{cases} \tag{3}$$

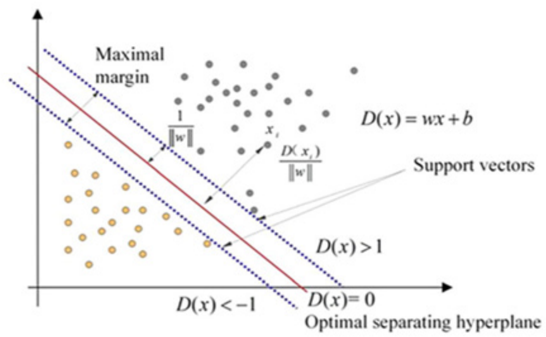

Fig. 1. Algorithm to support vector machine SVM (Aref A., et al., 2021)

Fig. 2. Deo Ca traffic tunnel

Where, C is capacity or penalty parameter, C>0; $\varepsilon_k, \varepsilon_k^*$ are slack variables, $\in$ is the coverage area. Using the Lagrange method in equation (1):

$$f(x) = \min\left(\sum_{k=1}^{s}(a_k - a_k^*)K(x, x_k) + b\right) \tag{4}$$

Where: a_k và a_{ik}^* are Lagrange coefficients, K is Kernel function. Expand equation (3) as follows:

$$W(a_k, a_k^*) = \sum_{k=1}^{s} y_i(a_k - a_k^*) - \epsilon \sum_{k=1}^{s}(a_k + a_k^*) - \frac{1}{2}\sum_{k=1}^{s}\sum_{t=1}^{s}(a_k - a_k^*)(a_t - a_t^*)K(x_k, x_t) \tag{5}$$

The above equation must satisfy the conditions:

$$\sum_{k=1}^{s}(a_k - a_k^*) = 0;\ 0 \le a_k \le C, k = 1, 2, \ldots s;\ 0 \le a_k^* \le C, k = 1, 2, \ldots s. \tag{6}$$

2.2. Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is an information processing model of a computer based on the way biological neural systems in the human brain process information. An artificial neural network ANN is made up of a definite number of elements (Hecht-Nielsen R, 1987; Simpson PK, 1990). The elements of the artificial neural network are connected to each other through links (called link weights). A neuron is considered a basic component of a neural network (a structural element of a neural network) and an information processing unit. A model of working together between neurons in hidden layers with input signals processing neurons (Input) and output signals processing neurons (Output) - The ANN model to determine the relationship between desired input data and output data.

An ANN artificial neural model consists of the following main components (Esmaeili, M. et al., 2014; Koopialipoor, M. et al., 2017):

- Set of input signals of the model: these are the input signals of artificial neurons, these signals are usually put in the form of a vector with m-dimensionality;
- Set of links: each link is represented by a weight (Synaptic weight). The effect of weighting is to create a link between the jth input signal and the k neuron, usually denoted wjk. When the network initialization, weights were randomly initialized and were continuously updated during the training of the network.
- Summing function: this Summing function was used to count the sum of the product of the inputs data with the corresponding Synaptic weights.
- Bias: in the transfer function, bias is defined as a component.
- Transfer function (Activation function): the transfer function was used to limit the output range of each neuron in the ANN model. The transfer function takes as input the result of the given sum and threshold function. These transfer functions can be linear or nonlinear.

3. Data to build ANN and SVR models

In order to build ANN and SVM models, capable of predicting and calculating the cross-sectional area of the tunnel after blasting with high accuracy, it is necessary to use the data collected on actual construction sites. In this paper, 110 construction data at Deo Ca traffic tunnel construction site, Phu Yen, Vietnam has been collected, processed, and used to train and test ANN and SVR models. These data include the design area of the tunnel face S_{tk} (m^2); the average boreholes length l (m); The rock mass rating (RMR); specific charge q (kg/m^3). The above-mentioned parameters are evaluated as those that have a great influence on the value of the cross-sectional area of the tunnel after blasting during construction.

In order to be reasonable for the use of data in building artificial intelligence models for the purpose of predicting and calculating the cross-sectional area of the tunnel after the blasting with high accuracy, the data should be processed and returned to the range of [-1, 1] according to the formula:

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{7}$$

Tab. 1. Parameters of data in building ANN and SVR models

Parameters	The symbol	Unit	Category	Min	Max	Average
The design cross-sectional area of tunnel	S_{tk}	m^2	Input	49,26	64,86	52,52
The average boreholes length	l	m	Input	1,0	3,2	1,75
The rock mass rating	RMR	-	Input	5	67	45,76
The specific charge	q	kg/m^3	Input	0,32	2,51	1,31
The cross-sectional area of tunnel after the blasting	SC	m^2	Output	50,276	71,049	56,6

Tab. 2. The results of R^2 in ANN models for different neuron numbers in the hidden layer

The neuron numbers in the 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

Tab. 3. The results of RMSE in ANN models for different neuron numbers in the hidden layer

The neuron numbers in the hidden layer	Model 1		Model 2		Model 3		Model 4		Model 5		Average RMSE	
	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

Tab. 4. The rank of models obtained from five different datasets for different neuron numbers in the hidden layer

The neuron numbers in the hidden layer	Average R^2				Average RMSE				Sum Rank
	Training	Rank	Testing	Rank	Training	Rank	Testing	Rank	
4	0.890766	4	0.842634	2	0.158869	4	0.207387	3	13
5	**0.909122**	**2**	**0.871239**	**1**	**0.144178**	**1**	**0.17297**	**1**	**5**
6	0.915949	1	0.806986	3	0.149605	2	0.194097	2	8
7	0.902315	3	0.806689	4	0.152629	3	0.214703	4	14
8	0.880296	5	0.756452	5	0.166232	5	0.230151	5	20

Tab. 5. Model selection for optimal results in ANN models

The neuron numbers in the hidden layer, n=5	Training				Testing				Sum rank
	R^2	Rank	RMSE	Rank	R^2	Rank	RMSE	Rank	
Model 1	0.9267	2	0.1378	2	0.7740	5	0.1700	3	12
Model 2	0.8955	4	0.1606	5	0.8819	3	0.1729	4	16
Model 3	**0.9030**	**3**	**0.1473**	**3**	**0.9107**	**2**	**0.1497**	**2**	**10**
Model 4	0.9301	1	0.1225	1	0.8726	4	0.2236	5	11
Model 5	0.8903	5	0.1526	4	0.9170	1	0.1487	1	11

Where X and X_n represent the measured and normalised values, respectively. X_{min} is the minimum measured parameters value and X_{max} is the maximum measured parameters value, respectively. X_{min}=-1 and X_{max}=1 (Esmaeili, M., et al., 2014).

To evaluate the accuracy of the ANN and SVR models for predicting the cross-sectional area of tunnel after the blasting, the paper compared the prediction values obtained from the models. The author evaluated the accuracy of the models through two coefficients, the coefficient of determination R^2 and the root mean square error (RMSE).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}((y_i - y_i')^2} \quad (8)$$

$$R^2 = \left[\frac{\sum_{i=1}^{N}(y-\bar{y})(y'-\bar{y}')}{\sum_{i=1}^{N}(y-\bar{y})^2\sum_{i=1}^{N}(y'-\bar{y}')^2}\right]^2 \quad (9)$$

Where y_i are the observations, y'_i predicted values of a variable, and n the number of observations available for analysis.

4. Results and discussion

ANN and SVR models were built to predict and calculate the cross-sectional area of a tunnel during tunnel construction. In this paper, 110 data were obtained during the actual construction of the Deo Ca tunnel, including relevant evaluated parameters that had the greatest influence on the cross-sectional area of the tunnel after the blasting. These data were determined, collected, processed, and used to build

Tab. 6. Results of SVR models with different parameter C values

C	Training		Testing	
	R^2	RMSE	R^2	RMSE
10.5	0.89861893	0.151327	0.913373	0.149332
10	0.8989008	0.150997	0.913737	0.149332
9	0.89874298	0.151327	0.91334	0.149666
8	0.89843964	0.151327	0.91299	0.149666
7	0.89855903	0.151327	0.913697	0.149332
6	0.89913427	0.150997	0.913264	0.150333
5	0.89886603	0.151658	0.910816	0.154272
4	0.89840493	0.151658	0.909924	0.155242
3	0.89853552	0.151658	0.909979	0.155242
1	0.89257087	0.156844	0.91136	0.156205
0.5	0.89296119	0.160624	0.911244	0.164924
0.25	0.8924826	0.176918	0.910708	0.186279
0.15	0.86392173	0.244336	0.876024	0.260192
0.05	0.64571197	0.37229	0.684102	0.379868
0.03	0.53810729	0.413884	0.589071	0.416893

Tab. 7. The rank of SVR models with different C parameter values

C	Training Rank		Testing Rank		Sum Rank
	R^2	RMSE	R^2	RMSE	
10.5	5	5	3	3	16
10	**2**	**1**	**1**	**1**	**5**
9	4	4	4	4	16
8	8	5	6	4	23
7	6	6	2	3	17
6	1	3	5	6	15
5	3	7	9	7	26
4	9	8	12	9	38
3	7	9	11	9	36
1	11	10	7	10	38
0.5	10	11	8	11	40
0.25	12	12	10	11	45
0.15	13	13	13	13	52
0.05	14	14	14	14	56
0.03	15	15	15	15	60

Tab. 8. Survey results of SRV models with different Kernel values with C=10.5

Kernel	Training		Testing	
	R^2	RMSE	R^2	RMSE
5	0.90187817	0.14866069	0.91340272	0.15033296
4	0.91649036	0.13747727	0.90625765	0.16000000
3	0.93311381	0.12288206	0.90552194	0.17088007
2	**0.95402171**	**0.10198039**	**0.89597588**	**0.17748239**
1	0.97650525	0.07280110	0.79020098	0.23515952
0.5	0.98330894	0.07280110	0.65963997	0.32171416
0.25	0.98760436	0.06082763	0.10956368	0.44497191
0.075	0.98840993	0.06324555	0.05317605	0.46141088
0.05	0.98838461	0.06324555	0.03312009	0.46658333
0.03	0.98834682	0.06324555	0.02283761	0.46989360
0.02	0.98834230	0.06324555	0.02152737	0.47233463
0.01	0.98834288	0.06324555	0.02153341	0.47655010

Tab. 9. Ranking of SVR models by surveyed Kernel parameter values

Kernel	Training Rank		Testing Rank		Sum Rank
	R^2	RMSE	R^2	RMSE	
5	12	12	1	1	26
4	11	11	2	2	26
3	10	10	3	3	26
2	**9**	**9**	**4**	**4**	**26**
1	8	8	5	5	26
0.5	7	7	6	6	26
0.25	6	6	7	7	26
0.075	**1**	**2**	**8**	**8**	**19**
0.05	2	3	9	9	23
0.03	3	4	10	10	27
0.02	5	5	11	11	32
0.01	4	6	12	12	34

Note: As per the ranking in Table 9, models with Kernel values of 0.075 and 0.05 have the lowest SumRank, with values of 19 and 23 respectively. However, these values are rejected due to the coefficient of determination R^2 in the test dataset being less than 0.6.

ANN and SVR models. Input data for the ANN and SVR models included the rock mass rating RMR, the design area of the tunnel face S_{tk} (m^2), the average boreholes length l (m); specific charge q (kg/m^3). The K-Means Clustering Algorithm was used to train and test the model, ensuring the accuracy of the model results. Here, the total database was divided into 5 equal parts, with each part containing 22 data points. Four parts were used to build and train the ANN and SVM prediction models, while the remaining part was used as testing data for the built models.

4.1. Result of Artificial Neural Network models

In the ANN algorithm, one hidden layer is used to build models capable of predicting the cross-sectional area of a tun-

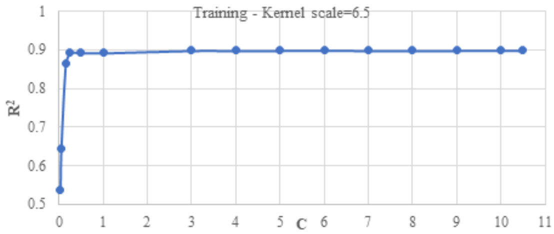

Fig. 3. The graph shows the dependence of the coefficient of determination R^2 with the regularization parameter C in the training dataset of the SVR optimum model

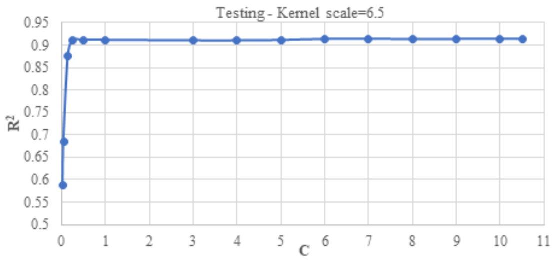

Fig. 4. The graph shows the dependence of the coefficient of determination R^2 on the regularization parameter C in the testing dataset of the SVR optimum model

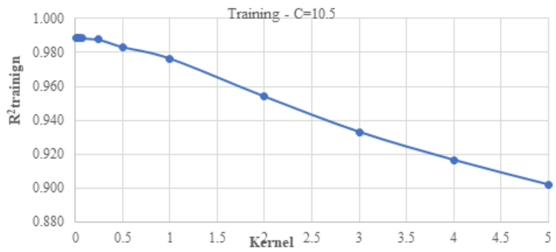

Fig. 5. The graph shows the dependence of the coefficient of determination R^2 on the Kernel scale in the training dataset of the optimal SVR model

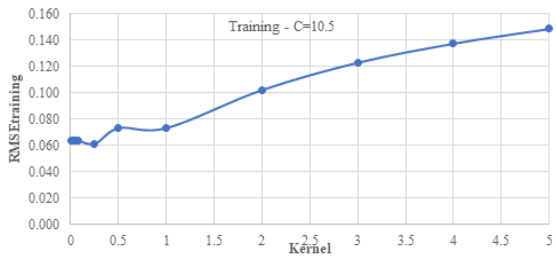

Fig. 6. The graph shows the dependence of the RMSE on the Kernel scale in the training dataset of the optimum SVR model

nel after blasting. With a hidden layer, the accuracy of ANN models still ensures accuracy when predicting only one output variable and reduces the complexity and processing time of the model (Chi T.N., et al., 2022). The transfer function used in ANN models is tanh(x). Run the ANN models with different neuron numbers in the hidden layer to select the optimal neuron numbers that can ensure the highest accuracy for the ANN models. According to Mohammad. E., et al., 2014, the neuron numbers in the hidden layer must be less than or equal to (2*N+1), where N is the number of input variables of the model.

Based on the results of ANN to predict and calculate the area of the tunnel face after the blasting in tables 2÷5, the ANN models had the optimal value when the neuron numbers in the hidden layer is n=5. When the neuron numbers in the hidden layer n=5, the coefficient of determination R^2 had the maximum value and the original mean the root mean square error RMSE of ANN models is the smallest (with the ranking value SumRank being the smallest). In Table 5, Model 3 with the corresponding databases is the optimal model.

4.2. Result of Support Vector Regression (SVR) models

Building predictive models of the cross-sectional area of a tunnel after blasting using Support Vector Regression (SVR) with different parameter values. Conducting a trial and error method to identify the optimal parameter values for the model (parameters include Kernel ratio, C-Regularization parameters). Through the aforementioned trial and error method, the optimal model was determined based on the parameters and characteristics of the model, including: Gaussian Kernel function (RBF Kernel - radial basis function) – the most commonly used function in SVR models as it yields highly accurate results (Aref A., et al., 2021; Nguyen H., et al., 2019), with a Kernel scale value of γ=2.0; Regularization parameter C=10.

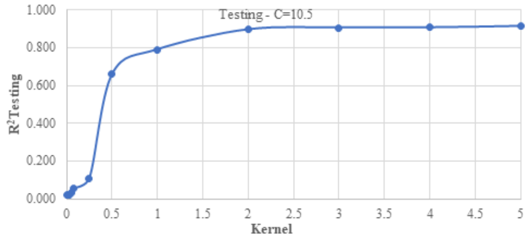

Fig. 7. The graph shows the dependence of R^2 on the Kernel scale in the testing dataset of the SVR optimum model

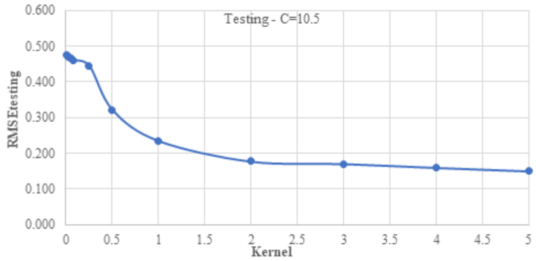

Fig. 8. The graph shows the dependence of RMSE on the Kernel scale in the SVR optimum model's testing dataset

4.3. The results of predicting the cross-sectional area of tunnel after the blasting are obtained from optimum models

Based on the results obtained from the ANN models in Table 2–5, it can be seen that model number 3 with the corresponding database is the model with the best predictive results for the cross-sectional area of the tunnel after the blasting. Using model 3 has been selected with the model's parameters such as 1 hidden layer, the number of neurons in the hidden layer is 5, the tanh function is used as the transfer function in the model to predict the cross-sectional area of the tunnel after the blasting. The obtained coefficient determined in the training dataset is $R^2_{training}$=0,903; the coefficient of determination in the test dataset is $R^2_{testing}$=0.9107; the root mean square error in the training dataset is $RMSE_{training}$=0.1473; the root mean square error in the testing data set is $RMSE_{testing}$=0.1497 (Figures 9, 10), when comparing the model's predictive results with the corresponding actual measured values (Figures 11, 12).

For the SVR optimum model that has been built and selected, based on the results obtained when using the model to estimate the cross-sectional area of the tunnel after the blasting in Tables 6–9 and Figures 13–16. It can be found that the model can predict the cross-sectional area of the tunnel after the blasting with high accuracy ($R^2_{training}$=0.9331; the coefficient of determination in the testing data set is $R^2_{testing}$=0.9055; root mean square in the training dataset $RMSE_{training}$=0.1228; root mean square error in the test dataset $RMSE_{training}$=0.1708). Based on the graphs showing the correlation between RMSE and R^2 of the training and testing data sets with the Kernel scale value, it is found that a Kernel scale value of 2 meets the accuracy of the results of the SVR model. At the Kernel scale value of 2, the RMSE and R^2 of the model with the testing dataset and training dataset are almost unchanged and reach good values (RMSE is small and R^2 is close to 1) and the RMSE values are also good (Figures 5 ÷ 8). For the investigation and determination of the optimal C - the regularization parameter, based on the obtained results and the graph in Figures 3, 4, it is found that in both the training dataset and the testing dataset, C=10 for the biggest values of the coefficient of determination R^2.

According to the results of this investigation, the cross-sectional area of the tunnel after the blasting values was found to be homogeneous in both models: ANN and SVR. There was no significant difference between the cross-sectional area of the tunnel after the blasting, as indicated by R^2 and RMSE, in the training dataset and the testing dataset.

5. Conclusion

The drilling-blasting method was one of the main methods used to construct tunnels and underground works in Vietnam because of the advantages of this method, such as low cost and no high technical requirements. This method can be used in most geological conditions in the area where underground works are arranged. Among the parameters that can be evaluated for the effectiveness of tunnel construction and underground works, the area of the tunnel face after the blasting is one of the most important parameters. This parameter determines the volume and properties of other works during the construction of underground work.

In practice, determining the cross-sectional area of the tunnel after the blasting has been extensively studied. However, due to its dependence on several parameters, such as the characteristics of the drilling-blasting method, the type of explosives used, the equipment employed in the construction process, and the tunnel's features, accurately determining the cross-sectional area of the tunnel after the blasting is challenging. This paper researched and applied artificial intelligence models, specifically ANN and SVR techniques, to develop predictive and calculation models for the cross-sectional area of the tunnel after the blasting. The models were constructed and chosen based on actual data collected during the construction of the Deo Ca traffic tunnel in Phu Yen. They exhibit high accuracy in predicting and calculating the cross-sectional area of the tunnel after the blasting, based on the comparison of the prediction results of these models with the values of the cross-sectional area of the tunnel after the blasting obtained from the actual construction with the help of various graphs and some statistical parameters. The following conclusions can be drawn from the results obtained using ANN and SVR models for predicting and calculating the

Fig. 9. The coefficient of determination R^2 of the ANN model selection at training step

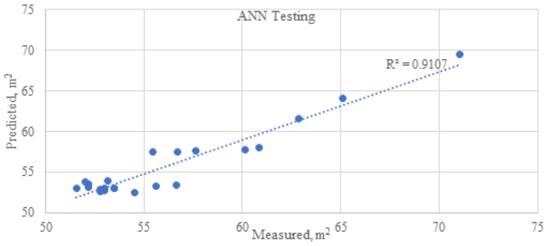

Fig. 10. The coefficient of determination R^2 of the ANN model selection at testing step

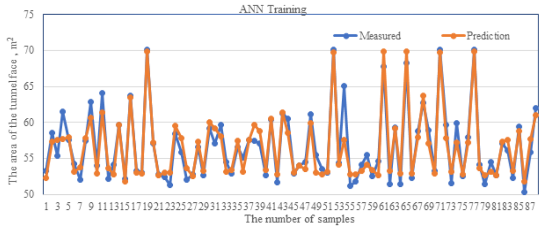

Fig. 11. Measured and predicted the values of the cross-sectional area of tunnel after the blasting obtained through the ANN model for training dataset

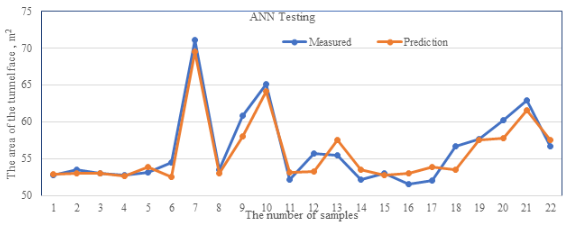

Fig. 12. Measured and predicted the values the cross-sectional area of tunnel after the blasting obtained through ANN model for testing dataset

cross-sectional area of the tunnel after the blasting:

- The accuracy of the models in the ANN artificial neural network depends a lot on the number of hidden layers and the neuron numbers in the hidden layers;
- The artificial neural network ANN model is capable of predicting and calculating the cross-sectional area of the tunnel after blasting. The coefficient of determination in the training dataset is $R^2_{training}$=0,903, and in the testing dataset it is $R^2_{testing}$=0.9107. The root mean square error in the training dataset is $RMSE_{training}$=0.1473, and in the testing dataset it is$RMSE_{training}$=0.1497;
- The SVR models depended a lot on the value of influential parameters during the model-building process, including the Kernel function, Kernel scale, and the regularization parameter C;
- In the case of the Kernel scale decreasing, the accuracy of the model in the training dataset increases; however, the accuracy of the model in the testing dataset decreases. Therefore, it is necessary to run SVR models with different values of Kernel scale, evaluate, and rank the results of the models to find the suitable Kernel scale value;
- If the Kernel scale decreases, the model's accuracy on the training dataset increases while its accuracy on the testing dataset decreases. Thus, it's vital to run SVR models with various Kernel scale values, assess their results, and rank them to determine the appropriate Kernel scale value.;
- The SVR model is capable to predict and calculate the cross-sectional area of the tunnel after the blasting with high accuracy. ($R^2_{training}$=0.9331; $R^2_{testing}$=0.9055; root mean square error in training dataset $RMSE_{training}$=0.1228; root mean square error in testing dataset $RMSE_{training}$=0.1708);

The rock mass rating RMR, the design area of the tunnel face S^{tk} (m^2), the average boreholes length l (m); specific charge q (kg/m^3) are important parameters that greatly influence the performance of ANN and SVR models. These models can predict the cross-sectional area of the tunnel after blasting accurately. The results of the ANN and SVR mod-

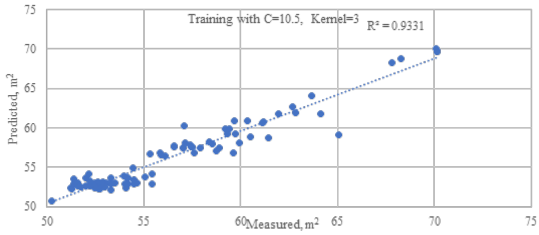

Fig. 13. The coefficient of determination R² of the SVR optimum model in training step

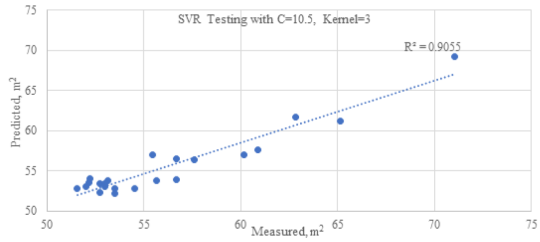

Fig. 14. The coefficient of determination R² of the SVR optimum model in testing step

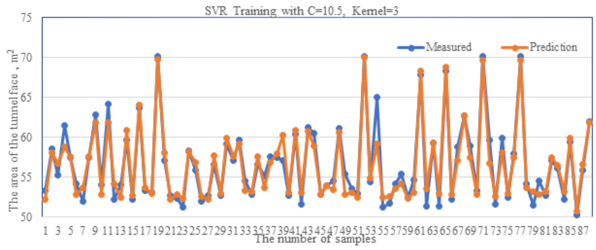

Fig. 15. Measured and predicted the values of the cross-sectional area of tunnel after the blasting obtained through the SVR model for training dataset

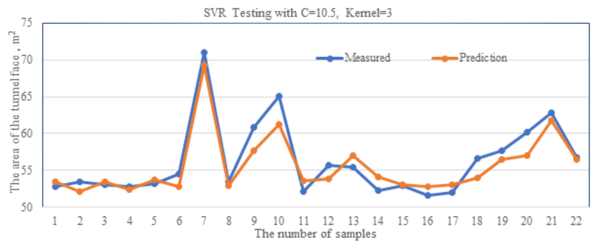

Fig. 16. Measured and predicted the values of the cross-sectional area of tunnel after the blasting obtained through the SVR model for testing dataset

els confirm the significance of these parameters in building accurate prediction models for the tunnel's cross-sectional area after blasting. Additionally, other parameters such as the cross-sectional shape of the tunnel, the characteristics of the drilling equipment used in the tunnel construction process, and the detailed characteristics of the borehole system arranged on the cross-section of the tunnel (quantity, distance, and angle of inclination created with the horizontal plane of boreholes) should also be mentioned and considered when building ANN and SVR models to predict and calculate the cross-sectional area of the tunnel after blasting in future studies. For different projects, it is necessary to update and change the actual values of the inputs in the data sets used to build predictive ANN and SVR models to ensure the accuracy and reliability of the model.

6. Acknowledgement

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7. Contributions of authors

Thanh Nguyen Chi: Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Writing - original draft. Nghia Viet Nguyen: Conceptualization, Supervision, Writing – review.

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