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A unified classification model for modeling of seismic liquefaction potential of soil based on CPT

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A B S T R A C T

The evaluation of liquefaction potential of soil due to an earthquake is an important step in geosciences. This article examines the capability of Minimax Probability Machine (MPM) for the prediction of seismic liquefaction potential of soil based on the Cone Penetration Test (CPT) data. The dataset has been taken from Chi–Chi earthquake. MPM is developed based on the use of hyperplanes. It has been adopted as a classification tool. This article uses two models (MODEL I and MODEL II). MODEL I employs Cone Resistance (q_c) and Cyclic Stress Ratio (CSR) as input variables. q_c and Peak Ground Acceleration (PGA) have been taken as inputs for MODEL II. The developed MPM gives 100% accuracy. The results show that the developed MPM can predict liquefaction potential of soil based on q_c and PGA.

Introduction

Liquefaction causes lot of damages during earthquake. So, the prediction of liquefaction potential of soil due to an earthquake is an important step for earthquake hazard mitigation. There are various techniques available for the determination of liquefaction potential of soil in the literature [1–13]. However, available methods have some limitations [14]. Researchers used Artificial Intelligence (AI) techniques for the prediction of liquefaction susceptibility of soil [14–25].

This article adopts Cone Penetration Test (CPT) based Minimax Probability Machine (MPM) for the prediction of seismic liquefaction potential of soil. The datasets have been collected from Chi–Chi earthquake at Taiwan. MPP is developed by Lanckriet et al. [26]. MPM is constructed in probabilistic framework. This article uses MPM as a classification problem. It has been successfully adopted for modeling different problems in engineering [27–29]. The magnitude of earthquake was 7.6. The epicenter of earthquake was at 23.87°N and 120.75E [30]. Extensive liquefaction was observed at Yuanlin, Wufeng, and Nantou. Many CPT tests were conducted after the earthquake [30]. Two models (MODEL I and MODEL II) have been used to get best performance. MODEL I adopts Cone Resistance (q_c) and Cyclic Stress Ratio (CSR) as input variables. q_c and Peck Ground Acceleration (PGA) have been used as inputs of the MODEL II. The database has been collected from the work of Ku et al. [31]. In this database, liquefaction is observed in 46 sites. The remaining 88 sites are non-liquefied. The developed MPM has been applied for the global data [16]. This article

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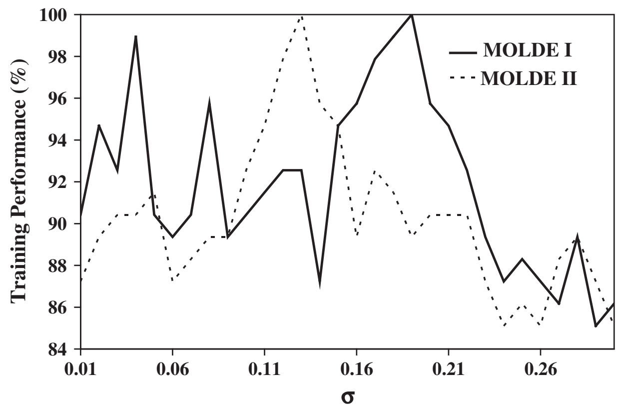

Fig. 1 Effect of σ on training performance (%).

Table 1 Performance of training dataset.

q_c (MPa)	PGA(gal)	CSR	Actual class	Predicted class	
				MODEL I	MODEL II
1.27	774	0.643	−1	−1	−1
0.72	774	0.665	−1	−1	−1
1.35	774	0.802	−1	−1	−1
11.66	774	0.836	1	1	1
13.89	774	0.853	1	1	1
20.05	774	0.826	1	1	1
0.94	420	0.34	−1	−1	−1
1.47	420	0.37	−1	−1	−1
11.56	420	0.37	1	1	1
12.89	420	0.46	1	1	1
16.3	420	0.43	1	1	1
1.41	420	0.35	−1	−1	−1
11.96	420	0.46	1	1	1
1.87	420	0.42	−1	−1	−1
5.77	420	0.48	−1	−1	−1
2.54	188	0.17	−1	−1	−1
7.46	188	0.22	1	1	1
7.62	188	0.22	1	1	1
8.03	188	0.21	1	1	1
7.02	188	0.2	1	1	1
7.72	188	0.22	1	1	1
7.68	188	0.18	1	1	1
2.22	188	0.2	−1	−1	−1
12.15	188	0.2	1	1	1
2.54	188	0.16	−1	−1	−1
8.15	188	0.21	1	1	1
10.08	188	0.21	1	1	1
12.43	188	0.2	1	1	1
1.62	188	0.16	−1	−1	−1
2.45	188	0.19	−1	−1	−1
6.7	188	0.21	1	1	1
13.65	188	0.2	1	1	1
17.08	188	0.2	1	1	1
2.66	188	0.18	−1	−1	−1
8.25	188	0.21	1	1	1
7.41	188	0.21	1	1	1
2.54	188	0.2	−1	−1	−1
12.77	188	0.2	1	1	1
1.18	188	0.16	−1	−1	−1
2.96	188	0.2	−1	−1	−1
8	188	0.2	1	1	1
8.74	188	0.19	1	1	1
11.26	188	0.17	1	1	1
7.52	207	0.23	1	1	1
6.61	188	0.22	1	1	1
8.3	188	0.2	1	1	1
8.32	188	0.21	1	1	1
3	188	0.18	−1	−1	−1
2.09	188	0.2	−1	−1	−1
2.78	188	0.24	−1	−1	−1
3.05	188	0.22	−1	−1	−1
14.67	188	0.2	1	1	1
10.61	188	0.2	1	1	1
13.65	188	0.19	1	1	1
1.28	121	0.13	−1	−1	−1
0.64	121	0.13	−1	−1	−1
5.16	121	0.14	1	1	1
3.26	121	0.11	−1	−1	−1
7.4	121	0.14	1	1	1
7.04	121	0.15	1	1	1
7.47	121	0.15	1	1	1
6.54	121	0.14	1	1	1
6.64	121	0.14	1	1	1
5.59	121	0.15	1	1	1
6.85	121	0.14	1	1	1
6.68	121	0.14	1	1	1
5.21	121	0.14	1	1	1
7.18	121	0.14	1	1	1
5.91	121	0.15	1	1	1
5.38	121	0.15	1	1	1
7.99	121	0.14	1	1	1
7.38	121	0.14	1	1	1
7.41	121	0.14	1	1	1
6.73	121	0.15	1	1	1
6.49	121	0.14	1	1	1
5.47	121	0.14	1	1	1
0.92	121	0.11	−1	−1	−1
1.5	121	0.13	−1	−1	−1
6.05	121	0.15	1	1	1
6.76	121	0.15	1	1	1
2.49	121	0.12	−1	−1	−1
1.89	121	0.14	−1	−1	−1
1.54	121	0.14	−1	−1	−1
7.43	121	0.14	1	1	1
6.61	121	0.14	1	1	1
7.12	121	0.14	1	1	1
6.08	121	0.14	1	1	1
9.48	121	0.12	1	1	1
0.2	121	0.12	−1	−1	−1
5.93	121	0.13	1	1	1
7.57	121	0.14	1	1	1
7.24	121	0.14	1	1	1
6.21	121	0.14	1	1	1
8.83	121	0.14	1	1	1

gives charts for classifying liquefiable and non-liquefiable soil.

Details of MPM

In MPM, it is assumed that positive definite covariance matrices exist in each of the two classes. In MPM, the probability of

Table 2 Performance of testing dataset.

q_c (MPa)	PGA(gal)	CSR	Actual class	Predicted class	
				MODEL I	MODEL II
1.79	774	0.749	−1	−1	−1
14.45	774	0.829	1	1	1
11.32	420	0.46	1	1	1
6.01	420	0.4	−1	−1	−1
0.9	420	0.39	−1	−1	−1
8.27	188	0.21	1	1	1
2.7	188	0.18	−1	−1	−1
6.67	188	0.22	1	1	1
6.23	188	0.21	1	1	1
2.62	188	0.18	−1	−1	−1
16.89	188	0.2	1	1	1
9.19	188	0.21	1	1	1
1.82	188	0.19	−1	−1	−1
8.3	188	0.21	1	1	1
1.73	207	0.21	−1	−1	−1
10.05	188	0.18	1	1	1
2.61	188	0.19	−1	−1	−1
11.58	188	0.2	1	1	1
2.69	188	0.22	−1	−1	−1
14.74	188	0.19	1	1	1
5.46	121	0.14	1	1	1
2.65	121	0.13	−1	−1	−1
7.68	121	0.14	1	1	1
7.58	121	0.14	1	1	1
6.12	121	0.14	1	1	1
6.62	121	0.15	1	1	1
7.03	121	0.14	1	1	1
6.32	121	0.14	1	1	1
0.64	121	0.13	−1	−1	−1
2.01	121	0.13	−1	−1	−1
7.72	121	0.14	1	1	1
7.76	121	0.14	1	1	1
7.94	121	0.14	1	1	1
0.18	121	0.12	−1	−1	−1
1.97	774	0.665	−1	−1	−1
3.86	420	0.37	−1	−1	−1
6.8	188	0.21	1	1	1
8.01	188	0.2	1	1	1
0.23	121	0.11	−1	−1	−1
6.83	207	0.23	1	1	1

misclassification of future data is minimized [26]. In MPM, following optimal hyperplane is used for separating the two classes of points.

$$a^T z = b \quad a, z \in R^n; \quad b \in R \tag{1}$$

In MPM, the following optimization problem is constructed [20]:

$$\max_{\alpha, b, a \neq 0} \alpha \quad \text{Constraint}: \begin{array}{l} \inf P_r\{a^T x \geq b\} \geqslant \alpha \\ \inf P_r\{a^T y \leq b\} \geqslant \alpha \end{array} \tag{2}$$

where α is called the worst-case accuracy.

The above optimization problem (2) is solved by Lagrangian Multiplier. So, it takes the following form.

$$\max_{\kappa, a} \kappa \quad \text{Constraint}: \begin{array}{l} -b + a^T x \geqslant \kappa \sqrt{a^T \sum_x a} \\ -b - a^T y \geqslant \kappa \sqrt{a^T \sum_y a} \end{array} \tag{3}$$

Table 3 Performance of the global data [16].

Site	q_c (MPa)	PGA (g)	Actual class	Predicted class
Kawagishicho	3.2	0.16	−1	1
Kawagishicho	1.6	0.16	−1	−1
Kawagishicho	7.2	0.16	−1	−1
Kawagishicho	5.6	0.16	−1	−1
Kawagishicho	5.45	0.16	−1	1
Kawagishicho	8.84	0.16	−1	−1
Kawagishicho	9.7	0.16	−1	−1
Kawagishicho	8	0.16	1	1
Kawagishicho	14.55	0.16	1	1
Noshirocho	10	0.23	1	−1
Noshirocho	16	0.23	1	1
Noshirocho	15.38	0.23	1	1
Noshirocho	1.79	0.23	−1	−1
Noshirocho	4.1	0.23	−1	−1
Noshirocho	7.95	0.23	−1	−1
Noshirocho	8.97	0.23	−1	−1
T-10	1.7	0.4	−1	−1
T-10	9.4	0.4	−1	1
T-10	5.7	0.4	−1	1
T-10	7.6	0.4	−1	−1
T-11	1.5	0.4	−1	−1
T-11	1	0.4	−1	1
T-11	5	0.4	−1	−1
T-12	2.5	0.4	−1	−1
T-12	2.6	0.4	−1	−1
T-12	3.2	0.4	−1	−1
T-12	5.8	0.4	−1	1
T-12	3.5	0.4	−1	−1
T-12	8.4	0.4	−1	−1
T-13	1.7	0.4	−1	1
T-13	3.5	0.4	−1	−1
T-13	4.1	0.4	−1	−1
T-14	5.5	0.4	−1	−1
T-14	9	0.4	−1	1
T-15	7	0.4	−1	−1
T-15	1.18	0.4	−1	−1
T-15	4.24	0.4	−1	−1
T-16	11.47	0.4	1	1
T-16	15.76	0.4	1	1
T-17	11.39	0.2	1	1
T-17	12.12	0.2	1	1
T-17	17.76	0.2	1	−1
T-23	2.65	0.2	−1	1
T-24	4.4	0.2	−1	−1
T-24	3	0.2	−1	−1
T-25	9	0.2	−1	1
T-26	2	0.1	−1	−1
T-27	1.1	0.2	−1	−1
T-28	15.5	0.1	1	1
T-28	6.5	0.1	1	1
T-29	9	0.1	1	1
T-29	2.5	0.1	1	1
T-29	16.5	0.1	1	1
T-30	13.65	0.1	1	1
L-1	8.47	0.2	1	−1
L-1	4.55	0.2	1	1
L-1	5.79	0.2	1	−1
L-2	2.48	0.2	−1	−1
L-2	1.57	0.2	−1	−1
L-2	1.45	0.2	−1	−1
L-2	2.15	0.2	−1	−1
L-2	2.6	0.2	−1	−1

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Table 3 (*continued*)

Site	q_c (MPa)	PGA (g)	Actual class	Predicted class
L-3	2.73	0.2	−1	1
L-3	1.78	0.2	−1	−1
L-5	7.64	0.2	1	1
Heber Road	25.6	0.8	1	1
A1	24.7	0.8	1	1
A1	31.4	0.8	1	1
A2	1.43	0.8	−1	−1
A2	2.48	0.8	−1	1
A3	4.03	0.8	−1	−1
A3	3.3	0.8	1	1
A4	8.8	0.8	1	1
A4	6.7	0.8	1	1
T-18	1.65	0.2	−1	−1
T-18	3.65	0.2	−1	−1
T-19	1.03	0.2	−1	−1
T-19	5	0.2	−1	−1
T-19	2.91	0.2	−1	−1
T-19	6.06	0.2	−1	−1
T-20	13.24	0.2	1	1
T-20	13.06	0.2	1	−1
T-20	16.59	0.2	1	1
T-21	10.59	0.2	1	1
T-21	9.12	0.2	1	1
T-21	11.29	0.2	1	1
T-22	1.94	0.2	−1	−1
T-22	5	0.2	−1	−1
T-23	2.24	0.2	−1	−1
T-30	14.12	0.1	1	1
T-30	18.94	0.1	1	1
T-31	3.52	0.2	−1	−1
T-31	2.73	0.2	−1	−1
T-32	3.29	0.2	−1	1
T-32	4.12	0.2	−1	−1
T-32	2.94	0.2	−1	−1
T-33	3	0.2	−1	−1
T-33	5.85	0.2	−1	−1
T-33	9	0.2	−1	−1
T-34	1.8	0.2	−1	−1
T-35	2.55	0.2	−1	−1
T-35	4.5	0.2	−1	−1
T-35	4.24	0.2	−1	−1
T-36	8	0.2	1	1
Dimbovitza site	5.22	0.22	−1	1
Dimbovitza site	3.73	0.22	−1	−1
Dimbovitza site	3.11	0.22	−1	−1
Dimbovitza site	1.32	0.22	−1	−1
Dimbovitza site	5.22	0.22	−1	−1

The optimization problem (3) is written in the following form:

$$\min_{a} \sqrt{a^T \sum_y a} + \lambda \sqrt{a^T \sum_x a}$$

$$\text{Subjected to}: a^T(x - y) = 1 \quad (4)$$

The above optimization problem (4) is solved by convex programming technique.

To develop the above MPM, non-liquefied sites are denoted by +1 and liquefied sites are denoted by −1. In MPM, training dataset is adopted to develop the model and a testing is

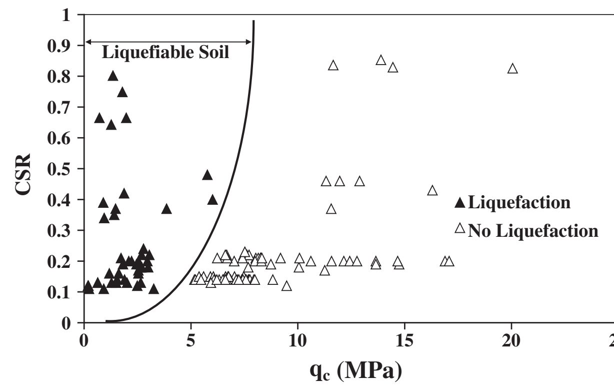

Fig. 2 Plot between CSR and q_c.

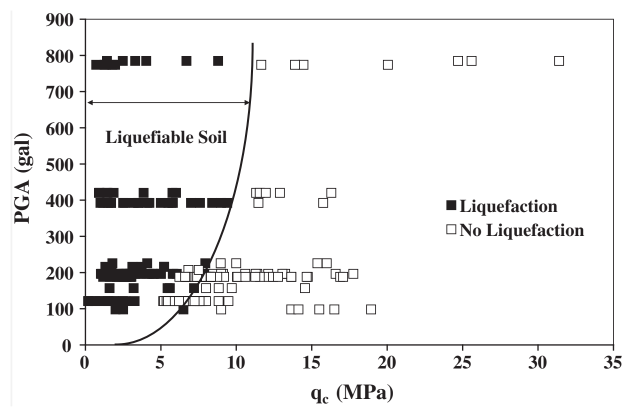

Fig. 3 Plot between PGA and q_c.

employed to verify the developed MPM. Ninety-four datasets have been adopted as training datasets. The 40 remaining datasets have been employed as testing datasets.

In this article, the datasets are scaled between 0 and 1. This study adopts radial basis function ($K(x_i, x) = \exp\left[\frac{-(x_i-x)(x_i-x)^T}{2\sigma^2}\right]$) (where σ is width of radial basis function) as kernel function for developing the MPM. This article employs MATLAB software for constructing MPM.

Results and discussion

The success of MPM depends on the choice of proper value of σ. This study adopts trial and error approach for the determination of the design value of σ. Training and testing performance have been determined by using the following equation.

$$\text{Training/Testing performance}(\%) = \left(\frac{\text{No of data predicted accurately by MPM}}{\text{Total data}}\right) \times 100 \quad (5)$$

Fig. 1 shows the effect of σ on training performance (%) for MODEL I. It is observed from Fig. 1 that the developed MPM gives best training performance at σ = 0.19 for MODEL I. The developed MPM gives 100% training performance. The performance of testing dataset is also 100%. Tables 1 and 2 illustrate the performance of MPM for training and testing dataset respectively. The classification of MPM has been plotted in Fig. 2.

For MODEL II, the effect of σ on training performance has been shown in Fig. 1. It is clear from Fig. 2 that the best training performance has been achieved at $\sigma = 0.13$. The developed MPM produces 100% training as well as testing performance. So, the developed MODEL II gives same performance as given by MODEL II. The performance of MPM for training and testing dataset has been depicted in Tables 1 and 2, respectively.

Fig. 3 plots the results of MODEL II. The generalization capability of developed MODEL II has been examined by the global datasets [16]. These global datasets consists information about liquefiable and non-liquefiable soil of five earthquakes. The developed MODEL II correctly classifies 100 datasets out of 109. Therefore, the developed MPM shows good generalization capability. Table 3 shows the performance of global data.

Conclusions

This article successfully applied MPM for the determination of seismic liquefaction potential of soil. Two models (MODEL I and MODEL II) have been tried to get best performance. The performance of MPM for MODEL I and II is excellent. This study shows that the developed MPM can predict liquefaction potential of soil based on q_c and PGA. Geotechnical engineers can use the developed charts for the determination of seismic liquefaction potential of soil. The developed MPM shows good generalization capability. MPM model can be adopted for modeling different problems in geosciences.

Conflict of interest

The authors have declared no conflict of interest.

Compliance with Ethics Requirements

This article does not contain any studies with human or animal subjects.

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