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Utilization of a nonlinear support vector machine to predict blasting vibration characteristic parameters in opencast mine

***Abstract**. Characteristic parameters of blasting vibration (BVCP) have great effects on its damage level. The prediction of BVCP is helpful to study blasting vibration effect. In this paper, an attempt has been made to predict blast-induced ground vibration using support vector machine (SVM) to avoid the limitation of the prediction with only one index and to improve the prediction precision. A Grid search method-based SVM prediction model for BVCP was established on the basis of nonlinear model-based SVM. To construct the model, nine factors affecting blasting vibration characteristic variables are taken as input parameters, whereas, peak particle velocity (PPV), dominant frequency (D_f) and its time duration (D_t) are considered as output parameters. A database consisting of 108 datasets was collected from Tonglvshan copper mine in China. From the prepared database, 93 datasets were used for the training of the model, whereas 15 randomly selected datasets were used for the validation of the SVM model. To compare the performance of the developed SVM model with that of artificial neural network (ANN) model, the same database was applied. Superiority of the proposed SVM model over ANN model was examined by calculated coefficient of determination for predicted and measured values of PPV, D_f and D_t. Concluded remark is that the prediction's BVCP can reliably be estimated from the indirect methods using SVM analysis.*

***Streszczenie.** Przy przewidywaniu efektów i szkód wibracji wybuchowych ważny jest parametr BVCP – blasting vibration characteristic parameter. W artykule przedstawiono model matematyczny do prognozowania efektów drgań wybuchowych z wykorzystaniem metody SVM. (**Wykorzystanie metody SVM do prognozowania parametrów wibracji wybuchowych w kopalniach odkrywkowych**)*

Keywords: Opencast mine, blast vibration, blasting vibration characteristic parameters (BVCP), support vector machine (SVM), prediction.
Słowa kluczowe: kopalnie odkrywkowe, wibracje wybuchowe, SVM.

1. Introduction

Blasting is still being considered to be one the most important applicable alternatives for mining and civil construction projects. Ground vibration generated for blasting is an undesirable phenomenon which is harmful for the nearby habitants, facilities and dwellings and should be prevented [1]-[3]. Along with rock mass blasting engineering increasing in China, how to analyze and predict the BVCP of rock mass from monitor data becomes a focus problem.

In order to study blasting vibration effect for mining and civil construction projects, a number of vibration predictors were proposed by many researchers for the prediction of PPV [1]-[10]. Various predictors [4] estimate the PPV mainly based on two parameters (maximum charge used per delay and distance between blast face and monitoring point). And formula prediction is still the most direct and easy method for designers in China. The Chinese standard predicting equation is Sadaovsky's empirical formula. Iphar et al. [5] investigated the applicability of a relatively new soft computing method called for the adaptive neuro fuzzy inference system (ANFIS) to predict PPV. However, few predictors considered the attenuation/damping factor [2], [6]. To solve this problem, Frequency and PPV are most commonly used parameters for assessment of ground vibrations, and the ANN was introduced to predict characteristic variables caused by blasting vibration, and have achieved some results [4]-[6]. Khandelwal and Singh [7] studied the blast vibration and frequency using rock, blast design and explosive parameters with the help of ANN and multivariate regression analysis. Mostafa [8] also applied ANN for the prediction and control of blast vibration on limestone quarries. But the damage of buildings rests not only on amplitude of PPV, but on vibration frequency and duration. Recently, a rough set-based fuzzy neural network prediction model for characteristic variables of blasting vibration was established by Shi et al. [9] based on analysis of factors affecting blast vibration characteristic variables. Shi and Zhou [10]-[11] proposed the bayes discriminant analysis model and distance discriminant analysis model to predict the extent of housing damage considering the three factors of ground vibrations. Research shows that, the developed ANN model has some limitations, such as black box approach, arriving at local minima, less generalization capability, slow convergence speed, overfitting problem and absence of probabilistic output [2], [6]-[9]. Furthermore, there is no proper method to determine the number of hidden layers in the ANN model. The developed ANFIS model determines the fuzzy rules with difficulty [5]. Therefore, it is imperative to explore a more reasonable way to study of BVCP.

In the last several years, support vector machine (SVM) by Vapnik [12] had become one of the most promising learning machines because of its high generalization performance and wide applicability for classification as well as for regression [13]-[17]. It is therefore motivating to investigate the capability of SVM in BVCP prediction. The purpose of this study was to explore a method which could avoid the limitation of the prediction with only one index and to improve the prediction precision. In the present investigation, an attempt has been made to predict three blasting vibration characteristic parameters with the help of SVM by used relevant parameters of rock mass, explosive characteristics and blast design.

The remaining paper is structured in the following manner. Section 2 presents a brief introduction to SVM. Section 3 describes the development of an SVM-based prediction model, and explains the research methodologies adopted by this research, results of comparative study with the ANN model and the experiments values are also discussed. Section 4 concludes the paper and provides suggestions for future research.

2. Methodology

2.1 The basic of SVM model

SVM [12]-[17] are linear learning machines which means that a linear function ($J(x)=wx+b$) is always used to solve the regression problem. The best line is defined to be that line which minimises the following cost function (Ω):

$$\Omega = C\sum_{i=1}^{q}\lambda^{\varepsilon}(x_i, y_i, f) + 1/2\|w\|^2 \quad (1)$$

$$\text{subject to} \begin{cases} y_i - (wx_i + b) \le \varepsilon + \theta_i \\ (wx_i + b) - y_i \le \varepsilon + \theta_i^* \\ \theta_i \cdot \theta_i^* \ge 0 \end{cases} \quad (2)$$

The first part of this cost function is a weight decay which is used to regularize weight sizes and penalizes large weights. Due to this regularization, the weights converge to smaller values. Large weights deteriorate the generalization ability of the SVM because they can cause excessive variance. The second part is a penalty function which penalizes errors larger than $\pm\varepsilon$ using a so-called ε-insensitive loss function λ^{ε} for each of the N training points. The positive constant C determines the amount up to which deviations from c are tolerated. Errors larger than $\pm\varepsilon$ are denoted with the so-called slack variables θ (above ε) and θ^* (below ε), respectively. The third parts of the equation are constraints that are set to the errors between regression predictions (wx_i+b) and true values (y_i). The values of both ε and C have to be chosen by the user and the optimal values are usually data and problem dependent.

The minimisation of Eq. (2) is a standard problem in optimisation theory: minimisation with constraints. This can be solved by applying Lagrangian theory and from this theory it can be derived that the weight vector, ***w***, equals the linear combination of the training data

$$\mathbf{w} = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) x_i \tag{3}$$

In this formula, α_i and α_i^* are Lagrange multipliers that are associated with a specific training point. The asterisk again denotes difference above and below the regression line. From Eqs. (2) and (3), the following solution is obtained for an unknown data point x:

$$J(x) = b + \sum_{i=1}^{q} (\alpha_i - \alpha_i^*) \cdot (x_i, x) \tag{4}$$

By using a mapping function, the regression function Eq. (4) can be changed into:

$$J(x) = b + \sum_{i=1}^{q} (\alpha_i - \alpha_i^*) \cdot K(x_i, x) \tag{5}$$

In Eq. (5), K is the so-called kernel function which is proven to simplify the use of a mapping. The most used kernel functions are the Gaussian RBF with a width of g: $K(x_i, x)=\exp(-0.5||x-x_i||^2/g^2)$, x_i, x are the input feature vectors. Thus the type of kernel function is RBF in the current study. Further detailed mathematical description over SVM can be referred from Ref. [13]-[17].

3. A case studey

3.1 Input and output parameters

To develop and train the SVM, input and output vectors were identified. The nature and intensity of blast induced ground vibrations and frequency is largely dependent on various factors. In accordance with Shi [2] [5] [9]-[11], the following input parameters were used: 1) Maximum charge per delay (Q_{max}) in kg; 2) total charge weight (Q_t) in kg; 3) Distance for monitoring point from blasting face (D) in m; 4) height difference (HD) in m; 5) front-row burden (B) in m; 6) Pre-crack penetration (%); 7) the integrity coefficient of rock mass (K_v); 8) the angle between measuring point and the direction of least resistance line (α) in degree; 9) Velocity of detonation for explosive (VoD) in m/s. The outputs of the SVM are the peak particle velocity (PPV, cm/s), dominant frequency (D_f, Hz) and its time duration (D_t, ms).

3.2. Dataset

In this study, the dataset comprised the field experimental results of Shi [2] at Tonglvshan copper opencast mine of China. Seismic YBJ-1 type of blasting induced vibrations self-recording instrument produced by Yangtze River Scientific Research Institute and CD-1 type of velocity recording instrument supplied by Beijing Instrument Factory were adopted in this study. The total database containing 108 datasets were used for constructing nonlinear models-based SVM, and 93 test results were selected as training samples of model in this paper. Table 1 indicates the relevant parameters as well as their respective symbols used to develop BVCP prediction models range with their max, min, mean, standard deviation and skew, respectively. The boxplot of the original data set is given in Fig. 1. For the most of the data groups, the median is not in the centre of the box, which indicates that the distribution of the most of the data groups is not symmetric (Fig. 1). In addition, dependent variables of Q_t, HD, B, PPR, K_v, α, VoD, D_t do not have any outliers whereas Q_{max}, D, PPV and D_f have at least one outlier. Another 15 test results (approximately 14% of all data) were used as the testing samples for accuracy of the model [2], which are shown in Tab.2. In the present study, training and testing analysis of SVM have been carried out using Matlab [18]. And all the input and output parameters were scaled between 0 and 1. The following equation was used for the scaling of input and output parameters:

(6) $\text{Scaled}_{\text{value}} = (\text{max.}_{\text{value}} - \text{unscaled.}_{\text{value}})/(\text{max.}_{\text{value}} - \text{min.}_{\text{value}})$

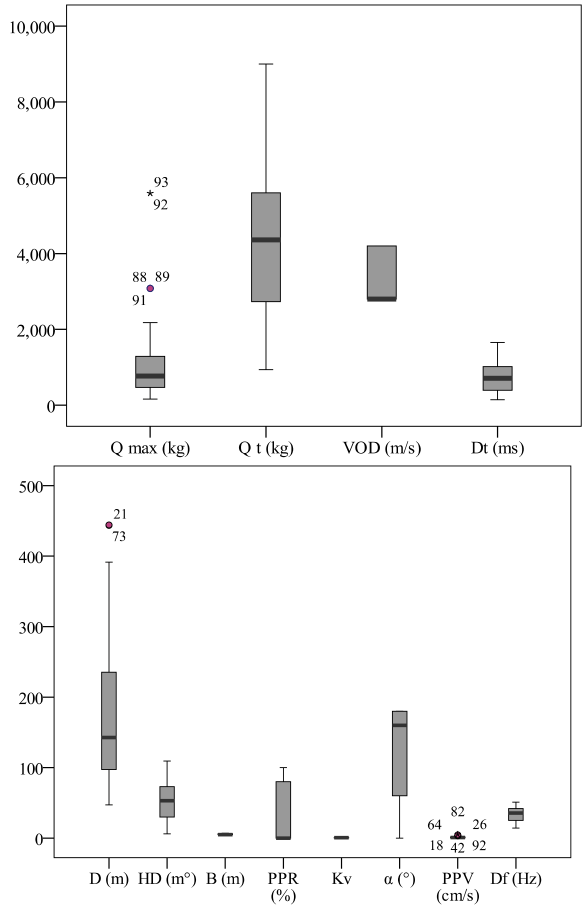


Fig. 1 Boxplot of the original data set of BVCP

Table 1 Descriptive statistics of the input and output parameters for SVM modeling

Type of data	Parameter	Max	Min	Average	Standard deviation	Skew
Inputs	Q_{max} (kg)	5590.0	160.0	1081.194	968.59	2.647
	Q_t (kg)	9000.0	936.0	4263.892	2087.07	0.422
	D (m)	444.3	47.1	176.682	98.91	0.957
	HD (m°)	109.3	6.0	54.494	24.58	0.534
	B (m)	7.0	4.0	5.409	0.81	-0.135
	PPR (%)	100.0	0.0	29.570	42.04	0.797
	K_v	0.8	0.3	0.559	0.14	-0.133
	α (°)	180.0	0.0	128.011	62.70	-0.798
	VoD (m/s)	4200.0	2800.0	3387.097	694.58	0.332
Outputs	PPV (cm/s)	5.4	0.1	1.209	1.18	1.585
	D_f (Hz)	51.1	14.3	33.955	9.96	-0.111
	D_t (ms)	1655.0	145.0	722.097	375.27	0.288

Table 2 Testing data of BVCP

No.	Q_{max} (kg)	Q_t (kg)	D (m)	HD (m)	B (m)	PPR (%)	K_v	α(°)	VoD (m/s)	PPV (cm/s)	D_f (Hz)	D_t (ms)
1	350	1050	114.7	16.8	5	80	0.38	160	2800	0.42	26.5	195
2	370	2150	70.3	42	7	0	0.73	180	4200	4.75	48.6	985
3	370	2150	101.2	54	7	0	0.56	115	4200	1.55	49.5	790
4	494	3952	122.6	62.1	5	0	0.32	120	2800	0.61	41.7	610
5	730	4380	115.7	50.9	6	50	0.42	180	4200	1.60	25.3	635
6	840	5660	214.7	75.1	6	0	0.52	120	4200	0.22	38.4	890
7	890	1800	72.1	42.0	5	100	0.73	80	4200	3.19	39.2	345
8	890	1800	53.2	30	5	100	0.65	50	4200	2.39	41.6	415
9	1090	5450	231.9	30.0	5	100	0.72	90	4200	0.50	27.8	650
10	1290	3870	177.6	73.0	6	0	0.56	180	4200	1.10	40.4	415
11	1410	6780	189.9	64.0	5	0	0.51	180	4200	1.05	38.3	985
12	1636	4980	125.1	42.2	4	0	0.55	180	4200	2.12	40.6	830
13	1790	5370	393.1	98.0	4	60	0.71	50	2800	0.30	16.2	505
14	1850	8500	68.5	30.0	6	0	0.50	180	2800	3.88	40.6	1380
15	2180	4360	226.9	106.0	5	0	0.46	60	4200	0.50	26.8	565

3.3. Criterion for model performance

To test and validate the SVM model, the data sets were chosen, which was not used while training the proposed model, was employed. So the trained models are applied to predicting the BVCP of the other 15 samples. In estimating the SVM Model prediction performance, the results of SVM models are compared with ANN [2], computing indexes such as correlation coefficient (R^2) and Root Mean Square Error (RMSE) can be used to evaluate the prediction accuracy of SVM and MRVR model. These indexes can be calculated by the following formula (8) and (9):

(8) $$R^2 = 1 - \sum_i (P_i - Q_i)^2 / \sum_i (P_i)^2$$

(9) $$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - Q_i)^2}$$

Where, Q_i, P_i and n represent the measured output, the predicted output and the number of input-output data pairs, respectively.

3.4 Nonlinear Models-Based SVM and Its Apllications

Then, BVCP prediction with nonlinear model-based SVM can be carried out as follows: firstly, the factors influenced BVCP should be determined; secondly, training and predicting samples were collected; thirdly, the model were trained, and reasonable parameters of SVM structures were obtained; finally, the trained models were applied to predicting BVCP, as shown in Fig. 2. Q_{max}, Q_t, HD, D, B, PPR, K_v, α, VoD, PPV, D_f and D_t were selected as the input variables. PPV, D_f and D_t were selected as outputs of the SVM model. So the mapping $\Omega^n \rightarrow$ PPV, $\Omega^n \rightarrow D_f$ and $\Omega^n \rightarrow D_t$, were established. Ω^n is input variables of the proposed model, n is the variable dimension.

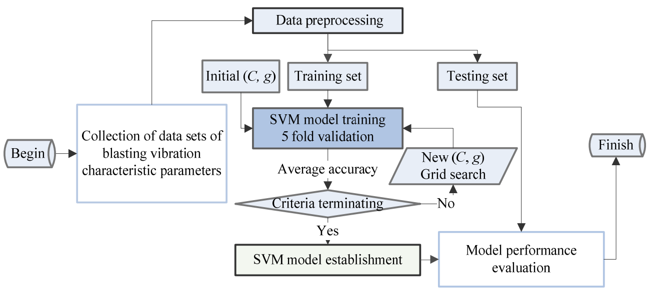
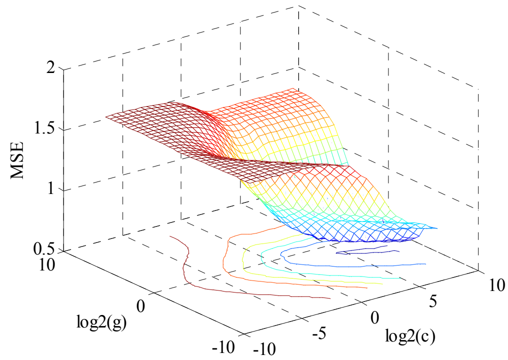


Fig. 2 Research architectures for the proposed SVM-based approach with grid search method (GSM) method

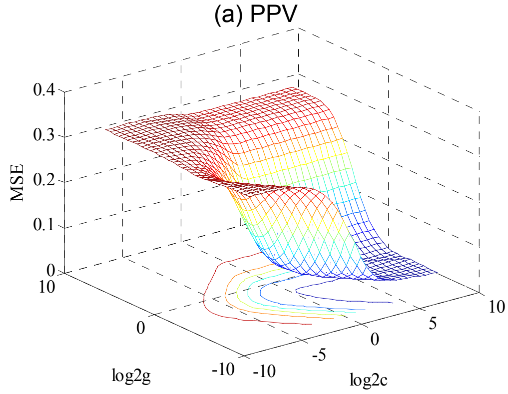
When applying SVM, the good performance is determined by the penalty factor C and insensitive parameter g. Libsvm [19] provides a parameter selection tool using the RBF kernel: cross validation via parallel grid search method (GSM) [15]-[17],[20]. As shown in Fig.2, the framework of optimizing the SVM's parameters with GSM is presented, for the grid search, currently we support only C-SVM with two parameters C and g. In this study, the free parameters of SVM were selected followed a 5-fold cross-validation experiment to control generalization capability of SVM, and the RBF kernel is used as the kernel function of the SVM because it tends to give better performance. Fig. 3 shows an example of the GSM result, where the x-axis and the y-axis are $\log_2 C$ and $\log_2 g$, respectively. The z-axis is the 5-fold average performance. The findings of this experiment were that SVM is quite robust against parameter selections.

3.5. Evaluation and Discussion

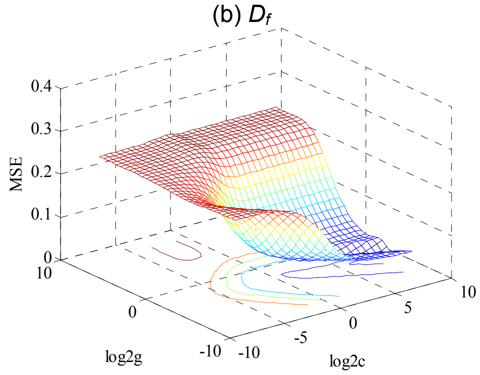
The result of the SVM parameter selection by GSM is shown in Fig. 3, when the penalty factor C is 256.0, g=0.0156 and the average value of MSE for PPV is CVmse = 0.0815. the penalty factor C is 22.6, g=0.0313 and the average value of MSE for D_f is CVmse = 0.0396. the penalty factor C is 256.0, g=0.0221 and the average value of MSE for D_t is CVmse = 0.0396, respectively. 93 sets of training sample data were back evaluated one by one using the SVM model of BCVP and compared with the actual situation. The compared predicted and measured of BCVP test results of training data are shown in Fig. 4. The regression mean-square error of the study for PPV, D_f, D_t is 0.0326, 0.0170, 0.0112, respectively, and the square correlation coefficient is 0.8407, 0.9443, 0.9546, respectively (Table 3). From Fig. 4, SVM have good performance for regression forecast, which prove that the model has stable and reliable prediction ability. Therefore, the SVM model is feasible and effective for BVCP forecasting and can be put into use. Shown in Fig. 4, the prediction curve obtained by SVM training sample fits good.



(a) PPV

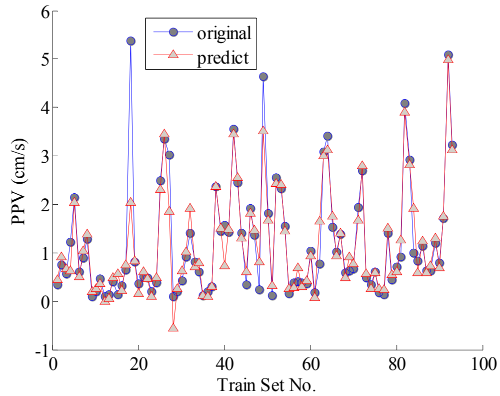


(b) D_f

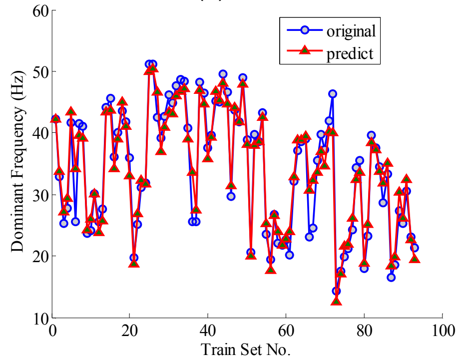


(c) D_t

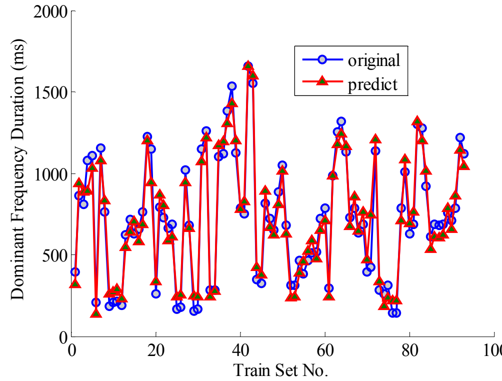
Fig. 3 The fitness curve of selecting best parameters by GSM



(a) PPV



(b) D_f



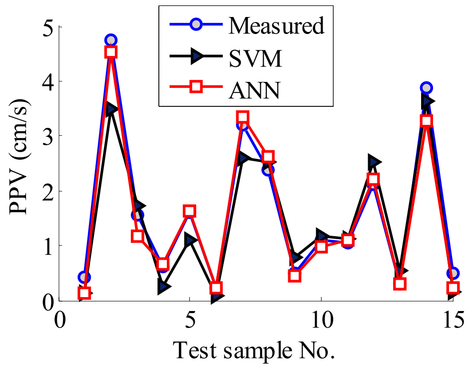
(c) D_t

Fig. 4 Predicted and Measured of BVCP results of train sample by SVM method

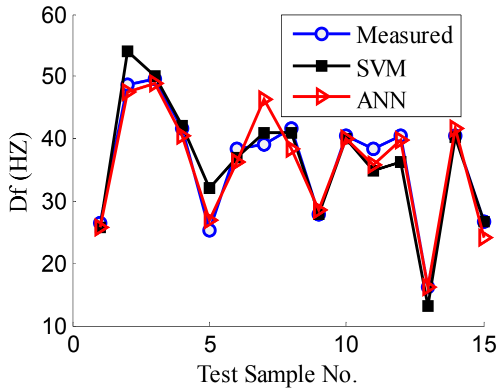
Results of SVM were compared to that of ANN [2], and measured datas, which are presented in Table 4 and Fig. 5. To compare the accuracy of SVM to ANN, the relative errors of two methods were listed in Table 4. From Table 4 and Fig. 5, the following summarizes the results and conclusions drawn from this study: (1) The trained SVM showed good performance in the training and testing stage; (2) we know that the results using SVM are more feasible and precise than that using ANN, providing justification for using this approach; (3) Various factors affected the blast vibration effect, as long as the corresponding data can be input to the SVM as variables, and the number of factors is not limited. Therefore, SVM can be more comprehensive consideration of blasting vibration effect and the relationship between factors; (4) The test results usually cost a lot of manpower and material resources. In the case of limited training samples, SVM based on small samples have more feasible and precise accuracy than ANN. Nonlinear Model-based SVM have good generalization ability and nonlinear dynamic data processing capabilities. It has a very good state of adaptability to the BVCP prediction.

Table 3. Performance statistics of all models

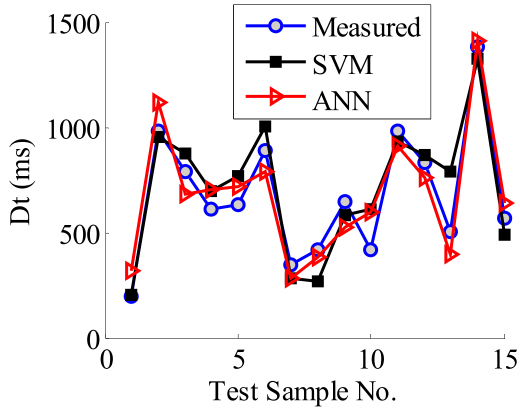
	Best C	Best g	CV_{mse}		Train Set		Test Set	
					MSE	R^2	MSE	R^2
PPV	256.0	0.0156	0.0815		0.0326	0.8407	0.0305	0.9050
D_f	22.6	0.0313	0.0396		0.0170	0.9443	0.0339	0.8757
D_t	256.0	0.0221	0.0396		0.0112	0.9546	0.0246	0.8575



(a) PPV



(b) D_f



(c) D_t

Fig. 5. Comparison of forecasting results of test samples

Table 4. Compared results of BVCP by SVM and ANN

No.	SVM			Relative errors(%)			ANN[2]			Relative errors(%)		
	PPV (cm/s)	D_f (Hz)	D_t (ms)	PPV (cm/s)	D_f (Hz)	D_t (ms)	PPV (cm/s)	D_f (Hz)	T (ms)	PPV (cm/s)	D_f (Hz)	D_t (ms)
1	0.13	25.8	205	68.74	2.5	5	0.12	25.8	316	70.26	2.6	62
2	3.50	54.0	954	26.47	11.2	3	4.52	47.5	1118	4.99	2.3	14
3	1.72	50.1	878	10.50	1.1	11	1.17	48.8	683	24.71	1.4	14
4	0.25	42.0	700	58.52	0.7	15	0.65	40.6	702	7.57	2.6	15
5	1.10	32.0	767	31.23	26.6	21	1.64	26.9	720	2.63	6.3	13
6	0.08	36.9	1006	62.95	3.9	13	0.24	36.2	786	10.09	5.7	12
7	2.60	41.0	285	18.63	4.5	18	3.35	46.3	279	4.92	18.1	19
8	2.52	41.0	266	5.44	1.4	36	2.62	38.3	385	9.67	7.9	7
9	0.78	27.9	581	57.11	0.4	11	0.45	28.6	525	9.27	2.9	19
10	1.17	40.0	614	5.84	1.1	48	0.99	40.0	598	10.53	1.0	44
11	1.13	34.8	934	7.66	9.2	5	1.11	35.9	914	6.11	6.3	7
12	2.53	36.2	871	19.25	10.9	5	2.22	39.8	759	4.33	2.0	9
13	0.55	13.1	787	82.97	19.2	56	0.31	16.3	398	2.98	0.6	21
14	3.65	40.3	1325	6.02	0.7	4	3.27	41.7	1411	15.80	2.7	2
15	0.15	26.6	489	70.78	0.7	13	0.23	24.2	641	53.41	9.7	13

4. Conclusions

This paper describes the development and testing of a nonlinear model-based SVM that is suitable for predicting of characteristic variables caused by blasting vibration. This note has presented the architecture of an SVM and compared predicted BVCP using the SVM with ANN [2] and measured data. The 93 samples were trained by proposed models, the other 15 samples were tested by trained models. The correlation coefficients of SVM model for predicting the BVCP is more than 0.85, which show the models are highly correlated and have good fitting performance. The accuracy of SVM was compared to that of ANN; the relative errors of two methods were obtained. Results show that prediction accuracy of SVM has improved more greatly than that of the ANN. Nonlinear Model-based SVM have good generalization ability and nonlinear dynamic data processing capabilities, which has a very good state of adaptability to BVCP prediction. Overall, the SVM showed good performance and it was able to satisfactorily predict three BVCP. The architecture and approach described in this paper may be of interest to researchers and engineers trying to develop empirical tools for predicting rock or other complex behavior often encountered in geotechnical and mining engineering.

Acknowledgements

This research is financially supported by supported by the National 11th Five-Year Science and Technology Supporting Plan Projects (2006BAB02A02) of China; the National Basic Research (973) Program Project (2010CB732004) of China and the Graduated Students' Research and Innovation Fund Project (CX2011B119) of Hunan Province. The authors would like to express thanks to these foundations.

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