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Prediction of unconfined compressive strength ahead of tunnel face using measurement-while-drilling data based on hybrid genetic algorithm

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Abstract. Measurement of the unconfined compressive strength (UCS) of the rock is critical to assess the quality of the rock mass ahead of a tunnel face. In this study, extensive field studies have been conducted along 3,885 m of the new Nagasaki tunnel in Japan. To predict UCS, a hybrid model of artificial neural network (ANN) based on genetic algorithm (GA) optimization was developed. A total of 1350 datasets, including six parameters of the Measurement-While- Drilling data and the UCS were considered as input and output parameters respectively. The multiple linear regression (MLR) and the ANN were employed to develop contrast models. The results reveal that the developed GA-ANN hybrid model can predict UCS with higher performance than the ANN and MLR models. This study is of great significance for accurately and effectively evaluating the quality of rock masses in tunnel engineering.

Keywords: unconfined compressive strength; measurement-while-drilling data; ANN; genetic algorithm; tunnel face

1. Introduction

Accurate assessment of the geological conditions ahead of a tunnel face is crucial for safe and economical tunnel construction (Inazaki *et al.* 1999, Utsuki and Tsuruta 2018, Han *et al.* 2020). The measurement of the unconfined compressive strength (UCS) of the rock is of great importance in this assessment (Bieniawski 1974, Yilmaz 2009b, Nazir *et al.* 2013). The UCS standard test of the rock is directly determined in the laboratory by the measurement of compression characteristics of rock specimen under the axial load. This test is standardized by the American Society for Testing and Materials (ASTM 2006) and the International Society for Rock Mechanics (ISRM and Hudson 2007). Nevertheless, some shortcomings exist in this kind of direct laboratory test. It is not easy to obtain a sufficiently perfect core sample if the rock of interest is weak, thinly bedded, or densely fractured. In addition, the direct laboratory test is time-consuming and costly (Zorlu *et al.* 2008, Dehghan *et al.* 2010, Mohamad *et al.* 2015, Wang *et al.* 2020). Some researchers report that due to standard UCS test methods require costly equipment, it is economical and convenient to use the indirect test methods to measure UCS (Yagiz *et al.* 2012, Othman *et al.* 2018, Mokhtari and Behnia 2019).

In indirect test methods, in order to avoid the difficulties in preparing and testing core samples by direct method, many researchers have developed some prediction methods, such as Schmidt hammer rebound number, point load index, p-wave velocity and physical properties to related with the UCS using regression techniques or artificial intelligence techniques (Shakoor and Bonelli 1991, Kahraman 2001, Yılmaz and Sendır 2002, Tsiambaos and Sabatakakis 2004, Toghroli *et al.* 2018, Yagiz 2019). Compared with the UCS direct test, these index tests need relatively few samples, which have the advantages of quick and easy fast operation, portability and low costs. Nevertheless, Zhang (2016) pointed out that when considering different rock types, different strength values can be calculated by different empirical formulas. Moreover, Meulenkamp and Grima (1999) described that statistical regression methods have the disadvantage of predicting only the average value; Therefore, over prediction of low UCS value and under estimation of high UCS value may occur. At the same time, many scholars also proposed that the regression analysis technology has limitations on the prediction accuracy of solving complex nonlinear tasks (Baykasoğlu *et al.* 2004). In addition, according to the research of Meulenkamp and Grima (1999), in contrast to the statistical regression analysis, the UCS value predicted by artificial neural network (ANN) is not force to be the average value, so the existing variance of measurement data can be retained and employed. For the assessment of the rock mass quality ahead of a tunnel face, although these existing direct and indirect test techniques can be applied to measure the UCS of the exposed rock, it is very difficult to predict the UCS values of the unexposed rocks ahead of the tunnel face.

Recently, with the rapid development of measurement-while-drilling (MWD) technology, the evaluation technology of rock mass quality ahead of a tunnel face has been improved (Schunnesson 1996, Sugawara *et al.* 2003, Høien and Nilsen 2014, Galende-Hernández *et al.* 2018); Therefore, as long as the original data is properly processed

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and effectively analyzed, the MWD technology can be regarded as a robust method for detailed characterization of large rock mass. Many scholars have done a lot of research in this field. By analyzing the change of drilling parameters, Scoble *et al.* (1989) determined different geological structures. The original MWD system was developed by Aoki *et al.* (1999); The geological conditions of different ground depths were evaluated by analyzing the data obtained by drilling in rock with a hydraulic drill. Peck (1989) verified that MWD parameters can be used to estimate the compressive and shear strength of rocks. Teale (1965) introduced specific energy as a composite MWD parameter, and connected the bit performance parameters in rotary drilling with the concept of energy required to excavate rock per unit volume. Hatherly *et al.* (2015) described that the wear of the bit affects the recognition accuracy of rock mass characteristics. Schunnesson *et al.* (2012) proposed a method to estimate the range of rock strength values based on the MWD hardness parameter index recorded by Atlas Copco software. Celada *et al.* (2009) investigated the correlation between specific energy and rock mechanical parameters through laboratory tests, and demonstrated that the specific energy value has a certain correlation with rock mass rating index. Kahraman *et al.* (2016) evaluated the feasibility of estimating UCS, Brazilian tensile strength, point load strength and Schmidt hammer test value by penetration rate parameter. However, limited by the difficulty of efficient analysis and processing of the MWD data, the technology of predicting UCS ahead of a tunnel face using the MWD data has not been effectively applied in the field.

In recent decades, the ANN has been applied to solve geotechnical engineering problems as a powerful tool (Alimoradi *et al.* 2008, Yilmaz 2009a, Ocak and Seker 2012, Kwon and Lee 2018, Xue 2019). However, the disadvantages of slow learning speed and easy to fall into local minima exist in the realization of ANN (Jadav and Panchal 2012, Momeni *et al.* 2014). In order to solve these problems, optimization algorithms such as genetic algorithm (GA) can be used to enhance the performance of ANN (Bhatti *et al.* 2011, Karimi and Yousefi 2012, Khandelwal *et al.* 2018).

The main purpose of this research is to establish a hybrid optimization model, GA-ANN, to predict of UCS utilizing the MWD data acquired from the new Nagasaki tunnel (east) of the West Kyushu line of the high-speed railway project in Japan. A conventional regression model and simple ANN model are developed. Subsequently, the hybrid optimization model of GA-ANN is developed. Finally, the best prediction model is selected by comparing the results of these models. The results can contribute to the accurate, effective and objective assessment of rock mass quality ahead of a tunnel face.

2. Data collection and regression analysis

2.1 Project description

As a mountainous country, if the construction of roads and railways in Japan adopts the construction around mountains, the project cost will be huge. Therefore, it is

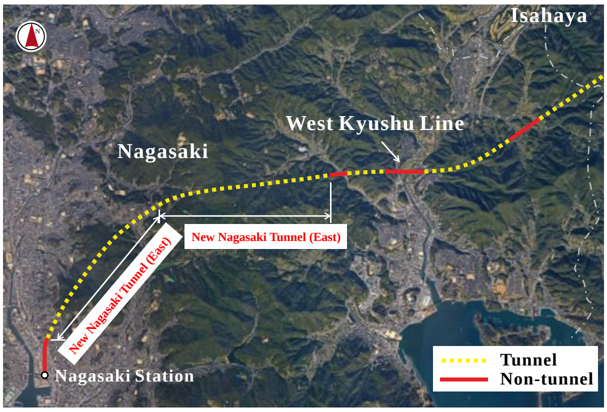


Fig. 1 The location of the project tunnel

inevitable to need a lot of tunnel excavation in highway and railway construction. The complicated and dangerous geological conditions such as water gushing, mud bursting and cavity are very common in mountain tunnels, which is more common in southern Japan. The new Nagasaki tunnel is part of Japan's West Kyushu line with a total length of 7.46 km. The New Nagasaki tunnel is divided into two parts, namely, the new Nagasaki tunnel (east) and the new Nagasaki tunnel (west) (Fig. 1). As the research object of this study, the new Nagasaki tunnel (east) was started in March 2013 and completed in 2017. The length of the two tunnels is 3.885 km and 3.575 km respectively. The New Austrian Tunneling Method is the main method of tunnel excavation. The shape of the tunnel is a horseshoe with a height of 9.3 m and a width of 10.4 m. The main rock type that the tunnel passes through is pyroxene andesite with poor surrounding rock geological conditions and elastic wave velocity range of 2.5-3.5 km/sec.

2.2 Data collection

In the field measurement, important parameters including the MWD data and the UCS values were recorded. Situ tests, i.e., advanced drilling data (the MWD data) and Schmidt hammer rebound number were recorded at the same time in the same tunnel section. It should be noted that due to the reason that some field measurements are difficult to carry out, the MWD data used in this paper have not been obtained from all tunnel sections.

The MWD data of this study comes from the hydraulic rotary percussion drill, which carries out drilling operation ahead of the tunnel face. In order to eliminate the influence of the error, the drilling data of a certain location is processed averagely within one meter. The parameters of MWD data including the penetration rate (PR), hammer pressure (HP), rotation pressure (RP), feed pressure (FP), hammer frequency (HF) and specific energy (SE). Among these MWD parameters, the specific energy is a composite parameter, which refers to the energy consumed to destroy the rock per unit volume, as shown in Eq. (1) (Masayuki *et al.* 2001):

$$E_s = \frac{ALN_s f}{vS} \times k \tag{1}$$

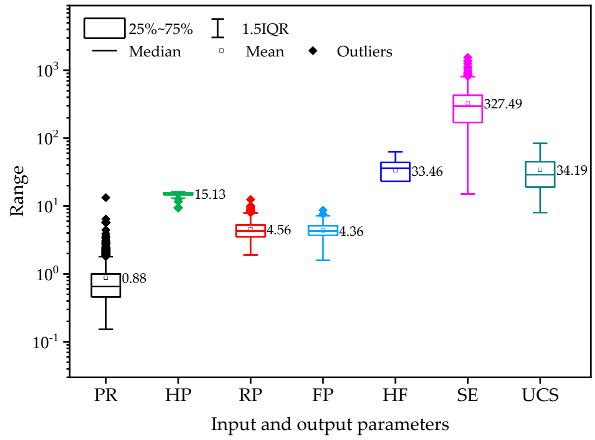


Fig. 2 Distribution of the parameters of the input data and output data

Table 1 Basic statistics of dataset parameters

Item	Symbol	Unit	Mean	Min	Max	Std. Dev
Input	PR	m/min	0.88	0.15	13.30	0.80
	HP	MPa	15.13	9.40	16.10	0.97
	RP	MPa	4.56	1.90	12.50	1.35
	FP	MPa	4.36	1.59	8.70	1.05
	HF	1/s	33.46	0.00	63.00	13.96
	SE	J/cm^3	327.49	15.10	1549.80	191.40
Output	UCS	MPa	34.19	8.00	84.00	19.16

where E_s is the specific energy (J/cm^3), f is hammer frequency (1/min), v is penetration rate (cm/min), S is cross-sectional area of the drill hole (cm^2), k is loss coefficient, A is piston com pression area (cm^2), L is piston stroke(cm), N_s is the hammer pressure (MPa). The function of the k is to eliminate the energy loss caused by the friction between the drill pipe and the wellbore. It was determined based on laboratory rock drilling tests.

Considering the time-consuming and high cost of the standard uniaxial compression test, Schmidt hammer test is generally employed to measure the UCS of rock as an indirect method. This indirect method has the advantages of simple operation, no sample preparation and convenient field application (Goudie 2006, Demirdag *et al.* 2009, Hoseinie *et al.* 2012). The operation procedure of Schmidt hammer test is as follows:

• Press on the surface of the rock material with a Schmidt hammer. After the switch is turned, the piston in Schmidt hammer hits the plunger.

• The hammer test should be carried out at five different representative points perpendicular to the core samples, and the spacing between these representative points should be at least twice the diameter of the plunger.

In the construction of the new Nagasaki tunnel (east), detailed observation report of the exposed tunnel face is used to comprehensively evaluate the surrounding rock of the tunnel. The UCS is one of the important terms in the observation report, which is calculated indirectly by Schmidt hammer rebound number.

In this study, MWD data, and UCS were collected in situ in the new Nagasaki tunnel (east phase). A total of 1350 datasets from 1350 sections of the tunnel were recorded and collected. To predict the UCS value, the MWD data (PR, HP, RP, FP, HF and SE) are regarded as input parameters of the ANN, and the UCS values are regarded as output parameters. Table 1 summarizes the descriptive statistical distribution of all parameters in the database. Their visual statistic distribution is provided in Fig. 2. According to the analysis in Table 1 and Fig. 2, the values of these parameters are widely distributed. It should be noted that a small number of singular values exist in the MWD data. In order to investigate the robustness of ANN, the original data are not filtered in this paper.

2.3 Regression analysis

In addition, the correlation between each MWD parameter and their corresponding UCS was investigated. Fig. 3 summarizes the input datasets used and shows the relationship matrix between all data.

The correlations between input parameters (PR, HP, RP, FP, HF and SE) and output parameters (UCS) were determined by simple regression models. For fitting problem, the correlation coefficient (R^2), root mean square error (RMSE) and variance account for (VAF) are often used as evaluation indexes to evaluate the performance of the developed models, as employed by Grima and Babuška (1999), Yilmaz (2009b), Kayabasi (2012). The equations were evaluated with taking into consideration an evaluation index of R^2. The most suitable equation types for predicting UCS were evaluated and selected by power, exponential and linear equations based on the values of R^2. The equations used for the prediction of UCS are listed in Fig. 4. As shown in Fig. 4, the results of R^2 was calculated as 0.082, 0.198, 0.173, 0.117, 0.003, and 0.276, for PR, HP, RP, FP, HF and SE, respectively. The correlation between UCS and SE is better than the correlation among the other parameters; however, a low coefficient of determination (R^2 = 0.276) is obtained. These results show a low correlation between a single MWD parameter and the UCS. Therefore, using all or part of the MWD parameters to develop prediction model requires further study. In the following sections, attempt for applying an advanced hybrid ANN technology to predict the UCS based on multiple MWD parameters will be carried out.

Before developing the prediction models, to minimize the influence of order of magnitude on the prediction results, the database was normalized to the range of 0-1 by the following equation:

$$X_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

where X_{norm} and x are normalized and measured data, respectively. x_{min} and x_{max} are the minimum and maximum value, respectively, of x.

The datasets were divided into training set and testing set to develop and evaluate the established networks. Swingler (1996), Looney (1996) and Nelson and Illingworth (1991) suggested that 80%, 75% and 70-80%,

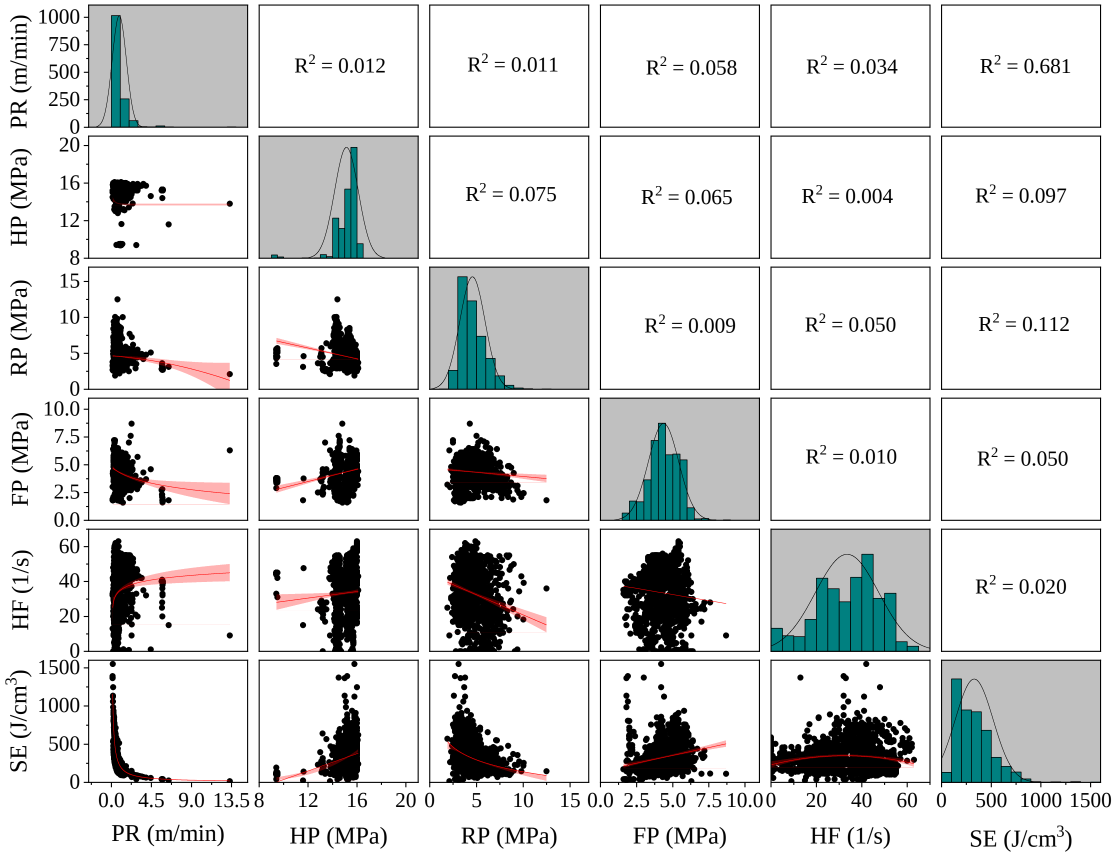


Fig. 3 General information related to the input parameter

respectively, of the whole datasets should be used as training set. Therefore, in this research, 1350 data sets were divided into training set and testing set by 80% and 20% ratio, respectively. A total of 1080 training sets and 270 testing sets were conducted to develop the UCS prediction models.

3. Methods

3.1 MLR

MLR is based on the development of simple linear regression technology, attempting to find an equation through measured data to describe the relationship between two or more interpretive variables (characteristics) and dependent variables (output). MLR is widely used in various branches of science and technology (Preacher *et al.* 2006, Nathans *et al.* 2012, Khademi *et al.* 2017). The mathematical form of MLR is as follows:

$$y = b_1x_1 + b_2x_2 + \cdots + b_nx_n + c \tag{3}$$

where, x_i, y, c and b_i are the i^{th} independent variable, i^{th} dependent variable, a constant (intercept) and the vector of regression coefficients (slope).

3.2 ANN

As an information processing program, ANN was first proposed by McCulloch and Pitts (McCulloch and Pitts 1943). Three layers, input layer, hidden layer and output layer, constitute a typical ANN. Groups of processor elements (or nodes) exist in each layer, which relates to each other between layers. The input signal of the previous layer is weighted to get the output signal as the next layer input. The activation function exists in each node of the hidden layer and the output layer. These activation functions are used to calculate the output of each node. The number of nodes in the input and output layer is determined by the dimension of their respective variables. However, it is difficult to determine the number of the hidden layer nodes. Generally, according to the problem to be solved, the optimal number of hidden layer nodes is determined by trial and error procedure. There are several training algorithms for ANN. The error back-propagation algorithm is the well-known and often used training algorithm. In this algorithm, the continuous adjustment of the connection weight between nodes is to reduce the error between the measured and the predicted output through the neural network iteration, and the error will spread to the input layer. If the error level between the output and the expected value is high, the adjustment of weight and deviation will continue. Therefore, the back-propagation algorithm was selected as a training algorithm in this research. Fig. 5 shows the ANN model of predicted UCS with six input and one output variables in this study.

3.3 GA

GA was developed by professor Holland of the

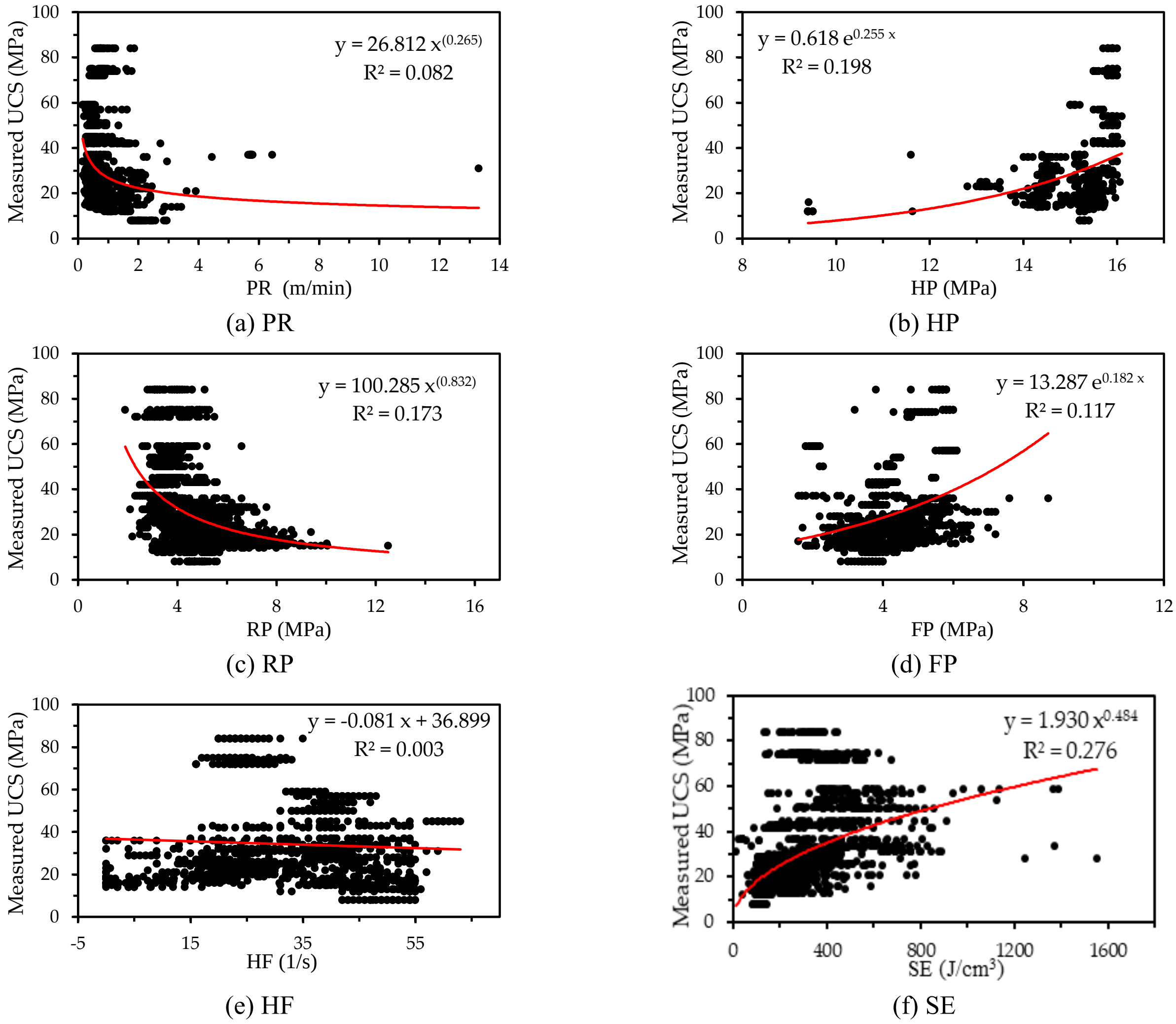


Fig. 4 The best simple regression model of each input parameter

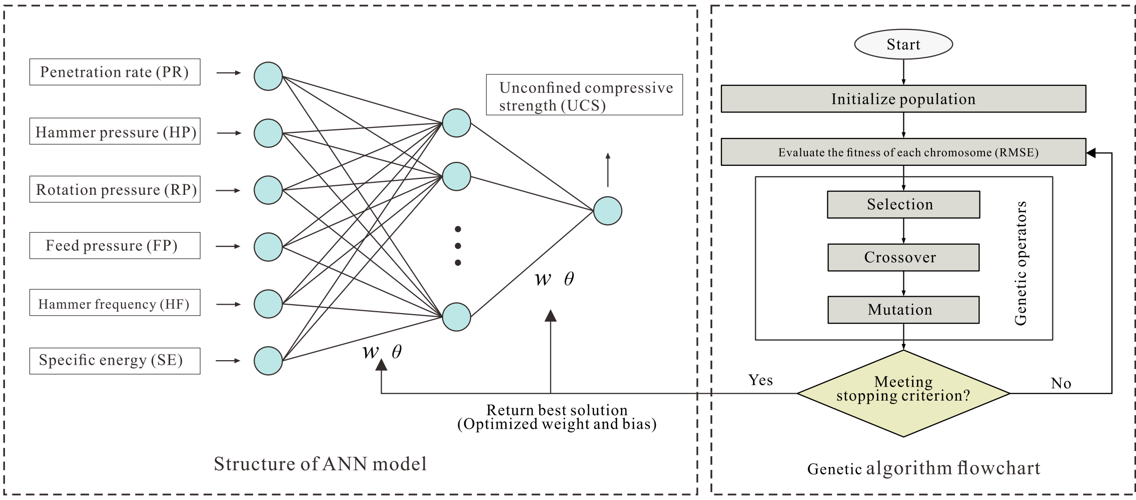
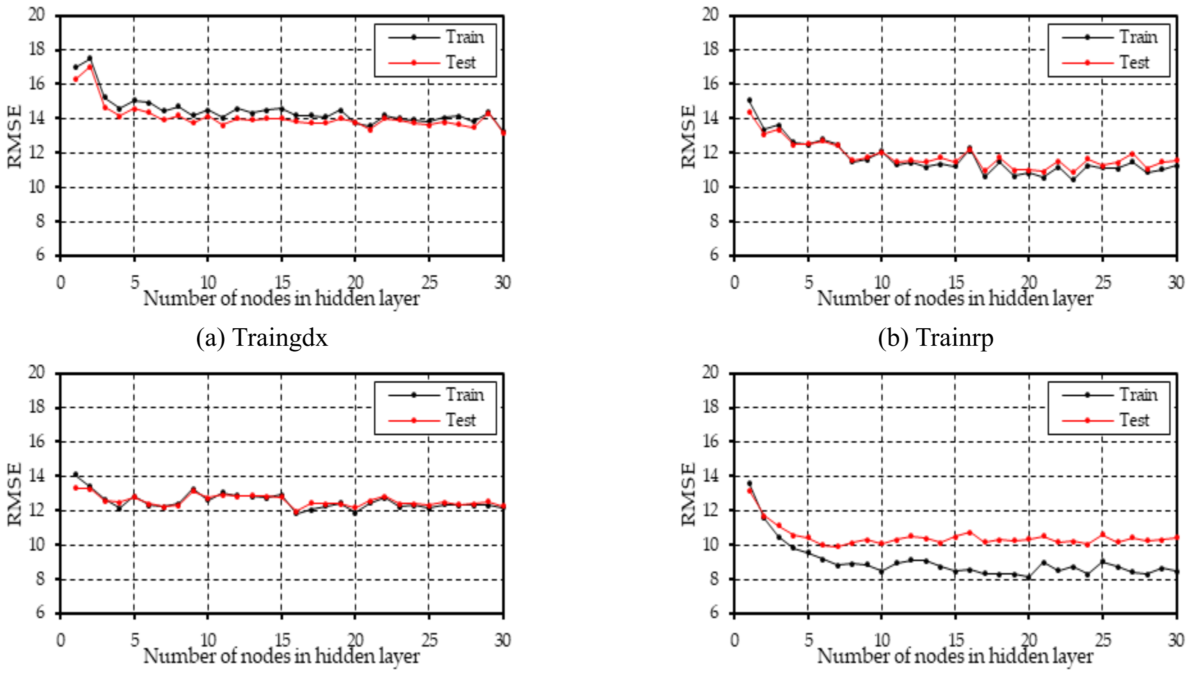


Fig. 5 Framework of the ANN model and the flowchart of GA

university of Michigan (Holland 1992). As an algorithm in the computer science field, GA is a heuristic search algorithm for solving optimization problems. This algorithm is often used in optimization and search solutions. Heredity, mutation, natural selection and hybridization are used in GA. It has the advantages of simple principle and operation, strong generality, unlimited constraints, implicit parallelism and global solution searching ability, and is widely employed in combinatorial optimization problems. However, the biggest disadvantage is that when the



(a) Traingdx (b) Trainrp

(c) Trainscg (d) Trainlm

Fig. 6 The various trials with 1-30 nodes with four training functions

selection of activation function is not appropriate, the GA may only converge to the local optimal, but not the global optimal (Mohamad *et al.* 2017). The GA program is divided into three stages: chromosome fitness evaluation, parental chromosome selection, and the application of genetic operators on parental chromosomes. The new chromosome produced becomes the next generation population, and the process is iterated until the stop condition is reached. GA has a large number of application cases in civil engineering, traffic engineering and other engineering fields due to its excellent performance. The detailed description of genetic algorithm and its application can be acquired from the studies (Whitley 1994, Kosakovsky Pond *et al.* 2006, Kumar *et al.* 2010, Qiu *et al.* 2015, Jahed Armaghani *et al.* 2018).

4. Modeling

4.1 MLR modeling

In this research, training datasets were applied to calculate the MLR models to correlate the UCS to the input parameters of PR, HP, RP, FP, HF and SE of the training datasets. Eq. (4) shows the results obtained from the regression analysis.

$$\begin{aligned} JH= & -36.498-0.381PR+5.052HP-4.022RP \\ & +2.776FP-0.181HF+0.021SE \end{aligned} \tag{4}$$

Eq. (4) shows that parameters including HP, FP and SE have a direct relationship with UCS. Whereas, PR, RP and HF have an inverse relationship with UCS. The evaluation of the developed MLR model with testing datasets will be discussed in Sect. 5.

4.2 ANN modeling

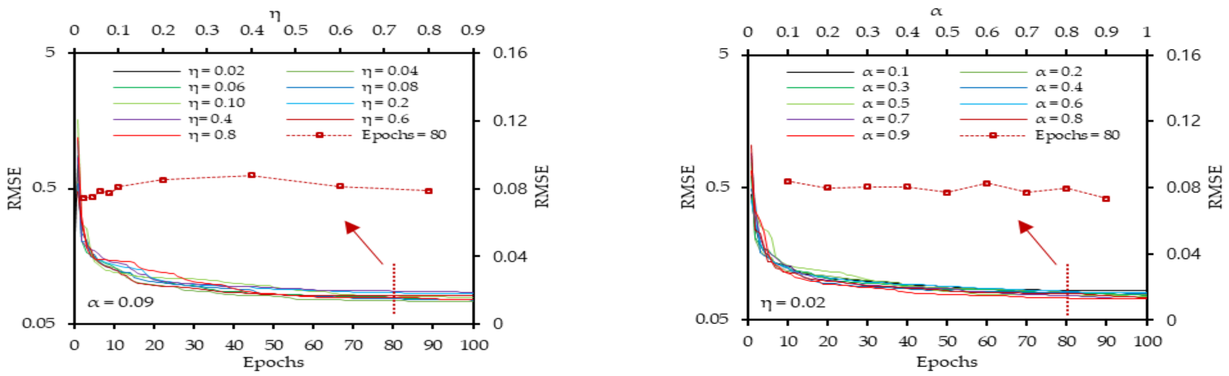
The construction of ANN model was carried out in this section. As previously mentioned, the multi-layer perceptron was applied for predicting the UCS. The parameters of PR, HP, RP, FP, HF and SE were designated as the inputs, and the parameter of UCS was designated as the outputs.

4.2.1 ANN parameters

The most effective parameters of ANN are training function, learning rate (η), momentum term (α), number of hidden layers and number of hidden layer nodes. The establishment of the ANN prediction model is to determine these main parameters. In order to predict the UCS accurately, these parameters were studied in detail to determine the optimal ANN parameters. According to the suggestion of Hasanipanah *et al.* (2016), Levenberg Marquardt algorithm is used to train neural network prediction model. As many researchers (Hecht-Nielsen 1987, Hornik *et al.* 1989, Garson 1998) introduced, the ANN with one hidden layer has enough performance to solve overwhelming majority engineering prediction tasks. Therefore, in this study, all the prediction models are designed with a hidden layer. To develop the ANN model, the difficulty is encountered in determining the learning rate, the momentum term and the number of hidden layer nodes.

4.2.2 Training function

The training function is generally divided into two types: one is a heuristic algorithm using the steepest descent method, such as resilient back-propagation (trainrp) and variable learning rate algorithms (traingdx); the other is a



(a) η (b) α

Fig. 7 Effects of learning rate and momentum parameters on ANN

standard numerical algorithm, such as Scaled Conjugate Gradient (trainscg) and Levenberg-Marquardt (trainlm). To select the optimal training function, several models were developed using these four training functions. The ANN architecture of 6-15-1, the η of 0.01 and α of 0.5 were utilized, and the performance indices of RMSE were employed to assess the developed models. The results of various ANN experiments with 1-30 nodes trained by traingdx, trainrp, trainscg and trainlm are shown in Fig. 6. Fig. 6 illustrates that in all functions, traindx had the weakest performance. Among them, the trainlm fluctuation reduces the errors during nodes and shows the best performance in both training and testing stage. Thus, the trainlm was chosen as the optimum the best training function.

4.2.3 ANN parameters

To choose the best values of η and α, several ANN models were constructed with η values of 0.02, 0.04, 0.06, 0.08, 0.1, 0.2, 0.4, 0.6 and 0.8, respectively, and α values of 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9, respectively. The ANN architecture of 6-15-1 and trainslm training function were applied. RMSE values were applied to evaluate the capacity of these models. Based on the evaluation, the optimal η and α values were chosen as 0.02 and 0.9, respectively, as shown in Fig. 7. Therefore, these values were chosen as the optimal value of η and α.

4.2.4 The number of hidden layer nodes

The number of hidden layer nodes has a great influence on the prediction performance of ANN (Kanellopoulos and Wilkinson 1997, Gao 1998, Monjezi *et al.* 2011). To evaluate this influence, different experiments of artificial neural network model with hidden layer nodes in 1-60, input layer nodes and output layer nodes in 1 and 6 respectively were set up, as shown in Appendix (A). The prediction performance of the developed models was assessed by performance index RMSE and R^2. Superior models have lower value of RMSE and higher values of R^2. However, it is difficult to choose the optimal prediction model. For this reason, Zorlu *et al.* (2008) recommended a easier method based on sorting method to realize this choice. On the basis of this method, each performance index was sorted, and the sorting value indicates the strength of performance. For example, RMSE values of 13.72, 11.87, 10.42, 9.86, 9.22, 9.75, 9.48, 9.22, 9.06, 8.42, 9.02, 7.98, 8.84, 8.87, 9.09, 8.30, 9.78, 7.95, 8.66, 8.64, 8.15, 8.50, 8.68, 7.81, 8.18 and 8.39 were obtained from training sets of models 1-26 shown in Appendix (A), respectively. Therefore, the sorting result value were 1, 2, 3, 4, 9, 6, 7, 8, 11, 19, 12, 24, 14, 13, 10, 21, 5, 25, 16, 17, 23, 18, 15, 26, 22 and 20, respectively. The result value of R^2 was also carried out in this way. After that, the training stage and testing stage were sorted respectively, and the total rank was the sum of the sorting values of the two stages, as shown in Appendix (A). As the results shown in Appendix (A), the No.12 model was selected as the model with the best performance in all the developed models. The average RMSE was 7.98 and 10.11, respectively, and R^2 was 0.827 and 0.721, respectively. Therefore, the ANN structure of 6–12–1 was finally determined as the optimum model for UCS value prediction. The optimal prediction model of ANN (run 5 times) will be further discussed in Sect. 4.3. In Sects. 4.3, note that GA-ANN hybrid model of the neural network structure was developed based on 6–12–1, and indices of RMSE and R^2 were also used to evaluate the developed prediction models.

4.3 GA-ANN modeling

To solve the problems of slow convergence and local optimization, many researchers employed GA to optimize the weights and biases of ANN, and successfully complete many engineering tasks (Balasubramanian *et al.* 2008, Yazdanmehr *et al.* 2009, Benyelloul and Aourag 2013, Khandelwal and Armaghani 2016). The hybrid GA-ANN algorithm flowchart is shown in Fig. 5. The steps of structuring the hybrid GA-ANN predictive model for UCS is detailed in the following section.

4.3.1 GA parameters

To developing GA models, population size (S_{pop}), methods of selection, number of generations (N_{gen}), mutation probability and crossover probability are the critical parameters set by the user. In this study, after the trial and error procedure, the mutation probability was determined as 25 % and the crossover probability was used with 70%. For the selection of crossover operation methods,

Table 2 Effect of the population size on the hybrid GA-ANN in predicting UCS

No.	Population size	Ga-ANN results				Rank value				Total rank
		Training		Testing		Training		Testing		
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
1	25	0.797	8.636	0.711	10.226	1	1	4	4	10
2	50	0.807	8.434	0.700	10.452	2	2	2	3	9
3	75	0.833	7.821	0.742	9.736	8	8	7	7	30
4	100	0.844	7.596	0.733	9.947	10	10	5	5	30
5	150	0.830	7.924	0.753	9.487	7	6	12	12	37
6	200	0.817	8.195	0.748	9.535	4	4	9	11	28
7	250	0.836	7.770	0.698	10.718	9	9	1	1	20
8	300	0.829	7.913	0.761	9.300	6	7	14	14	41
9	350	0.821	8.085	0.746	9.567	5	5	8	9	27
10	400	0.848	7.495	0.737	9.849	12	12	6	6	36
11	450	0.846	7.520	0.749	9.593	11	11	11	8	41
12	**500**	**0.854**	**7.334**	**0.755**	**9.467**	**14**	**14**	**13**	**13**	**54**
13	550	0.808	8.369	0.704	10.560	3	3	3	2	11
14	600	0.851	7.412	0.748	9.562	13	13	10	10	46

the roulette method is often used to create two offspring from parents (Yu *et al.* 2010). Hence, in this study, the roulette wheel method was utilized for crossover operations.

4.3.2 Value of the S_{pop}

As shown in Table 2, many GA-ANN models were developed to select the optimal population size. The population size (S_{pop}) was set as 25-600, the ANN structure was set at 6–12–1, and the maximum generation was set as 100. As in the previous section, performance indexes R^2 and RMSE are applied to evaluate the developed models and the optimal model was select ed using a simple ranking process. As shown in the total rank results in Table 2, model No. 12 has the highest prediction performance compared with other models. Hence, the value of 500 was determined as the optimal $S_{pop.}$

4.3.3 Value of the N_{gen}

In order to determine the optimal N_{gen}, different GA-ANN models were also developed with a fixed value of 1000 as the N_{gen} and the values of 25-600 of the S_{pop}. As shown in Fig. 8, the RMSE values for all models remains constant after more than 700 generations. Based on this, the value 700 is determined as the optimal N_{gen}.

4.3.4 Network modelling

In this step, predicted GA-ANN models were developed with the structure of 6-12-1 and the optimal GA parameters and trained 5 times. The prediction performance indices of the developed models are listed in Table 3. More valuation of the developed models will be carried out in Sect. 5.

5. Results and discussion

In the last stage of prediction model development, the MLR model was trained once for the final UCS prediction model, and the ANN and the GA-ANN model were trained five times. The indices of R^2, RMSE and VAF are utilized to assess these models.

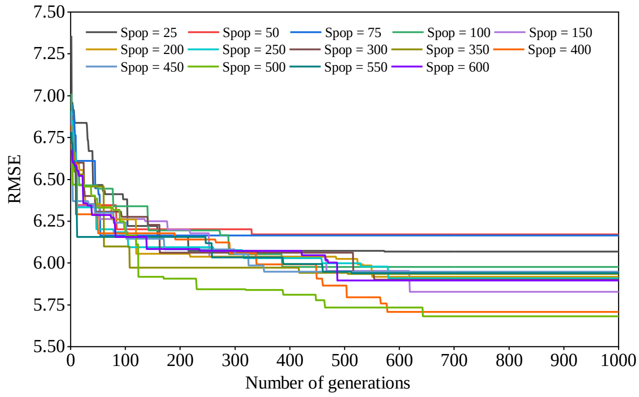


Fig. 8 The results of RMSE of different the GA-ANN models with different values of S_{pop}

Table 3 displays the results of the developed models. A larger total rank value indicates stronger prediction performance, and the optimal model is determined based on this principle. The total rank of all developed models is indicated in Table 4. As shown, ANN model No. 1 and GA-ANN model No. 3, have a total rank of 30 and 27, respectively, which indicates the highest performance for the modelling techniques. For a certain training dataset, note that only one prediction formula can be fitted using the MLR method. Therefore, only one prediction model of the MRL was developed in this study.

The best performance indices of the optimal models are expressed in Table 5. The results depict that the performance level of the MLR model can be increased from approximately 0.40 (for MLR model) to approximately 0.78

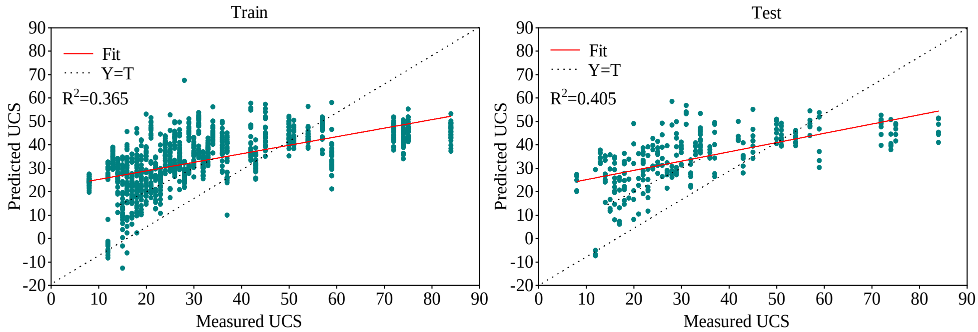
Table 3 The performance indices of the final developed models

Type	Phase	No.	R^2	RMSE	VAF	Rank value			Total rank
						R^2	RMSE	VAF	
MLR	Training	**1**	**0.365**	**15.324**	**0.365**	**1**	**1**	**1**	**1**
	Testing	**1**	**0.405**	**14.536**	**0.405**	**1**	**1**	**1**	**1**
ANN	Training	**1**	**0.846**	**7.538**	**0.846**	**5**	**5**	**5**	**15**
		2	0.842	7.658	0.841	3	3	3	9
		3	0.774	9.149	0.774	1	1	1	3
		4	0.845	7.567	0.845	4	4	4	12
		5	0.828	7.968	0.828	2	2	2	6
	Testing	**1**	**0.784**	**8.768**	**0.783**	**5**	**5**	**5**	**15**
		2	0.770	9.120	0.767	4	4	4	12
		3	0.677	10.909	0.666	2	2	2	6
		4	0.764	9.174	0.763	3	3	3	9
		5	0.610	12.555	0.556	1	1	1	3
GA-ANN	Training	1	0.865	7.056	0.865	3	3	3	9
		2	**0.881**	**6.629**	**0.881**	**5**	**5**	**5**	**15**
		3	0.881	6.641	0.881	4	4	4	12
		4	0.845	7.600	0.844	2	2	2	6
		5	0.841	7.677	0.841	1	1	1	3
	Testing	1	0.802	8.430	0.800	3	3	4	10
		2	0.818	8.175	0.697	4	4	1	9
		3	**0.819**	**8.102**	**0.815**	**5**	**5**	**5**	**15**
		4	0.793	8.629	0.791	2	2	3	7
		5	0.783	8.892	0.779	1	1	2	4

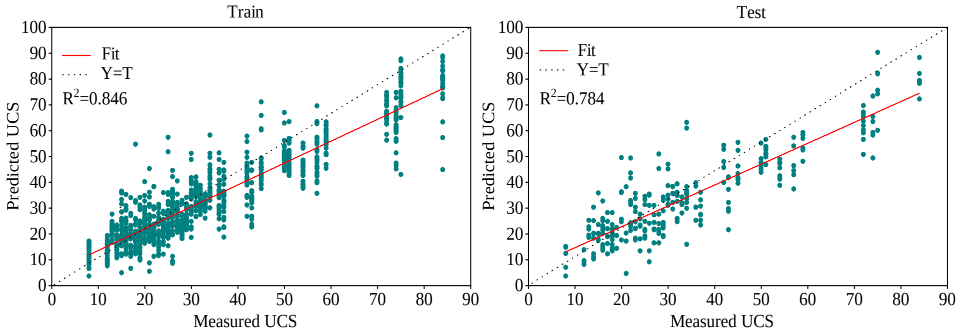
Table 4 The total rank of all phases of the final developed models

Type	No.	Total rank
MLR	**1**	**1**
ANN	**1**	**30**
	2	21
	3	9
	4	21
	5	9
GA-ANN	1	19
	2	24
	3	**27**
	4	13
	5	7

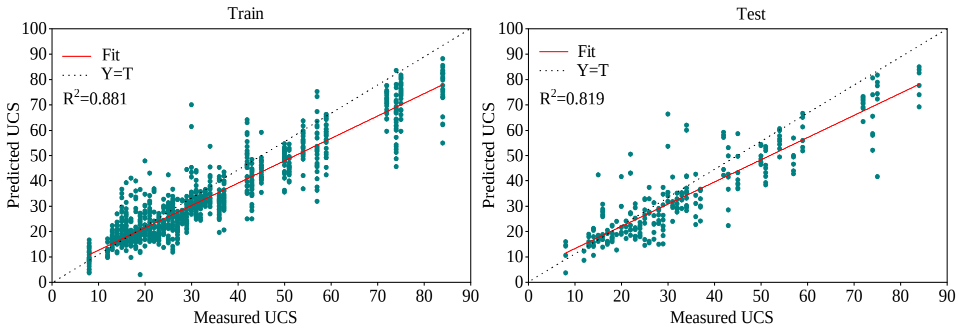
(for ANN models) based on R^2 by developing the ANN model. The performance level of the ANN model can be increased based on R^2 by developing a hybrid GA-ANN model from approximately 0.78 (for ANN models) to approximately 0.82 (for GA-ANN models). The results of MLR (with R^2, RMSE and VAF values of 0.365, 15.324 and 0.365 for training, respectively, and R^2, RMSE and VAF values of 0.405, 14.536 and 0.405 for testing, respectively); ANN (with R^2, RMSE and VAF values of 0.846, 7.538 and 0.846, respectively, for training and R^2, RMSE and VAF values of 0.784, 8.768 and 0.783 for testing, respectively); and GA-ANN (with R^2, RMSE and VAF values of 0.881, 6.641 and 0.881, respectively, for training and R^2, RMSE and VAF values of 0.819, 8.102 and 0.815, respectively, for testing) are obtained for each optimal model of the developed MLR, ANN and GA-ANN models. Moreover,



(a) The MLR models

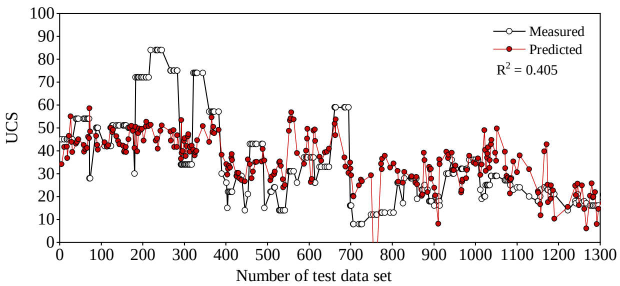


(b) The ANN models

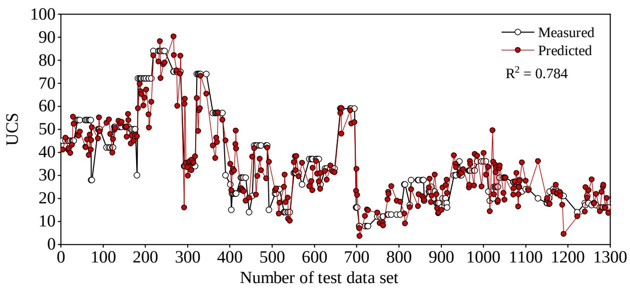


(c) The GA-ANN models

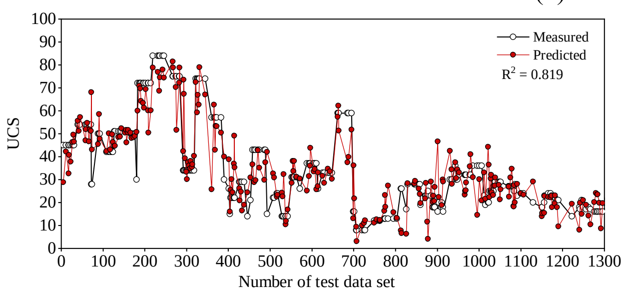
Fig. 9 Correlation coefficients of the optimal models



(a) The MLR models



(b) The ANN models



(c) The GA-ANN models

Fig. 10 Comparison of the predicted and measured UCS in the optimal models with testing data sets the correlation index values of R^2 between the measured values of UCS and the predicted values predicted by the optimal MLR, ANN and GA-ANN model are graphically shown in Fig. 9. The comparison between measured UCS and predicted UCS using all three models with testing datasets are shown in Fig. 10. The results show that the ANN and GA-ANN models have better prediction ability than the MLR models. When both the training dataset and testing dataset are considered, R^2 values of 0.846 and 0.784 and R^2 values of 0.881 and 0.819 for the ANN technique and GA-ANN technique, respectively, indicate that the GA-ANN model has slightly higher prediction performance compared with other models.

6. Conclusions

The accurate prediction of the Unconfined compressive strength (UCS) utilizing measurement-while-drilling (MWD) data is one of the most influential factors in tunnel safety construction. One of the most important advantages of artificial neural network (ANN) methods is that they can solve complex multivariate nonlinear mapping problems. However, ANN methods have significant drawbacks: the disadvantages of slow learning speed and easy to fall into local minima. In this study, therefore, an optimization algorithm of the genetic algorithm (GA), was employed to develop hybrid model of GA-ANN to estimate the UCS value ahead of tunnel face. For this purpose, 1350 datasets, including six measure-while-drilling parameters of penetration rate (PR), hammer pressure (HP), rotation pressure (RP), feed pressure (FP), hammer frequency (HF) and specific energy (SE), were collected from the new Nagasaki tunnel (east) of the West Kyushu Line high-speed railway in Japan and set as inputs, while the UCS was set as output. To evaluate the prediction performance of the hybrid models, MLR and ANN models were also developed to estimate the UCS.

A comparison among these developed models was performed by three performance indices, i.e., R^2, RMSE and VAF. The results indicate that the ANN and GA-ANN models have a high degree of accuracy and efficiency. However, the hybrid GA-ANN model has slightly higher prediction performance for predicting the UCS compared with other models. The results of R^2 = 0.881 and 0.819, RMSE = 6.641 and 8.102 and VAF = 0.881 and 0.815 for the training sets and testing sets were obtained for the GA-ANN model, respectively. The findings demonstrate that the GA-ANN model is better than MLR and ANN model.
Although the UCS of the rocks ahead of the tunnel face can be estimated via the MWD data using optimized ANN model, some problems should be considered further. How to apply stronger optimization techniques to further improve the accuracy of prediction. What is the effect of different combination of MWD parameters on prediction results. These are still outstanding issues, so it is necessary to study these further.

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References

Alimoradi, A., Moradzadeh, A., Naderi, R., Salehi, M.Z. and Etemadi, A. (2008), "Prediction of geological hazardous zones in front of a tunnel face using TSP-203 and artificial neural networks", *Tunn. Undergr. Sp. Technol.*, **23**(6), 711-717. https://doi.org/10.1016/j.tust.2008.01.001.

Aoki, K., Shirasagi, S., Yamamoto, T., Inou, M. and Nishioka, K. (1999), "Examination of the application of drill Logging to predict ahead of the tunnel face", *Proceedings of the 54th Annual Conference of the Japan Society of Civil Engineers*, Tokyo, Japan, September.

ASTM, D. (2006), *Standard Test Method for Unconfined Compressive Strength of Cohesive Soil*, ASTM Standard D2166: 2006.

Balasubramanian, M., Paglicawan, M.A., Zhang, Z.X., Lee, S.H., Xin, Z.X. and Kim, J.K. (2008), "Prediction and optimization of mechanical properties of polypropylene/waste tire powder blends using a hybrid artificial neural network-genetic algorithm (GA-ANN)", *J. Thermoplast. Compos. Mater.*, **21**(1), 51-69. https://doi.org/10.1177/0892705707084543.

Baykasoğlu, A., Dereli, T. and Tanış, S. (2004), "Prediction of cement strength using soft computing techniques", *Cement Concrete Res.*, **34**(11), 2083-2090. https://doi.org/10.1016/j.cemconres.2004.03.028.

Benyelloul, K. and Aourag, H. (2013), "Bulk modulus prediction of austenitic stainless steel using a hybrid GA-ANN as a data mining tools", *Comput. Mater. Sci.*, **77**, 330-334. https://doi.org/10.1016/j.commatsci.2013.04.058.

Bhatti, M.S., Kapoor, D., Kalia, R.K., Reddy, A.S. and Thukral, A.K. (2011), "RSM and ANN modeling for electrocoagulation of copper from simulated wastewater: Multi objective optimization using genetic algorithm approach", *Desalination*, **274**(1), 74-80. https://doi.org/10.1016/j.desal.2011.01.083.

Bieniawski, Z.T. (1974), "Estimating the strength of rock materials", *J. S. Afr. Inst. Min. Metall.*, **74**(8), 312-320.

Celada, B., Galera, J., Muñoz, C. and Tardáguila, I. (2009), "The use of the specific drilling energy for rock mass characterisation and TBM driving during tunnel construction", *Proceedings of the ITA-AITES World Tunnel Congress*, Budapest, Hungary, May.

Dehghan, S., Sattari, G., Chehreh Chelgani, S. and Aliabadi, M.A. (2010), "Prediction of uniaxial compressive strength and modulus of elasticity for Travertine samples using regression and artificial neural networks", *Min. Sci. Technol.*, **20**(1), 41-46. https://doi.org/10.1016/S1674-5264(09)60158-7.

Demirdag, S., Yavuz, H. and Altindag, R. (2009), "The effect of sample size on Schmidt rebound hardness value of rocks", *Int. J. Rock Mech. Min. Sci.*, **46**(4), 725-730. https://doi.org/10.1016/j.ijrmms.2008.09.004.

Galende-Hernández, M., Menéndez, M., Fuente, M.J. and Sainz-Palmero, G.I. (2018), "Monitor-While-Drilling-based estimation of rock mass rating with computational intelligence: The case of tunnel excavation front", *Autom. Construct.*, **93**, 325-338. https://doi.org/10.1016/j.autcon.2018.05.019.

Gao, D. (1998), "On structures of supervised linear basis function feedforward three-layered neural networks", *Chin. J. Comput.*, **1**.

Garson, G.D. (1998), *Neural Networks: An Introductory Guide for Social Scientists*, Sage.

Goudie, A.S. (2006), "The Schmidt Hammer in geomorphological research", *Progress Phys. Geography*, **30**(6), 703-718.

https://doi.org/10.1177/0309133306071954.

Grima, M.A. and Babuška, R. (1999), "Fuzzy model for the prediction of unconfined compressive strength of rock samples", *Int. J. Rock Mech. Min. Sci.*, **36**(3), 339-349. https://doi.org/10.1016/S0148-9062(99)00007-8.

Han, W., Li, G., Sun, Z., Luan, H., Liu, C. and Wu, X.J.S. (2020), "Numerical investigation of a foundation pit supported by a composite soil nailing structure", *Symmetry*, **12**(2), 252. https://doi.org/10.3390/sym12020252.

Hasanipanah, M., Noorian-Bidgoli, M., Jahed Armaghani, D. and Khamesi, H. (2016), "Feasibility of PSO-ANN model for predicting surface settlement caused by tunneling", *Eng. Comput.*, **32**(4), 705-715. https://doi.org/10.1007/s00366-016-0447-0.

Hatherly, P., Leung, R., Scheding, S. and Robinson, D. (2015), "Technical note", *Int. J. Rock Mech. Min. Sci.*, **78**(C), 144-154. https://doi.org/10.1016/j.ijrmms.2015.05.006.

Hecht-Nielsen, R. (1987), "Kolmogorov's mapping neural network existence theorem", *Proceedings of the International Conference on Neural Networks*, New York, U.S.A.

Høien, A.H. and Nilsen, B. (2014), "Rock mass grouting in the Løren Tunnel: Case study with the main focus on the groutability and feasibility of drill parameter interpretation", *Rock Mech. Rock Eng.*, **47**(3), 967-983. https://doi.org/10.1007/s00603-013-0386-7.

Holland, J.H. (1992), *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*, MIT Press, U.S.A.

Hornik, K., Stinchcombe, M. and White, H. (1989), "Multilayer feedforward networks are universal approximators", *Neural Networks*, **2**(5), 359-366.

Hoseinie, S.H., Ataei, M. and Mikaiel, R. (2012), "Comparison of some rock hardness scales applied in drillability studies", *Arab. J. Sci. Eng.*, **37**(5), 1451-1458. https://doi.org/10.1007/s13369-012-0247-9.

Inazaki, T., Isahai, H., Kawamura, S., Kurahashi, T. and Hayashi, H. (1999), "Stepwise application of horizontal seismic profiling for tunnel prediction ahead of the face", *Leading Edge*, **18**(12), 1429-1431.

ISRM, U.R. and Hudson, J. (2007), *The Complete ISRM Suggested Methods for Rock Characterization, Testing and Monitoring: 1974-2006*, Kozan, Ankara, Turkey.

Jadav, K. and Panchal, M. (2012), "Optimizing weights of artificial neural networks using genetic algorithms", *Int. J. Adv. Res. Comput. Sci. Electron. Eng.*, **1**(10), 47-51.

Jahed Armaghani, D., Hasanipanah, M., Mahdiyar, A., Abd Majid, M.Z., Bakhshandeh Amnieh, H. and Tahir, M.M.D. (2018), "Airblast prediction through a hybrid genetic algorithm-ANN model", *Neural Comput. Appl.*, **29**(9), 619-629. https://doi.org/10.1007/s00521-016-2598-8.

Kahraman, S. (2001), "Evaluation of simple methods for assessing the uniaxial compressive strength of rock", *Int. J. Rock Mech. Min. Sci.*, **38**(7), 981-994. https://doi.org/10.1016/S1365-1609(01)00039-9.

Kahraman, S., Rostami, J. and Naeimipour, A. (2016), "Review of ground characterization by using instrumented drills for underground mining and construction", *Rock Mech. Rock Eng.*, **49**(2), 585-602. https://doi.org/10.1007/s00603-015-0756-4.

Kanellopoulos, I. and Wilkinson, G.G. (1997), "Strategies and best practice for neural network image classification", *Int. J. Remote Sens.*, **18**(4), 711-725. https://doi.org/10.1080/014311697218719.

Karimi, H. and Yousefi, F. (2012), "Application of artificial neural network–genetic algorithm (ANN–GA) to correlation of density in nanofluids", *Fluid Phase Equilib.*, **336**, 79-83. https://doi.org/10.1016/j.fluid.2012.08.019.

Kayabasi, A. (2012), "Prediction of pressuremeter modulus and limit pressure of clayey soils by simple and non-linear multiple regression techniques: A case study from Mersin, Turkey", *Environ. Earth Sci.*, **66**(8), 2171-2183. https://doi.org/10.1007/s12665-011-1439-4.

Khademi, F., Akbari, M., Jamal, S.M. and Nikoo, M. (2017), "Multiple linear regression, artificial neural network, and fuzzy logic prediction of 28 days compressive strength of concrete", *Front. Struct. Civ. Eng.*, **11**(1), 90-99. https://doi.org/10.1007/s11709-016-0363-9.

Khandelwal, M. and Armaghani, D.J. (2016), "Prediction of drillability of rocks with strength properties using a hybrid GA-ANN technique", *Geotech. Geol. Eng.*, **34**(2), 605-620. https://doi.org/10.1007/s10706-015-9970-9.

Khandelwal, M., Marto, A., Fatemi, S.A., Ghoroqi, M., Armaghani, D.J., Singh, T.N. and Tabrizi, O. (2018), "Implementing an ANN model optimized by genetic algorithm for estimating cohesion of limestone samples", *Eng. Comput.*, **34**(2), 307-317. https://doi.org/10.1007/s00366-017-0541-y.

Kosakovsky Pond, S.L., Posada, D., Gravenor, M.B., Woelk, C.H. and Frost, S.D.W. (2006), "GARD: A genetic algorithm for recombination detection", *Bioinformatics*, **22**(24), 3096-3098. https://doi.org/10.1093/bioinformatics/btl474.

Kumar, M., Husian, M., Upreti, N. and Gupta, D. (2010), "Genetic algorithm: Review and application", *Int. J. Inform. Technol. Knowledge Manage.*, **2**(2), 451-454.

Kwon, S. and Lee, C. (2018), "THM analysis for an in situ experiment using FLAC3D-TOUGH2 and an artificial neural network", *Geomech. Eng.*, **16**(4), 363-373. http://doi.org/10.12989/gae.2018.16.4.363.

Looney, C.G. (1996), "Advances in feedforward neural networks: demystifying knowledge acquiring black boxes", *IEEE T. Knowledge Data Eng.*, **8**(2), 211-226. https://doi.org/10.1109/69.494162.

Masayuki, Y., Ishiyama, K., Yumura, T. and Tsukada, J. (2001), "Application of drilling survey system for weak rock with in-flow water", *Proceedings of the 31st Symposium on Rock Mechanics*, Tokyo, Japan, January.

McCulloch, W.S. and Pitts, W. (1943), "A logical calculus of the ideas immanent in nervous activity", *Bull. Math. Biophys.*, **5**(4), 115-133. https://doi.org/10.1007/bf02478259.

Meulenkamp, F. and Grima, M.A. (1999), "Application of neural networks for the prediction of the unconfined compressive strength (UCS) from Equotip hardness", *Int. J. Rock Mech. Min. Sci.*, **36**(1), 29-39. https://doi.org/10.1016/S0148-9062(98)00173-9.

Mohamad, E.T., Faradonbeh, R.S., Armaghani, D.J., Monjezi, M. and Majid, M.Z.A. (2017), "An optimized ANN model based on genetic algorithm for predicting ripping production", *Neural Comput. Appl.*, **28**(1), 393-406. https://doi.org/10.1007/s00521-016-2359-8.

Mohamad, E.T., Jahed Armaghani, D., Momeni, E. and Alavi Nezhad Khalil Abad, S.V. (2015), "Prediction of the unconfined compressive strength of soft rocks: A PSO-based ANN approach", *Bull. Eng. Geol. Environ.*, **74**(3), 745-757. https://doi.org/10.1007/s10064-014-0638-0.

Mokhtari, M. and Behnia, M. (2019), "Comparison of LLNF, ANN, and COA-ANN techniques in modeling the uniaxial compressive strength and static Young's modulus of limestone of the Dalan formation", *Nat. Resour. Res.*, **28**(1), 223-239. https://doi.org/10.1007/s11053-018-9383-6.

Momeni, E., Nazir, R., Jahed Armaghani, D. and Maizir, H. (2014), "Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN", *Measurement*, **57**, 122-131. https://doi.org/10.1016/j.measurement.2014.08.007.

Monjezi, M., Ghafurikalajahi, M. and Bahrami, A. (2011), "Prediction of blast-induced ground vibration using artificial neural networks", *Tunn. Undergr. Space Technol.*, **26**(1), 46-50.

https://doi.org/10.1016/j.tust.2010.05.002.

Nathans, L.L., Oswald, F.L. and Nimon, K. (2012), "Interpreting multiple linear regression: A guidebook of variable importance", *Pract. Assess. Res. Eval.*, **17**(9).

Nazir, R., Momeni, E., Armaghani, D.J. and Amin, M.M. (2013), "Prediction of unconfined compressive strength of limestone rock samples using L-type Schmidt hammer", *Electron. J. Geotech. Eng.*, **18**, 1767-1775.

Nelson, M.M. and Illingworth, W.T. (1991), "A practical guide to neural nets".

Ocak, I. and Seker, S.E. (2012), "Estimation of elastic modulus of intact rocks by artificial neural network", *Rock Mech. Rock Eng.*, **45**(6), 1047-1054. http://10.1007/s00603-012-0236-z.

Othman, B.S., Özcan, N.T., Kalender, A. and Sönmez, H. (2018), "Multivariate artificial neural network (ANN) models for predicting uniaxial compressive strength from index tests", *Proceedings of the 2018 European Rock Mechanics Symposium*, St. Petersburg, Russia, May.

Peck, J.P. (1989), "Performance monitoring of rotary blasthole drills", Ph.D. Dissertation, McGill University, Montreal, Canada.

Preacher, K.J., Curran, P.J. and Bauer, D. (2006), "Computational tools for probing interactions in multiple linear regression, multilevel modeling, and latent curve analysis", *J. Edu. Behav. Stat.*, **31**(4), 437-448.

Qiu, M., Ming, Z., Li, J., Gai, K. and Zong, Z. (2015), "Phase-change memory optimization for green cloud with genetic algorithm", *IEEE T. Comput.*, **64**(12), 3528-3540. https://doi.org/10.1109/TC.2015.2409857.

Schunnesson, H. (1996), "RQD predictions based on drill performance parameters", *Tunn. Undergr. Sp. Technol.*, **11**(3), 345-351. https://doi.org/10.1016/0886-7798(96)00024-7.

Schunnesson, H., Poulopoulos, V., Bastis, K., Pettersen, N. and Shetty, A. (2012), "Application of computerized drill jumbos at the Chenani-Nashri tunnelling site in Jammu-Kashmir, India", *Proceedings of the 21st International Symposium on Mine Planning and Equipment Selection*, New Delhi, India.

Scoble, M.J.,Peck, J. and Hendricks, C. (1989), "Correlation beween rotary drill performance parameters and borehole geophysical logging", *Min. Sci. Technol.*, **8**(3), 301-312. https://doi.org/10.1016/S0167-9031(89)90448-9.

Shakoor, A. and Bonelli, R.E. (1991), "Relationship between petrographic characteristics, engineering index properties, and mechanical properties of selected sandstones", *Environ. Eng. Geosci.*, **28**(1), 55-71. https://doi.org/10.2113/gseegeosci.xxviii.1.55.

Sugawara, J., Yue, Z., Tham, L., Law, K. and Lee, C. (2003), "Weathered rock characterization using drilling parameters", *Can. Geotech. J.*, **40**(3), 661-668. https://doi.org/10.1139/t03-007.

Swingler, K. (1996), *Applying Neural Networks: A Practical Guide*, Morgan Kaufmann.

Teale, R. (1965), "The concept of specific energy in rock drilling", *Int. J. Rock Mech. Min. Sci. Geomech. Abstr.*, **2**(1), 57-73. https://doi.org/10.1016/0148-9062(65)90022-7.

Toghroli, A., Darvishmoghaddam, E., Zandi, Y., Parvan, M., Safa, M., Mu'azu, M., Heydari, A., Wakil, K., Gebreel, S. and Khorami, M. (2018), "Evaluation of the parameters affecting the Schmidt rebound hammer reading using ANFIS method", *Comput. Concrete*, **21**(5), 525-530. https://doi.org/10.12989/cac.2018.21.5.525.

Tsiambaos, G. and Sabatakakis, N. (2004), "Considerations on strength of intact sedimentary rocks", *Eng. Geol.*, **72**(3), 261-273. https://doi.org/10.1016/j.enggeo.2003.10.001.

Utsuki, S. and Tsuruta, R. (2018), "Construction of a geological information management system using Ai, Cim and image processing technology", *Proceedings of the 52nd U.S. Rock Mechanics/Geomechanics Symposium*, Washington, U.S.A., August.

Wang, X., Yuan, W., Yan, Y. and Zhang, X.J.G.E. (2020), "Scale effect of mechanical properties of jointed rock mass: A numerical study based on particle flow code", *Geomech. Eng.*, **21**(3), 259-268. https://doi.org/10.12989/gae.2020.21.3.259.

Whitley, D. (1994), "A genetic algorithm tutorial", *Statistics Comput.*, **4**(2), 65-85. https://doi.org/10.1007/bf00175354.

Xue, X. (2019), "Application of a support vector machine for prediction of piping and internal stability of soils", *Geomech. Eng.*, **18**(5), 493-502. http://doi.org/10.12989/gae.2019.18.5.493.

Yagiz, S. (2019), "Comments on: The effects of density and porosity on the correlation between uniaxial compressive strength and P-wave velocity by Amin Jamshidi, Hasan Zamanian, Reza Zarei Sahamieh", Rock Mechanics and Rock Engineering (2018) 51, 1279-1286", *Rock Mech. Rock Eng.*, **52**(2), 635-638. https://doi.org/10.1007/s00603-018-1678-8.

Yagiz, S., Sezer, E.A. and Gokceoglu, C. (2012), "Artificial neural networks and nonlinear regression techniques to assess the influence of slake durability cycles on the prediction of uniaxial compressive strength and modulus of elasticity for carbonate rocks", *Int. J. Numer. Anal. Meth. Geomech.*, **36**(14), 1636-1650. https://doi.org/10.1002/nag.1066.

Yazdanmehr, M., Anijdan, S.H.M. and Bahrami, A. (2009), "Using GA-ANN algorithm to optimize soft magnetic properties of nanocrystalline mechanically alloyed Fe-Si powders", *Comput. Mater. Sci.*, **44**(4), 1218-1221. https://doi.org/10.1016/j.commatsci.2008.08.003.

Yilmaz, I. (2009a), "A case study from Koyulhisar (Sivas-Turkey) for landslide susceptibility mapping by artificial neural networks", *Bull. Eng. Geol. Environ.*, **68**(3), 297-306. https://doi.org/10.1007/s10064-009-0185-2.

Yilmaz, I. (2009b), "A new testing method for indirect determination of the unconfined compressive strength of rocks", *Int. J. Rock Mech. Min. Sci.*, **46**(8), 1349-1357. https://doi.org/10.1016/j.ijrmms.2009.04.009.

Yılmaz, I. and Sendır, H. (2002), "Correlation of Schmidt hardness with unconfined compressive strength and Young's modulus in gypsum from Sivas (Turkey)", *Eng. Geol.*, **66**(3), 211-219. https://doi.org/10.1016/S0013-7952(02)00041-8.

Yu, S., Guo, X., Zhu, K. and Du, J. (2010), "A neuro-fuzzy GA-BP method of seismic reservoir fuzzy rules extraction", *Expert Syst. Appl.*, **37**(3), 2037-2042. https://doi.org/10.1016/j.eswa.2009.06.074.

Zhang, L. (2016), *Engineering Properties of Rocks*, Butterworth-Heinemann, Wellington Square, Oxford, U.K.

Zorlu, K., Gokceoglu, C., Ocakoglu, F., Nefeslioglu, H.A. and Acikalin, S. (2008), "Prediction of uniaxial compressive strength of sandstones using petrography-based models", *Eng. Geol.*, **96**(3), 141-158. https://doi.org/10.1016/j.enggeo.2007.10.009.

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Appendix A

Table (A) The results of the developed ANN models with different number of hidden layer nodes

No.	Hidden layer nodes	Index	Results										Average result		Rank value		Total rank
			Run 1		Run 2		Run 3		Run 4		Run 5						
			Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing	
1	1		0.445	0.465	0.498	0.522	0.508	0.531	0.507	0.524	0.508	0.535	0.493	0.516	1	1	2
2	2		0.695	0.646	0.598	0.619	0.591	0.542	0.626	0.647	0.583	0.606	0.619	0.612	2	2	4
3	3		0.679	0.597	0.729	0.704	0.711	0.681	0.726	0.688	0.686	0.623	0.706	0.658	3	3	6
4	4		0.752	0.694	0.738	0.731	0.717	0.643	0.750	0.699	0.733	0.658	0.738	0.685	4	6	10
5	5		0.811	0.781	0.751	0.705	0.7310	0.602	0.777	0.711	0.778	0.737	0.770	0.707	9	18	27
6	6		0.749	0.681	0.772	0.739	0.700	0.663	0.686	0.674	0.803	0.759	0.742	0.703	6	17	23
7	7		0.718	0.643	0.751	0.706	0.798	0.692	0.789	0.713	0.728	0.678	0.757	0.686	7	8	15
8	8		0.813	0.727	0.754	0.689	0.759	0.669	0.794	0.729	0.726	0.601	0.769	0.683	8	5	13
9	9		0.798	0.698	0.702	0.655	0.783	0.695	0.809	0.714	0.79	0.683	0.776	0.689	11	9	20
10	10		0.843	0.732	0.808	0.711	0.710	0.665	0.870	0.762	0.796	0.691	0.805	0.712	20	20	40
11	11		0.842	0.743	0.826	0.715	0.696	0.619	0.737	0.644	0.783	0.708	0.777	0.686	12	7	19
12	**12**		**0.846**	**0.784**	**0.842**	**0.770**	**0.774**	**0.677**	**0.845**	**0.764**	**0.828**	**0.610**	**0.827**	**0.721**	**24**	**25**	**49**
13	13	R^2	0.764	0.711	0.793	0.710	0.785	0.666	0.799	0.696	0.803	0.709	0.789	0.698	14	13	27
14	14		0.791	0.715	0.803	0.700	0.779	0.713	0.780	0.655	0.785	0.664	0.788	0.689	13	10	23
15	15		0.795	0.697	0.636	0.641	0.815	0.697	0.815	0.740	0.808	0.735	0.774	0.702	10	16	26
16	16		0.748	0.683	0.799	0.717	0.84	0.778	0.883	0.556	0.792	0.734	0.812	0.693	21	12	33
17	17		0.708	0.659	0.608	0.600	0.782	0.704	0.804	0.722	0.790	0.696	0.738	0.676	5	4	9
18	18		0.844	0.72	0.787	0.718	0.888	0.721	0.804	0.697	0.813	0.733	0.827	0.718	25	23	48
19	19		0.743	0.666	0.820	0.704	0.743	0.680	0.842	0.756	0.828	0.765	0.795	0.714	16	21	37
20	20		0.761	0.691	0.892	0.739	0.785	0.703	0.762	0.695	0.776	0.675	0.795	0.701	15	15	30
21	30		0.849	0.772	0.842	0.722	0.856	0.715	0.741	0.676	0.803	0.706	0.818	0.718	23	24	47
22	40		0.747	0.664	0.789	0.710	0.801	0.753	0.849	0.758	0.829	0.687	0.803	0.714	19	22	41
23	50		0.771	0.69	0.801	0.698	0.762	0.665	0.807	0.713	0.838	0.730	0.796	0.699	17	14	31
24	60		0.844	0.742	0.798	0.706	0.845	0.780	0.803	0.685	0.879	0.635	0.834	0.710	26	19	45
25	70		0.868	0.771	0.898	0.739	0.725	0.685	0.805	0.725	0.774	0.699	0.814	0.724	22	26	48
26	80		0.803	0.719	0.641	0.646	0.918	0.631	0.801	0.732	0.844	0.726	0.801	0.691	18	11	29

Table (A) Continued

No.	Hidden layer nodes	Index	Results										Average result		Rank value		Total rank
			Run 1		Run 2		Run 3		Run 4		Run 5						
			Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing	
1	1		14.499	13.944	13.633	13.152	13.485	12.943	13.507	13.058	13.489	12.916	13.723	13.202	1	1	2
2	2		10.618	11.291	12.197	11.751	12.373	12.779	11.763	11.234	12.414	11.876	11.873	11.786	2	2	4
3	3		10.919	12.036	10.014	10.312	10.340	10.736	10.06	10.591	10.774	11.790	10.421	11.093	3	3	6
4	4		9.597	10.439	9.850	9.781	10.231	11.393	9.637	10.346	9.968	11.334	9.857	10.659	4	10	14
5	5		8.368	8.829	9.602	10.333	9.982	12.205	9.081	10.266	9.063	9.718	9.219	10.270	9	20	29
6	6		9.638	10.728	9.217	9.683	10.587	10.967	10.779	10.846	8.542	9.307	9.753	10.306	6	18	24
7	7		10.260	11.557	9.59	10.237	8.636	10.657	8.843	10.250	10.048	10.731	9.476	10.686	7	8	15
8	8		8.322	9.998	9.544	10.624	9.440	11.032	8.728	9.887	10.070	12.369	9.221	10.782	8	7	15
9	9		8.647	10.405	10.497	11.155	8.950	10.503	8.410	10.253	8.813	10.678	9.063	10.599	11	11	22
10	10		7.628	9.993	8.443	10.413	10.404	11.092	6.937	9.330	8.696	10.620	8.422	10.290	19	19	38
11	11		7.640	9.649	8.036	10.256	10.608	11.731	9.867	11.340	8.963	10.335	9.023	10.662	12	9	21
12	**12**		**7.538**	**8.768**	**7.658**	**9.120**	**9.149**	**10.909**	**7.567**	**9.174**	**7.968**	**12.555**	**7.976**	**10.106**	**24**	**25**	**49**
13	13	RMSE	9.346	10.277	8.748	10.418	8.923	11.132	8.624	10.432	8.536	10.307	8.835	10.513	14	13	27
14	14		8.799	10.113	8.526	10.429	9.047	10.099	9.023	11.203	8.959	11.143	8.871	10.598	13	12	25
15	15		8.764	10.532	11.701	11.461	8.277	10.613	8.290	9.739	8.430	9.816	9.092	10.432	10	16	26
16	16		9.827	10.955	8.638	10.239	7.697	8.970	6.580	14.303	8.768	9.802	8.302	10.854	21	6	27
17	17		10.421	11.234	12.158	11.987	8.982	10.347	8.509	10.070	8.840	10.688	9.782	10.865	5	5	10
18	18		7.590	10.276	8.885	10.158	6.434	10.482	8.520	10.544	8.328	9.879	7.952	10.268	25	21	46
19	19		9.756	10.989	8.170	10.555	9.745	10.800	7.645	9.436	7.972	9.151	8.658	10.186	16	23	39
20	20		9.410	10.629	6.334	9.991	8.917	10.348	9.421	10.506	9.123	10.921	8.641	10.479	17	15	32
21	30		7.477	9.079	7.641	10.135	7.298	10.506	9.784	10.796	8.529	10.366	8.146	10.176	23	24	47
22	40		9.666	11.066	8.835	10.276	8.581	9.425	7.481	9.306	7.949	10.931	8.503	10.201	18	22	40
23	50		9.207	10.616	8.576	10.598	9.394	11.018	8.456	10.262	7.778	10.032	8.682	10.505	15	14	29
24	60		7.603	9.742	8.648	10.450	7.581	8.858	8.542	10.749	6.691	12.347	7.813	10.429	26	17	43
25	70		7.002	9.278	6.154	10.052	10.095	10.648	8.488	10.003	9.150	10.425	8.178	10.081	22	26	48
26	80		8.534	10.118	11.702	11.401	5.518	12.929	8.577	9.851	7.601	10.182	8.386	10.896	20	4	24