Support Vector Machines-Based Prediction of Elastic Modulus for Granite Rock

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1 Introduction

For the construction of any structure on the rock mass, engineering properties (strength and deformation characteristics) of the rock play an important role. These properties are useful in planning and optimizing the utilization of the natural resources of the earth. The design of the structure resting on rock is influenced by the strength and elasticity response under different stress conditions. The major influencing factor is the stress–strain behavior and the elastic modulus (E). These are generally determined by the unconfined compressive strength test. Generally, these properties are dependent on the point load strength index 'Is (50)', rebound number 'Rn', P-wave velocity 'VP', and the porosity 'n' as reported in [1, 2]. It was reported by [3] that the basic rock index tests, such as physical tests, ultrasonic velocity test, point load index test, rebound number test, and Brazilian test, were easy to perform and were economical. In the present study, the elastic modulus (E) of the rock was predicted based on the index properties of the rock.

2 Background

Since the past decade, soft computing techniques have been becoming popular in the field of civil engineering, especially in geotechnical engineering [4–7]. However, the

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application of artificial neural network (ANN) is one of the most popular research areas in engineering applications due to its diversity. Though, as we know, ANNs have the ability to map the input to the output with the help of the anticipated independent input parameters for the prediction of the desired output parameter. However, the ANN is having the limitations such as the slow learning rate and entrapment of the local minima, as reported by [8, 9]. The support vector machines predict accurately in comparison to the ANN, M5P, and random forest regression [10–14]. Keeping the above in view, the support vector machine with poly kernel and RBF kernel was used in the present study to predict the elastic modulus for granite rock. These techniques (SVM) have been successfully used in the different engineering application areas [15–18]. To achieve the objective of the present study, the input parameters such as porosity '*n*', Schmidt hammer rebound number 'Rn', *P*-wave velocity 'VP', and point load strength index 'Is (50)' were utilized to predict the output (modulus of elasticity 'E').

3 Support Vector Machines

Support vector machines (SVMs) were introduced by [19] with an alternate ε-insensitive loss function. It allows for regression problems to use the definition of margin. However, the boundary is defined as the total of hyperplanes distances from the closest point of two categories. The main aim of the SVM is to find out a function having maximum ε deviation from the real target vectors for all the training data provided and it must be as flat as possible [20]. However, a kernel function concept was introduced by [19] for nonlinear SVM regression. The enthusiastic readers are advised to refer for more descriptions of supporting vector regression [19, 20].

3.1 Details of Kernel

In SVM a kernel function concept was used, where the nonlinear decision surface circumstances occurred [19]. A number of kernel functions are introduced in the past decade, but the literature [21–23] suggests that the polynomial kernel and radial basis kernels (RBF) perform better for geotechnical engineering applications. Hence, in the present article, polynomial kernel $K(x, y) = [(x.y)]^d$ and RBF kernel $e^{-\gamma|x-y|^2}$ were used (where d and γ are the kernel parameters). In order to use SVM, suitable user-defined parameters have to be set first. These used-defined parameters are playing a major role in SVM prediction. The SVM needs kernel-specific parameters in addition to the selection of a kernel. The appropriate values of the regulatory parameter C as well as the size of the error-insensitive zone ε should be determined. A manual procedure was followed to select user-defined parameters (i.e. C, γ, and d), which involves performing a series of trials by means of different combinations of C and d for the polynomial kernel; C and γ for the RBF kernel support vector

Table 1 Range of the parameters used in SVM modeling

Input parameters	Total data set			
	Min	Max	Avg	Standard deviation
Is (50) (MPa)	0.89	7.10	3.34	1.50
Rn	37.00	61.00	49.56	5.96
VP (m/s)	2823.00	7943.00	5580.74	1089.43
n (%)	0.10	0.57	0.37	0.13
E (GPa)	22.00	183.30	88.40	34.93

machines (SVMs). Correspondingly, several trials were conducted in order to find the appropriate value for ε the error-insensitive zone having a fixed value of C and defined kernel parameters. The value of $C = 0.011$ is found to be good for this study. In this article, the radial basis function kernel and the polynomial kernel of the support vector machines are represented as $\mathrm{SVM_{RBFK}}$ and $\mathrm{SVM_{POLYK}}$, respectively.

4 Data Collection

Data used in the present study are taken from an earlier study reported by [24] in which an artificial neural network (ANN) enhanced with the imperialist competitive algorithm (ICA) was used to associate the input index properties of the granite rock to predict the modulus of elasticity (E). To achieve the objective of the present study, a total of 71 data were collected from the literature [24]. It contains the point load strength index 'Is (50)', rebound hammer number 'Rn', P-wave velocity 'VP', porosity 'n', and Young's modulus 'E'. The range of these variables used for the SVM model was shown in Table 1. The input parameters were Is (50), Rn, VP, and n and the output parameter was the modulus of elasticity (E).

5 Statistical Testing Measures

The statistical testing measures (STMs) were used to assess the effectiveness of the poly kernel and the RBF kernel models during the training and the testing phase. The utilized STMs are correlations coefficient (r), coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The formulas for the statistical testing measures were reported in [25]. The predictive models with an r and R^2 equal to 1, MAPE less than 20%, and MAE, RMSE, and MAE close to zero indicate a perfect model [5–7, 25].

6 Results and Discussion

The statistical testing measures are the key aspects that were used to assess the performance of the SVM_{POLYK} and SVM_{RBFK} models. The user-defined parameters for the SVM_{POLYK} are C and d; for SVM_{RBFK} C and γ were chosen with different combinations to obtain the best performance of the models. The best user-defined parameters were tabulated in Table 2.

The best statistical testing parameters obtained for both SVM models are presented in Table 3 for the training as well as for the testing. For $SVM_{POLYK,}$ the measured versus predicted plots for the training and the testing were shown in Fig. 1a and b, respectively. Similarly, for the $SVM_{RBFK,}$ the training and the testing were shown in Fig. 2a and b, respectively. From the study of Table 3 and Figs. 1 and 2, it has been revealed that the SVM_{RBFK} is predicting the modulus of elasticity of the granite rock accurately as compared to the SVM_{POLYK}.

Finally, the measured modulus of elasticity and the predicted modulus of elasticity from the SVM_{POLYK} and SVM_{RBFK} were compared for the testing data and presented in Fig. 3. From Fig. 3, the reader can note the difference between the measured versus the predicted variation.

However, the results of the present study were compared with the previous study in terms of the coefficient of determination (R^2) and the comparison is shown in Fig. 4. This figure reveals that the present study models can predict the modulus of the elasticity of the granite rock accurately in comparison to the previously reported models which were developed using soft computing techniques, such as GA-NN, ANFIS, GA, and ICA-NN, and reported in the literature works [24, 26–28] for the rock masses.

Table 2 User-defined parameters

Support vector regression (SVM)			
SVM_{POLYK}		SVM_{RBFK}	
C	*D*	*C*	γ
1.2	5	1.5	7

Table 3 Statistical testing measures for the SVM polynomial kernel and SVM RBF kernel

Performance measures	SVM polynomial kernel		SVM RBF kernel	
	Training	Testing	Training	Testing
R^2	0.95	0.94	0.98	0.97
r	0.95	0.93	0.98	0.97
MAE	389.57	518.02	186.91	265.19
RMSE	19.74	22.76	13.67	16.28
MAE	13.45	16.98	7.27	13.32
MAPE	17.39	24.93	9.85	19.54

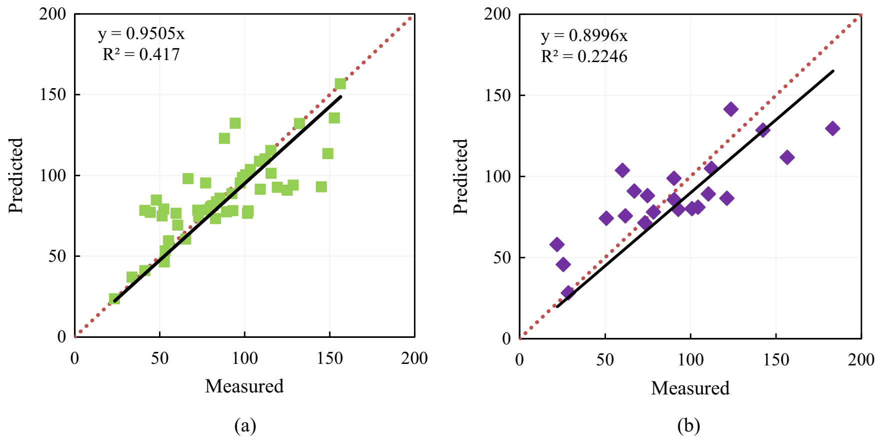

Fig. 1 Scattered plot for the measured versus predicted modulus of elasticity by SVM poly kernel. **a** Training and **b** testing

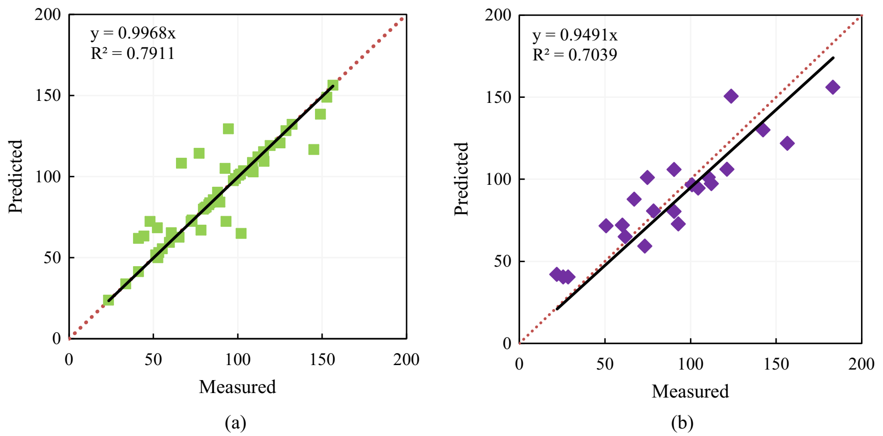

Fig. 2 Scattered plot for the measured versus predicted modulus of elasticity by SVM RBF kernel. **a** Training and **b** testing

6.1 Sensitivity Analysis

Generally, sensitivity analysis is conducted in soft computing techniques to see the influence of each of the input parameters on the output. In the present study, the same was carried out to see the individual input parameter influence on the output parameter prediction. However, the radial basis function kernel model was used in this study. The reason behind choosing the SVM_{RBFK} is that its prediction performance is superior to the polynomial kernel. The results of the sensitivity analysis are presented in Table 4. The study of this table reveals that porosity 'n' and Schmidt hammer rebound number

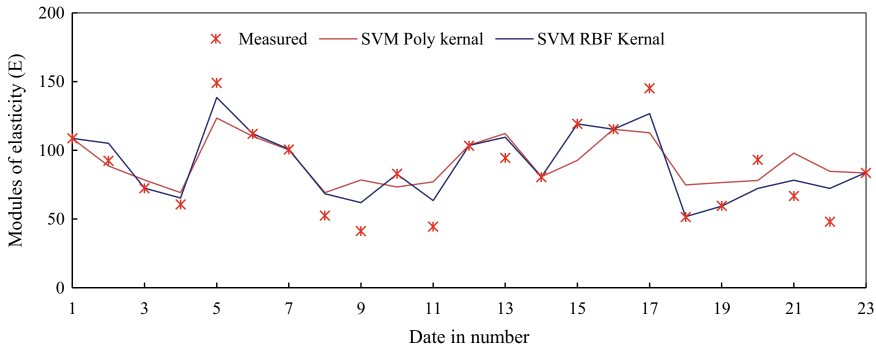

Fig. 3 Plot for the measure, SVM poly kernel and SVM RBF kernel comparison for the testing date of the modulus of elasticity

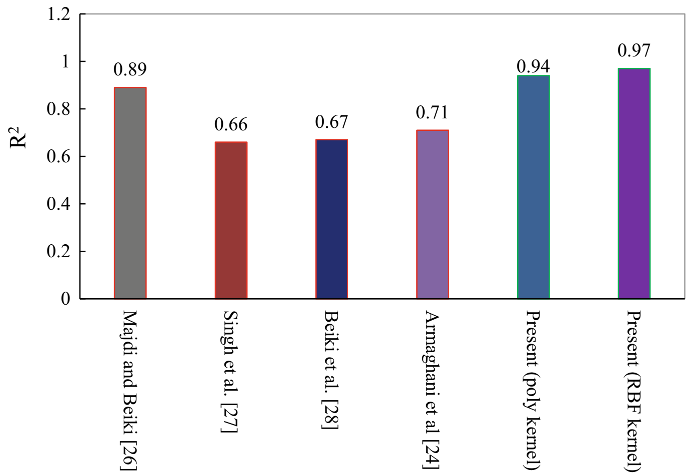

Fig. 4 R^2 for different studies

Table 4 Sensitivity analysis for the SVM_{RBFK}

Input combinations	Input parameter removed	SVM_{RBFK}					
		R^2	r	MAE	RMSE	MAE	MAPE
n, Rn, VP, and Is (50)	–	0.97	0.98	186.91	13.67	7.27	9.85
Rn, VP, and Is (50)	n	0.94	0.97	296.85	17.23	11.55	16.27
n, VP, and Is (50)	Rn	0.94	0.96	341.04	18.47	11.55	16.17
n, Rn, and Is (50)	VP	0.96	0.97	224.36	14.98	8.89	11.61
n, Rn, and VP	Is (50)	0.96	0.97	224.36	14.98	8.89	11.61

'Rn' are the most influencing parameters in comparison to the P-wave velocity 'VP' and point load strength index 'Is (50)'.

7 Conclusions

This study investigates the potential use of SVM polynomial and SVM RBF kernels in predicting the modulus of elasticity of the granite rock masses. The key conclusion that can be drawn from this study is that the SVM RBF kernel model predicted the modulus better than the SVM polynomial kernel. However, both the proposed models in the present study are suitable for predicting modulus of elasticity of granite rock. The results of comparison with the previous studies using soft computing techniques (GA-NN, ANFIS, GA, and ICA-NN) were inferior in comparison to the present techniques (SVM RBF and polynomial kernels). Finally, the sensitivity analysis reveals that the porosity '*n*' and Schmidt hammer rebound number 'Rn' were the most influencing parameters in comparison to the *P*-wave velocity 'VP' and point load strength index 'Is (50)'. The limitation of the present study is that the collected data was limited to one country and the number of the data was also less.

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