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Support vector machine for evaluating seismic-liquefaction potential using shear wave velocity

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ABSTRACT

The use of the shear wave velocity data as a field index for evaluating the liquefaction potential of sands is receiving increased attention because both shear wave velocity and liquefaction resistance are similarly influenced by many of the same factors such as void ratio, state of stress, stress history and geologic age. In this paper, the potential of support vector machine (SVM) based classification approach has been used to assess the liquefaction potential from actual shear wave velocity data. In this approach, an approximate implementation of a structural risk minimization (SRM) induction principle is done, which aims at minimizing a bound on the generalization error of a model rather than minimizing only the mean square error over the data set. Here SVM has been used as a classification tool to predict liquefaction potential of a soil based on shear wave velocity. The dataset consists the information of soil characteristics such as effective vertical stress (σ'_{v0}), soil type, shear wave velocity (V_s) and earthquake parameters such as peak horizontal acceleration (a_{max}) and earthquake magnitude (M). Out of the available 186 datasets, 130 are considered for training and remaining 56 are used for testing the model. The study indicated that SVM can successfully model the complex relationship between seismic parameters, soil parameters and the liquefaction potential. In the model based on soil characteristics, the input parameters used are σ'_{v0}, soil type, V_s, a_{max} and M. In the other model based on shear wave velocity alone uses V_s, a_{max} and M as input parameters. In this paper, it has been demonstrated that Vs alone can be used to predict the liquefaction potential of a soil using a support vector machine model.

1. Introduction

Liquefaction in soil is one of the major problems in geotechnical earthquake engineering. It is defined as the transformation of a granular material from a solid to a liquefied state as a consequence of increased pore-water pressure and reduced effective stress (Marcuson, 1978). This phenomena was brought to the attention of engineers more so after Niigata (1964) and Alaska (1964) earthquakes. Liquefaction will cause building settlement or tipping, sand boils, ground cracks, landslides, dam instability, highway embankment failures, or other hazards. Such damages are generally of great concern to public safety and are of economic significance. So the assessment of the liquefaction potential due to an earthquake at a site is an imperative task in earthquake geotechnical engineering. A procedure based on Standard Penetration Test (SPT) and cyclic stress ratio (CSR) has been developed by Seed et al. (Seed and Idriss, 1967, 1971; Seed et al., 1983, 1984) based on the use of peak ground acceleration to asses the liquefaction potential of soil. Although the SPT-based method is in use (as a standard method) around the world for evaluating liquefaction resistance, it has many drawbacks (Robertson and Campanella, 1985; Skempton, 1986). The first cone penetration test (CPT) based method for liquefaction evaluation was developed by Robertson and Campanella (1985) (Skempton, 1986). The CPT method has been revised and updated by many researchers to evaluate liquefaction resistance (Seed and de Alba, 1986; Stark and Olson, 1995; Olsen, 1997; Robertson and Wride, 1998). The engineering practitioners commonly use the above two penetration based methods (SPT and CPT) for assessment of liquefaction potential. On the other hand, shear wave velocity (V_s) may offer engineers a third tool that is lower cost and provides more physically meaningful measurements. The advantages of using V_s for evaluating liquefaction potential have been described by many researchers (Dobry et al., 1981; Seed et al., 1983; Stokoe et al., 1988; Tokimatsu and Uchida, 1990). Based on V_s, Andrus et al. (1999) and (Andrus and Stokoe (2000) have evaluated liquefaction potential for different sites.

A number of approaches based on Vs, both probabilistic and Artificial Neural Network (ANN) methods have been proposed. Juang

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et al. (2001) have proposed a probabilistic framework for liquefaction potential using V_s data. Goh (2002) successfully used probabilistic neural network (PNN) for assessing liquefaction potential from V_s data. A major disadvantage of ANN models is that, unlike other statistical models, they provide no information about the relative importance of the various parameters (Park and Rilett, 1999). In ANN, as the knowledge acquired during training is stored in an implicit manner, it is difficult to come up with reasonable interpretation of the overall structure of the network (Kecman, 2001). This lead to the term “black box”, which many researchers use while referring to ANN'S behavior. In addition, ANN has some inherent drawbacks such as slow convergence speed, less generalizing performance, arriving at local minimum and over-fitting problems.

This paper proposes an alternative approach based on the support vector machine (SVM) to predict the liquefaction of soil using shear wave velocity (V_s). SVM, originally developed by Vapnik, is a new machine learning method based on statistical learning theory (Vapnik, 1995). In this paper, two models have been developed using the SVM. The first model (model I) is based on soil characteristics, which uses the input parameters such as effective vertical stress (σ'_{v0}), soil type, shear wave velocity (V_s), peak horizontal acceleration (a_{max}) and earthquake magnitude (M). The second model (model II) is based on shear wave velocity, which uses V_s, a_{max} and M as input parameters. In this paper, the V_s database collected by Andrus and Stokoe (1997) has been used to develop two models to predict liquefaction resistance based on the SVM model. The dataset used in this study represents 88 sites that liquefied and 98 sites that did not liquefy. The dataset also contains the information about the soil type, earthquake magnitude, shear wave velocity, etc.

2. Evaluation of liquefaction resistance

A plot between earthquake load and liquefaction resistance has been shown in Fig. 1. A boundary has been drawn in Fig. 1 between earthquake load and liquefaction resistance combinations that have and have not produced liquefaction in past earthquakes based on case histories in terms of measured in situ test parameters (Whitman, 1971). In this method, cyclic stress ratio (CSR) is used as earthquake load and cyclic resistance ratio (CRR) is used as liquefaction resistance of a soil. CRR is generally assessed based on field methods such as SPT, CPT and shear wave velocity.

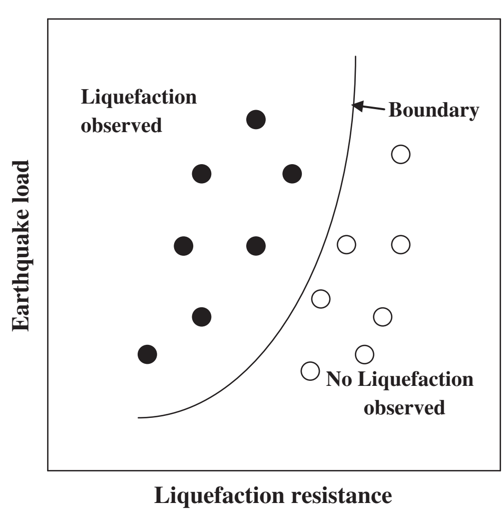

Fig. 1. Boundary indicates the minimum value of liquefaction resistance parameter required to prevent liquefaction.

The most comprehensive study of the application of field-based V_s measurements to seismic-liquefaction assessments has been presented by Andrus and Stokoe (2000). According to Andrus and Stokoe (2000), CRR has been calculated from the following formula:

$$CRR = 0.03\left(\frac{V_s}{100}\right)^2 + 0.9\left(\frac{1}{V_{slc}-V_{sl}} - \frac{1}{V_{slc}}\right) \quad (1)$$

where

$$V_{sl} = V_s\left(\frac{P_a}{\sigma'_{v0}}\right)^{0.25} \quad (2)$$

V_{sl}	overburden-stress correlated shear wave velocity;
P_a	atmospheric pressure approximated by 100 kPa;
σ'_{v0}	initial vertical effective stress in kPa

For sands and gravels

$$\begin{aligned} V_{slc} &= 220, \text{fine content(FC)} \le 5\% \\ &= 210, \text{FC} \approx 20\% \\ &= 200, \text{FC} \ge 35\%. \end{aligned}$$

The $CSR = \frac{\tau_{av}}{\sigma'_{v0}}$, at a particular depth in a level soil deposit has been calculated by using following formula (Seed and Idriss, 1971):

$$CSR = \frac{\tau_{av}}{\sigma_v} = 0.65\left(\frac{a_{max}}{g}\right)\left(\frac{\sigma_v}{\sigma'_v}\right)r_d \quad (3)$$

where τ_{av} = average equivalent uniform cyclic shear stress caused by the earthquake and is assumed to be 0.65 of the maximum induced stress; a_{max} = peak horizontal ground surface acceleration; g = acceleration of gravity; σ'_v = initial vertical effective stress at the depth in question; σ_v = total overburden stress at the same depth and r_d = shear stress reduction coefficient to adjust for the flexibility of the soil profile and it has been estimated from the chart by Seed and Idriss (1971).

3. Support vector machine (SVM) model

The SVM has recently emerged as an elegant pattern recognition tool and a better alternative to ANN methods. The method has been developed by Vapnik (1995) and is gaining popularity due to many attractive features. The formulation is based on Structural Risk Minimization (SRM) which has been shown to be superior to the Empirical Risk Minimization (ERM) used in conventional neural networks (Vapnik, 1995). This section of the paper serves an introduction to this relatively new technique. Details of this method can be found in Boser et al. (1992), Cortes and Vapnik (1995), Gualtieri et al. (1999), and Vapnik (1998). A binary classification problem is considered having a set of training vectors (D) belonging to two separate classes (liquefaction and no-liquefaction).

$$D = \left\{\left(x^1, y^1\right), \ldots\ldots\ldots, \left(x^1, y^1\right)\right\} \quad x \in R^n, y \in \{-1, +1\} \quad (4)$$

where $x \in R^n$ is an n-dimensional data vector with each sample belonging to either of two classes labelled as $y \in \{-1, +1\}$, and l is the number of training data. The main aim is to find a generalized classifier that can distinguish the two classes (−1, +1) from the set of the training vectors mentioned above (D). For a set of data, this would mean a linear hyperplane defined by Eq. (5) which can distinguish the two classes:

$$f(x) = w.x + b = 0 \quad (5)$$

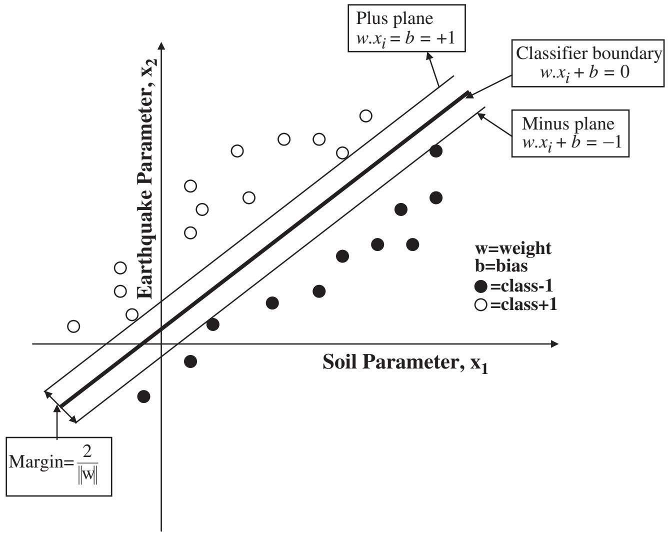

Fig. 2. Support vectors with maximum margin.

where, $w \in R^n$ determines the orientation of a discriminating hyperplane, $b \in R$ is a bias. For the linearly separable case, a separating hyperplane can be defined for the two classes (liquefaction and no-liquefaction cases) as:

$$\begin{aligned} &w.x_i + b \geq 1(\text{ for } y_i = 1) \rightarrow \text{No liquefaction} \\ &w.x_i + b \leq -1(\text{ for } y_i = -1) \rightarrow \text{Liquefaction}. \end{aligned} \tag{6}$$

The above two equation can be combined as:

$$y_i(w.x_i + b) \geq 1. \tag{7}$$

Sometimes, due to the noise or mixture of classes introduced during the selection of training data, variables $\xi_i > 0$, called slack variables, are used due to the effects of misclassification. So the Eq. (7) can be written as:

$$y_i(w.x_i + b) \geq 1 - \xi_i. \tag{8}$$

The perpendicular distance from the origin to the hyperplane for liquefaction class $w.x_i + b = -1$ is $\frac{|1+b|}{||w||}$. Similarly, the perpendicular distance from the origin to the hyperplane for non liquefaction cases $w.x_i + b = 1$ is $\frac{|b-1|}{||w||}$. The margin ($\rho(w,b)$) between the planes is simply:

$$\rho(w, b) = \frac{2}{||w||}. \tag{9}$$

The optimal hyperplane is located where the margin between two classes of interest is maximized and the error is minimized. The maximization of this margin leads to the following constrained optimization problem

$$\begin{aligned} &\mathit{Minimize}: \frac{1}{2}||w||^2 + C\sum_{i=1}^{l} \xi_i \\ &\mathit{Subjected}\text{ to}: y_i(w.x_i + b) \geq 1 - \xi_i. \end{aligned} \tag{10}$$

The constant (called capacity factor) $0 < C < \infty$, a parameter defines the trade-off between the number of misclassification in the training data and the maximization of margin. This optimization problem is solved by Lagrangian Multipliers (Vapnik, 1998). According to the Karush–Kuhn–Tucker (KKT) optimality condition (Fletcher, 1987), some of the multipliers will be zero. The nonzero multipliers are called support vectors (see Fig. 2). In conceptual terms, the support vectors are those data points that lie closest to the optimal hyperplane and are therefore the most difficult to classify. The value of w and b are calculated from $w = \sum_{i=1}^{l} y_i \alpha_i x_i$ and $b = -\frac{1}{2} w[x_{+1} + x_{-1}]$, where x_{+1} and x_{-1} are the support vectors of class labels +1(no-liquefaction) and −1(liquefaction) respectively. The classifier can then be constructed as:

$$f(x) = sign(w.x + b) \tag{11}$$

where sign is the signum function. It gives +1 if the element is greater than or equal to zero and −1 if it is less than zero.

In case where linear supporting hyperplane is inappropriate, SVM maps input data into a high dimensional feature space through

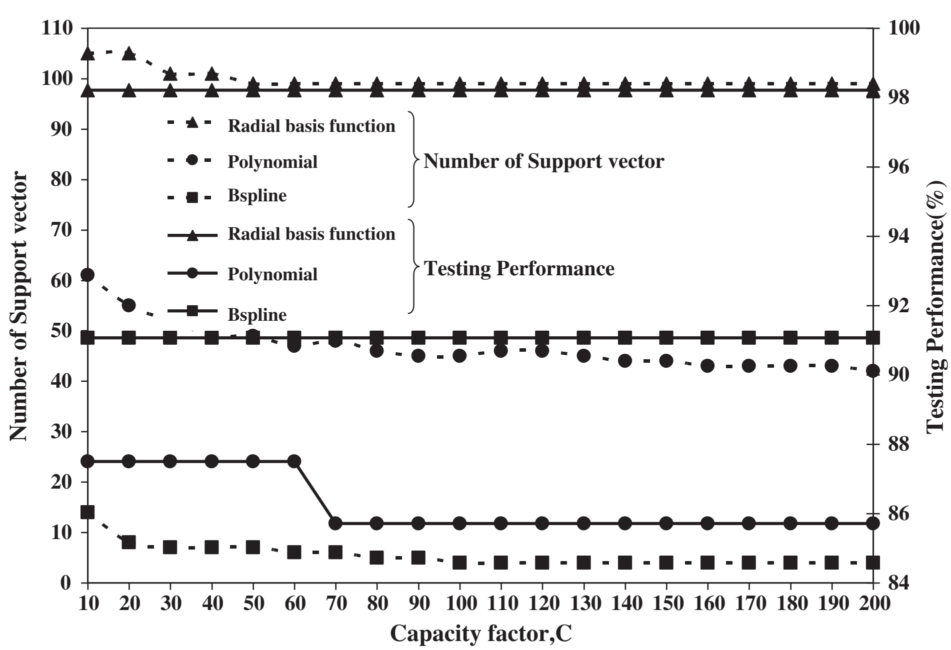

Fig. 3. Variation of testing performance (%) and the number of support vectors with capacity factor (C) values for the model based on soil characteristic data using different kernels.

Table 1
Different types of soil.

Soil description	Soil type number(T)
Gravel and gravelly sand (FC<5–10%)	4
Clean sand (FC<5%)	3
Sand mixture to sand (FC=5–15%)	2.5
Sand mixtures: sandy silt to silty sand (FC=15–35%)	2
Silt to sand mixtures (FC=35–70%)	1.5
Silt mixtures: silty clay to clayey silt	1

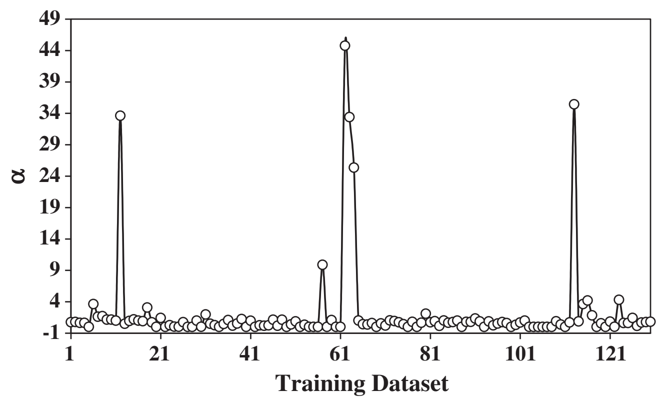

Fig. 4. Values of α for model I.

some non-linear mapping (Boser et al., 1992). This method easily converts a linear classification learning algorithm into a non-linear one, by mapping the original observations into a higher-dimensional non-linear space so that linear classification in the new space is equivalent to non-linear classification in the original space. Kernel function has been introduced instead of feature space($\Phi(x)$) to reduce computational demand (Cortes and Vapnik, 1995; Cristianini and Shawe-Taylor, 2000). Polynomial, radial basis functions and certain sigmoid functions has been used as a kernel functions. To get the Eq. (5), same procedures have been applied as in the linear case.

4. Methodology

The main scope of this study is to implement SVM in the prediction of liquefaction based on V_s measurements. Two models have been developed using SVM to predict liquefaction resistance based on field Vs data. In model I, based on soil characteristics, the input parameters are σ'_{v0}, soil type, V_s, a_{max}, and M. In the second method, model II, only shear wave velocity has been used to characterize the soil properties. In model II, V_s, a_{max}, and M have been chosen as input parameters. In this paper, binary classification is used (only Yes /No) for liquefaction classifier. However, one can attempt, multi-classification (Watanachaturaporn et al., 2004) to determine three types such as liquefaction, no-liquefaction and marginal liquefaction.

4.1. Model based on soil characteristics (model I)

Liquefaction of soils during earthquakes is dependent on both seismic and soil parameters. So, the parameters that have been selected as input parameters for the model based on soil characteristics are σ'_v, soil type and $V_{s,}$ and two earthquake parameters such as a_{max} and M. The data for the soil type has been taken from the work of Andrus and Stokoe (1997). The dataset represented 88 sites that liquefied and 98 sites that did not liquefy (Tables 3 and 4). The data is normalized against their maximum values (Sincero, 2003). To use these data for classification purpose, a value of −1 is assigned to the liquefied sites while a value of 1 is assigned to the non-liquefied sites. So, the output of the model will be either 1 or −1.

In carrying out the formulation, the data has been divided into two sub-sets such as

(a) A training dataset: This is required to construct the model. In this study, 130 out of the 186 data are considered for training. Table 3 shows the training dataset.
(b) A testing dataset: This is required to estimate the model performance. In this study, the remaining 56 data is considered for testing. Table 4 shows the testing dataset.

The data has been divided into training and testing datasets using the sorting method, to maintain statistical consistency. The statistical

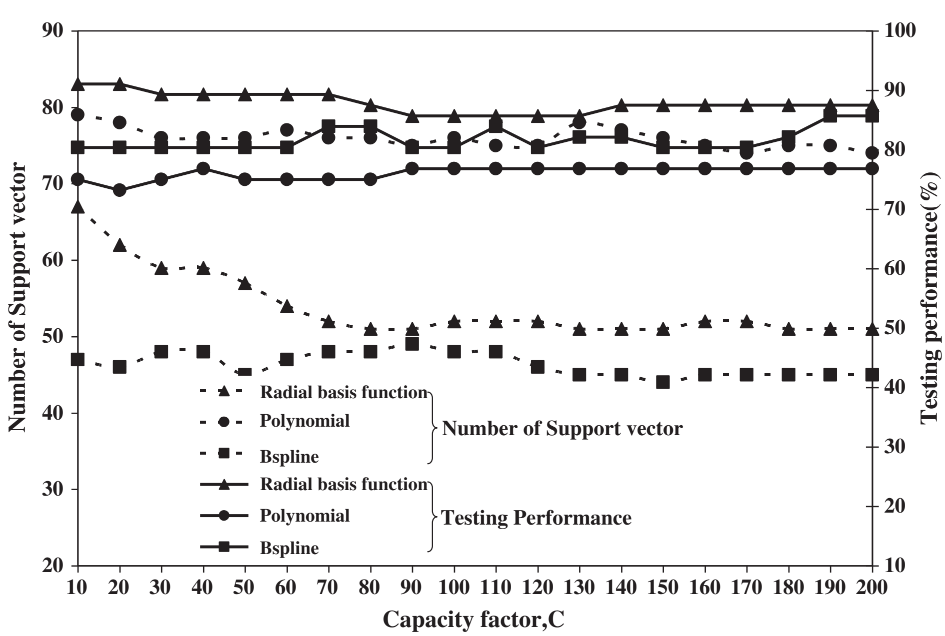

Fig. 5. Variation of testing performance (%) and the number of support vectors with capacity factor (C) values for the model based on shear wave velocity using different kernels.

Table 2
General performance of SVM for different kernels for model based on soil characteristic (model I).

Kernel	C	Training performance (%)	Testing performance (%)	Number of support vectors
Radial basis function $\left[exp\left(\frac{-\lvert x-y\rvert^2}{2\sigma^2}\right), \sigma \text{ is width}\right], \sigma=0.08$	50	100	98.21	99
Polynomial $[((x.y)+1)^d$, d = degree], d = 3	60	90	87.5	47
Bspline $[B_{2N+1}(x-y)$, N = degree], N = 2	100	100	91.07	4

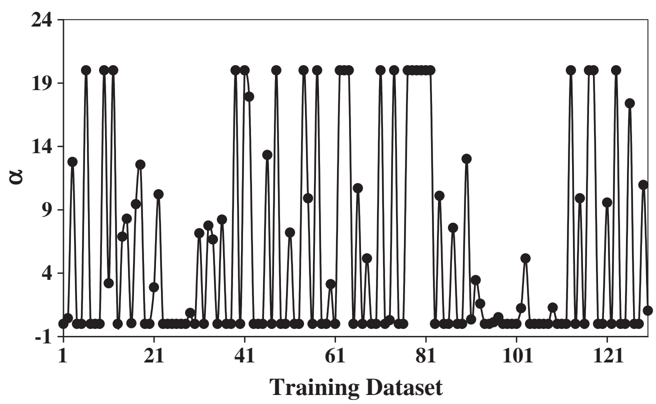

Fig. 6. Values of α for model II.

consistency of training and testing datasets improve the performance of the model and helps in evaluating them better (similar to what has been used for ANN by Shahin et al., 2000).

The application of the SVM for this problem requires the proper selection of different design parameters. In this study, the design parameters are selected by carrying out a parametric study. Through this parametric study, appropriate C value and kernel were selected. In case of SVM training, three types of kernel functions – namely, radial basis function kernel, polynomial kernel, and bspline kernel – have been used. The values of C as well as other kernel specific parameters have to be set to their optimal values during the model training process.

4.2. Model based on shear wave velocity (model II)

In the model based on soil characteristic, $\sigma'_{v,}$ soil type is used as input parameters. Multi channel analysis of surface wave (MASW) method or Spectral Analysis of Surface wave (SASW) methods are (for measurement of shear wave velocity profiles in field based on Raleigh waves) non destructive techniques and do not have a provision to get density or % of fines. In addition to the shear wave velocity survey, one needs to drill boreholes and collect the samples to obtain the information on density and %fines. Thus in this study, we have attempted to develop the model based on shear wave velocity alone to predict the liquefaction resistance. The parameters used in this model II are V_s along with earthquake parameters such as a_{max} and M. Even here, the training dataset, testing dataset, normalization technique and different kernel functions are same as the one used for model I.

Both the programs (model based on soil characteristic, model I, and only on shear wave velocity, model II) are constructed using the MATLAB (MathWork Inc., 1999).

5. Results and discussion

The optimum "C" value has been selected by carrying out a parametric study. A large value of C assigns higher penalties to errors so that the SVM is trained to minimize error with lower generalization while a small value of C assigns fewer penalties to errors; this allows the minimization of margin with errors, thus higher generalization ability. If C goes to infinitely large, the SVM would not allow the occurrence of any error and result in a complex model, whereas when C goes to zero, the result would tolerate a large amount of errors and the model would be less complex. So it is necessary to investigate the impact of the C value on testing performance (%) as well as the number of support vectors. The testing performance (%) is calculated by:

$$Testing\ performance(\%) = \left(\frac{No\ of\ data\ predicted\ accurately\ by\ SVM}{Total\ \ data}\right) \times 100. \tag{13}$$

From Fig. 3, it is clear that the C value does not affect the testing accuracy (%) of the model with radial basis function as well as bspline kernel in model I. Fig. 3 shows generally that the number of support vectors is decreasing with increasing C value for each kernel for model I. Table 1 shows training, testing performance and design C value for each kernel type with corresponding number of support vectors. For best model and best testing performance, less number of support vectors is desirable. It also shows that radial basis function gives the best performance (using design C value and corresponding number of support vectors as shown in Table 1) for model I (based on all soil characteristics). The radial basis function has an overall success rate of 98.21%, with no errors in training dataset and one data error in the testing dataset. Table 1 also highlights that the polynomial kernel produces the lowest number of support vectors.

For model II (based on shear wave velocity), Fig. 4 shows the variation of number of support vectors and testing performance (%) with the C value. It also shows that the number of support vector as well as testing performance (%) does not have any trend with the C value for different kernels (Fig. 5). The training and testing performance of each kernel, design C value and the number of support vector are summarized in Table 2. A testing accuracy (%) of 91.07% has been achieved with radial basis function kernel. Out of 56 testing data only five data has been incorrectly classified. For model II (based on shear wave velocity) radial basis function gives the best result (using design C value and corresponding number of support

Table 3
General performance of SVM for different kernels for model based on shear wave velocity (model II).

Kernel	C	Training performance (%)	Testing performance (%)	Number of support vectors
Radial basis function $\left[exp\left(\frac{-\lvert x-y\rvert^2}{2\sigma^2}\right), \sigma \text{ is width}\right], \sigma=0.1$	20	93.08	91.07	62
Polynomial $[((x.y)+1)^d$, d = degree], d = 3	170	80	76.79	74
Bspline $[B_{2N+1}(x-y)$, N = degree], N = 2	190	86.15	85.71	45

Table 4
Performance of training dataset for both models using radial basis function.

σ'_v	a_{max}	Soil type	M	V_s	Actual class	Predicted class	
						Model I	Model II
62.1	0.36	4	7.7	136	−1	−1	−1
58.2	0.36	4	7.7	173	−1	−1	−1
140.8	0.32	1.5	7.7	177	1	1	1
140.8	0.32	1.5	7.7	200	1	1	1
123.5	0.32	2.5	7.7	149	−1	−1	−1
54.7	0.16	3	7.5	115	−1	−1	−1
57.8	0.12	1	6.5	105	1	1	1
50.1	0.12	1.5	7.1	98	−1	−1	−1
43.6	0.12	1	7.1	101	−1	−1	−1
101.2	0.12	1	7.1	143	1	1	−1
36	0.46	4	6.9	206	1	1	1
55.8	0.21	2	6.5	90	−1	−1	−1
38.1	0.51	2	6.5	126	−1	−1	−1
48	0.5	2	6.5	131	−1	−1	−1
46.6	0.5	2.5	6.5	164	1	1	1
120.2	0.08	2	5.9	195	1	1	1
57.8	0.27	1.5	5.9	115	−1	−1	−1
55.8	0.2	2	5.9	90	−1	−1	−1
54.8	0.3	2.5	5.9	101	−1	−1	−1
48	0.02	2	5.9	133	1	1	1
77.5	0.14	2.5	7.1	178	1	1	1
79.4	0.16	2	7.1	121	−1	−1	−1
45.6	0.36	4	6.9	122	−1	−1	−1
32.9	0.36	4	6.9	128	−1	−1	−1
32.4	0.36	4	6.9	107	−1	−1	−1
38.1	0.36	4	6.9	154	−1	−1	−1
32.7	0.3	4	6.9	105	−1	−1	−1
28.7	0.29	4	6.9	106	−1	−1	−1
53.5	0.46	4	6.9	274	1	1	1
59.2	0.06	2	6	155	1	1	1
28.7	0.42	2	7.1	116	−1	−1	−1
35.4	0.22	1.5	6.6	127	1	1	1
35.4	0.18	1.5	6.6	146	1	1	1
35.4	0.18	1.5	6.6	130	1	1	1
35.4	0.04	1.5	6.2	127	1	1	1
70	0.19	4	8.3	144	−1	−1	−1
35.4	0.18	1.5	6.2	133	1	1	1
35.4	0.05	1.5	6.2	146	1	1	1
71	0.15	3	7.1	163	−1	−1	−1
35.4	0.05	1.5	6.2	130	1	1	1
35.4	0.16	1.5	7.6	127	1	1	1
35.4	0.16	1.5	7.6	130	1	1	1
53.9	0.12	1.5	5.9	127	1	1	1
55.8	0.11	2	5.9	90	1	1	1
38.1	0.06	2	5.9	126	1	1	1
57.8	0.24	1	5.9	105	1	1	1
46.6	0.03	2.5	5.9	164	1	1	1
57.9	0.2	3	6.9	135	−1	−1	−1
53.9	0.2	1.5	6.5	124	1	1	1
38.1	0.19	2	6.5	126	1	1	1
54.8	0.2	2.5	6.5	101	1	1	1
48	0.18	2	6.5	131	1	1	1
46.6	0.18	2.5	6.5	173	1	1	1
63.5	0.14	2	7.1	130	−1	−1	−1
83	0.14	2	7.1	157	−1	−1	−1
78.6	0.14	2	7.1	148	−1	−1	−1
90.6	0.14	2	7.1	137	−1	−1	−1
82.5	0.14	2	7.1	146	−1	−1	−1
48.8	0.14	3	7.1	154	−1	−1	−1
63.9	0.15	2.5	7.1	143	−1	−1	−1
78.8	0.16	1.5	7.1	117	−1	−1	−1
79.4	0.16	2	7.1	138	−1	−1	−1
82	0.16	2	7.1	145	1	1	−1
83.3	0.16	2	7.1	133	1	1	−1
92.4	0.24	2.5	7.1	148	−1	−1	−1
85.8	0.24	3	7.1	179	−1	−1	−1
86.2	0.24	3	7.1	145	−1	−1	−1
75.2	0.27	2.5	7.1	212	1	1	1
77	0.27	2.5	7.1	204	1	1	1
60.9	0.27	2.5	7.1	116	−1	−1	−1
82.2	0.15	2.5	7.1	120	−1	−1	−1
82.2	0.15	2.5	7.1	105	−1	−1	−1
105.7	0.15	3	7.1	220	1	1	1
58.2	0.19	4	7.1	161	1	1	1
58.2	0.19	4	7.1	173	1	1	1
140.8	0.15	1.5	7.1	195	1	1	1
123.5	0.15	2.5	7.1	131	1	1	−1
123.5	0.15	2.5	7.1	146	1	1	−1
123.5	0.15	2.5	7.1	168	1	1	1
41	0.42	2	7.1	126	1	1	−1
57.8	0.42	2	7.1	135	1	1	−1
30.5	0.42	3	7.1	126	−1	−1	−1
42.4	0.25	3	7.1	130	−1	−1	−1
87.7	0.25	3	7.1	209	−1	−1	−1
39.6	0.25	3	7.1	143	−1	−1	−1
98.8	0.5	4	6.9	197	−1	−1	−1
139.1	0.48	3	6.9	149	1	1	1
58.2	0.36	4	7.7	161	−1	−1	−1
123.5	0.32	2.5	7.7	131	−1	−1	−1
123.5	0.32	2.5	7.7	168	−1	−1	−1
73.7	0.12	1	7.1	103	−1	−1	−1
57.8	0.13	1.5	6.5	115	1	1	1
54.8	0.12	2.5	6.5	101	1	1	1
59.2	0.08	2	5.9	155	1	1	1
38.1	0.06	2	5.9	126	1	1	1
48	0.02	2	5.9	131	1	1	1
46.6	0.02	2.5	5.9	173	1	1	1
36	0.36	4	6.9	102	−1	−1	−1
33.8	0.36	4	6.9	131	−1	−1	−1
36	0.3	4	6.9	122	−1	−1	−1
27.8	0.29	4	6.9	105	−1	−1	−1
57.4	0.23	4	6.9	271	1	1	1
35.4	0.22	1.5	6.6	130	1	1	1
35.4	0.18	1.5	6.6	127	1	1	1
35.4	0.04	1.5	6.2	133	1	1	1
35.4	0.18	1.5	6.2	130	1	1	1
35.4	0.05	1.5	6.2	127	1	1	1
35.4	0.16	1.5	7.6	133	1	1	1
140.2	0.1	2.5	6.5	150	1	1	1
54.8	0.13	2.5	5.9	101	1	1	1
48	0.03	2	5.9	133	1	1	1
53.9	0.2	1.5	6.5	127	1	1	1
55.8	0.2	2	6.5	90	1	1	−1
46.6	0.18	2.5	6.5	164	1	1	1
83.7	0.14	2	7.1	157	−1	−1	−1
86.4	0.14	2	7.1	152	−1	−1	−1
84.7	0.16	1.5	7.1	143	−1	−1	−1
79.4	0.16	1.5	7.1	152	−1	−1	−1
82.4	0.24	2.5	7.1	134	−1	−1	−1
85.8	0.24	3	7.1	145	−1	−1	−1
75.2	0.27	2.5	7.1	193	1	1	1
60.9	0.27	2.5	7.1	97	−1	−1	−1
59.6	0.15	3	7.1	120	1	1	−1
140.8	0.15	1.5	7.1	177	1	1	1
140.8	0.15	1.5	7.1	199	1	1	1
48.1	0.42	2.5	7.1	145	−1	−1	−1
69.8	0.25	3	7.1	162	−1	−1	−1
59.5	0.25	3	7.1	171	−1	−1	−1
110.9	0.5	4	6.9	174	−1	−1	−1
111	0.12	3	6.9	179	1	1	1

vectors as shown in Table 2) which produces the lowest number of support vectors (Fig. 6). The performance of model I is slightly better than model II. This also demonstrates that for SVM classification, the possibility of finding optimum hyperplane to separate the classes is higher with 5 input variables in model I than with 3 input variables in model II. Tables 3 and 4 show the performance of both models using radial basis function for training and testing datasets respectively.

An additional dataset (as listed in Table 5) which is not part of the training and testing dataset (which was presented earlier)) has been collected from the work of Andrus and Stokoe (1997). The performance of the above two developed models has been assessed for this dataset and the same has been reported in Table 6. For both the models, only one data has been misclassified. The prediction has

Table 5
Performance of testing dataset for both models using radial basis function.

σ'_v	a_{max}	Soil type	M	V_s	Actual class	Predicted class	
						Model I	Model II
58.2	0.36	4	7.7	154	−1	−1	−1
140.8	0.32	1.5	7.7	199	1	1	1
35.3	0.12	1	7.1	122	−1	−1	−1
53.9	0.13	1.5	6.5	127	1	1	1
123.5	0.32	2.5	7.7	158	−1	−1	−1
53.9	0.27	1.5	5.9	127	−1	−1	−1
57.8	0.36	1	5.9	105	−1	−1	−1
49.4	0.36	4	6.9	109	−1	−1	−1
38.3	0.36	4	6.9	122	−1	−1	−1
53.9	0.13	1.5	6.5	124	1	1	1
35.4	0.22	1.5	6.6	133	1	1	1
35.4	0.04	1.5	6.2	146	1	1	1
35.4	0.18	1.5	6.2	127	1	1	1
35.4	0.16	1.5	7.6	146	1	1	1
53.9	0.12	1.5	5.9	124	1	1	1
48	0.03	2	5.9	131	1	1	1
57.8	0.2	1.5	6.5	115	1	1	1
48	0.18	2	6.5	133	1	1	1
60.9	0.14	2	7.1	131	−1	−1	−1
46.6	0.02	2.5	5.9	164	1	1	1
40.5	0.36	4	6.9	94	−1	−1	−1
78.8	0.24	2.5	7.1	146	−1	−1	−1
81.7	0.24	3	7.1	176	−1	−1	−1
59.6	0.27	2.5	7.1	125	−1	−1	−1
62.1	0.19	4	7.1	136	1	1	−1
140.8	0.15	1.5	7.1	200	1	1	1
120.2	0.06	2	6	195	1	1	1
46.9	0.25	3	7.1	116	−1	−1	−1
35.4	0.04	1.5	6.2	130	1	1	1
140.8	0.32	1.5	7.7	195	1	1	1
90.1	0.12	1.5	7.1	147	−1	−1	−1
53.9	0.27	1.5	5.9	124	−1	−1	−1
46.3	0.36	4	6.9	134	−1	−1	−1
35.4	0.22	1.5	6.6	146	1	1	1
35.4	0.18	1.5	6.2	146	1	1	1
57.8	0.12	1.5	5.9	115	1	1	1
57.8	0.21	1	6.5	105	1	1	1
35.4	0.05	1.5	6.2	133	1	1	1
86.2	0.24	3	7.1	142	−1	−1	−1
49.8	0.42	2	7.1	158	1	1	−1
58.2	0.19	4	7.1	154	1	1	1
33.4	0.19	4	8.3	79	−1	−1	−1
97.7	0.16	3	7.5	163	1	1	1
46.2	0.36	4	6.9	107	−1	−1	−1
84.7	0.16	1.5	7.1	135	−1	−1	−1
46.6	0.03	2.5	5.9	173	1	1	1
44.5	0.16	3	7.5	118	1	−1	−1
48	0.5	2	6.5	133	−1	−1	−1
82	0.16	2	7.1	148	1	1	−1
123.5	0.15	2.5	7.1	158	1	1	−1
69.2	0.14	2	7.1	136	−1	−1	−1
35.4	0.18	1.5	6.6	133	1	1	1
54.4	0.15	3	7.1	153	−1	−1	−1
53.1	0.25	2.5	7.1	150	−1	−1	−1
46.6	0.5	2.5	6.5	173	1	1	1
83.1	0.24	3	7.1	157	−1	−1	−1

been done with radial basis function for both models. The results presented in Table 5 highlights very clearly that SVM is good tool to predict liquefaction resistance of soils.

6. Conclusions

The application of the support vector machine (SVM) model in liquefaction prediction is presented in this study. This paper has demonstrated the usefulness of the SVM to model the complex relationship between the seismic parameters and soil parameters. The performance of the SVM model is improved as more input variables are provided. Model I based on soil characteristics predicts the liquefaction potential very accurately with the available training and testing data. The effect of C on model accuracy and number of support vectors has been investigated and presented. The optimum values of C and the kernel are selected based on a parametric study. Model II (based on shear wave velocity) presented clearly that only three parameters {Vs, a_{max}, and M} are sufficient for predicting liquefaction potential of a site with depth. One major advantage of the SVM is its optimization algorithm, which provides global minima in comparison to the presence of local minima due to the use of a non-linear optimization problem with the neural network approach. Other advantage with the SVM is that it uses data points (called support vectors) closest to the hyperplane in the classification process. The SVM models are simpler to apply than the conventional methods.

Table 6
Performance of additional dataset[a] for both models using radial basis function.

Site name	σ'_v	a_{max}	Soil type	M	V_s	Actual class	Predicted class	
							Model I	Model II
Larter Ranche	39	0.5	1.5	6.9	176	−1	−1	−1
Larter Ranche	38.4	0.5	1.5	6.9	153	−1	−1	1
Larter Ranche	40.5	0.5	1.5	6.9	183	−1	−1	−1
Whisky Springs	38.2	0.5	1.5	6.9	181	−1	−1	−1
Whisky Springs	31.7	0.5	1.5	6.9	210	−1	1	−1

[a] Ref: Andrus, R. D., and Stokoe, K. H. (1997).

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