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PROBABILITY-BASED LIQUEFACTION EVALUATION USING SHEAR WAVE VELOCITY MEASUREMENTS

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ABSTRACT

Three preliminary probability-based models and one artificial neural network model for evaluating soil liquefaction potential using shear wave velocity measurements are presented and compared with the deterministic curves developed by Andrus et al. The probability models are developed using logistic regression and Bayesian techniques applied to the same case history data used to develop the deterministic curves. The case history data consists of *in situ* shear wave velocity measurements at over 70 sites and field performance data from 26 earthquakes. The artificial neural network model is a high-order function capable of tracking the irregular boundary separating individual liquefaction and no liquefaction case histories. From the logistic regression and Bayesian models, the deterministic curve is characterized with a probability of about 30 %. This finding indicates that the shear wave-based deterministic curve and the SPT-based deterministic curve exhibit similar conservatism. The results provide a method for liquefaction risk analysis.

INTRODUCTION

In situ tests and simplified procedures are frequently used to evaluate the liquefaction potential of soils. The simplified procedure for evaluating soil liquefaction potential most widely used in North America and throughout much of the world was originally proposed by Seed and Idriss (1971) based blow counts from the Standard Penetration Test (SPT). Since 1971, this procedure has been revised and updated. In addition, simplified procedures based on other *in situ* tests, such as the Cone Penetration Test (CPT) and the small-strain shear wave velocity (V_s) measurement, have been proposed. Procedures that follow the general format of the Seed-Idriss simplified procedure were reviewed recently in a workshop report edited by Youd and Idriss (1997). This paper deals with the V_s-based procedure.

The V_s-based simplified procedure for evaluating soil liquefaction potential provides a promising alternative, and/or supplement, to penetration-based procedures. It is particularly useful in soils that are hard to sample, such as gravelly soils where penetration tests may be unreliable, and at sites where borings may not be permitted, such as capped landfills. In addition, the strong theoretical basis underlying V_s measurements allows for additional advances in the procedure.

During the past twenty years, several investigators have studied the relationship between V_s and liquefaction resistance (e.g., Dobry et al., 1981; Seed et al., 1983; Stokoe and Nazarian, 1985, Tokimatsu

Paper No. 4.25

and Uchida, 1990; Robertson et al., 1992; Andrus et al., 1999). The deterministic evaluation curves developed from these studies, as well as the penetration-based evaluation curves, rely heavily on subjective judgment. Probability and neural network methods provide a means of objectively calibrating the deterministic liquefaction evaluation curves.

Summarized in this paper are three probability-based models and one artificial neural network model developed using the case histories compiled by Andrus et al. (1999). The case histories consist of field performance data from 26 earthquakes and V_s measurements at over 70 sites. The probability models are derived using logistic regression and Bayesian techniques. They are compared with the liquefaction evaluation curves proposed in the project report by Andrus et al. (1999) and the paper by Andrus and Stokoe (in press).

LIQUEFACTION EVALUATION PROCEDURE

The liquefaction evaluation procedure by Andrus et al. (1999) follows the general format of the Seed-Idriss simplified procedure. It requires the calculation of three parameters: (1) the level of cyclic loading on the soil caused by the earthquake, expressed as a cyclic stress ratio; (2) the stiffness of the soil, expressed as a stress-corrected shear wave velocity; and (3) the resistance of soil to liquefaction, expressed as a cyclic resistance ratio. A brief review of each parameter is given below.

The cyclic stress ratio, CSR or τ_{av}/σ'_{v} , at a particular depth in a level soil deposit can be expressed as (Seed and Idriss, 1971):

$$CSR = \tau_{av}/\sigma'_{v} = 0.65 (a_{max}/g) (\sigma_{v}/\sigma'_{v}) r_{d}$$
(1)

where τ_{av} is the average equivalent uniform cyclic shear stress caused by the earthquake, a_{max} , is the peak horizontal ground surface acceleration, g is the acceleration of gravity, σ'_v is the initial effective vertical (overburden) stress at the depth in question, σ_v is the total overburden stress at the same depth, and r_d is a shear stress reduction coefficient to adjust for flexibility of the soil profile. In this study values of r_d are estimated from the average relationship published by Seed and Idriss (1971).

Following the traditional procedures for correcting SPT blow count to account for overburden stress, one can correct V_s to a reference overburden stress by (Sykora, 1987; Robertson et al., 1992):

$$V_{S1} = V_S (P_a/\sigma'_v)^{0.25}$$
(2)

where V_{S1} is the overburden stress-corrected shear wave velocity, P_a is a reference stress of 100 kPa, and σ'_v is initial effective overburden stress in kPa. In using Eq. (2), it is assumed that the initial effective horizontal stress, σ'_h , is a constant factor of the effective overburden stress, σ'_v and σ'_h are principal stresses, and V_S is measured with a major component of wave propagation or particle motion in the vertical direction.

The value of CSR separating liquefaction and non-liquefaction occurrences for a given V_{S1} , or corrected blow count, is called the cyclic resistance ratio, CRR. Andrus et al. (1999) proposed the following equation for determining CRR from V_{S1} :

where V_{S1}^{*} is the limiting upper value of V_{S1} for cyclic liquefaction occurrence, K_c a factor to correct for high V_{S1} values caused by cementation and aging, and MSF is the magnitude scaling factor. The first term of Eq. (3) is based on a modified relationship between V_{S1} and CSR for constant average cyclic shear strain suggested by R. Dobry (personal communication to R. D. Andrus, 1996). The second term is a hyperbola with a small value at low values of V_{S1} , and a very large value as V_{S1} approaches V_{S1}^{*} . Approximate values of V_{S1}^{*} range from 200 m/s for soils with fines content (FC) \geq 35 %, 208 m/s for FC = 20 %, and 215 m/s for FC \leq 5 %. Equation (3) with V_{S1}^{*} = 215 m/s provides a CRR value of about 0.6 at V_{S1} = 210 m/s. A V_{S1} value of 210 m/s is considered equivalent to a corrected blow count of 30 in sands with FC \leq 5 %, based on penetration- V_S correlations. The correction factor $K_c \approx 1$ for uncemented soils of Holocene age.

The magnitude scaling factor, which accounts for the effect of magnitude, is traditionally applied to CRR. It can be expressed by:

$$MSF = (M_w/7.5)^n$$
 (4)

where M_w is moment magnitude, and n is an exponent. The lower bound for the range of magnitude scaling factors recommended by the 1996 National Center for Earthquake Engineering Research (NCEER) Workshop on Evaluation of Liquefaction Resistance of Soils (Youd et al., 1997) is defined by Eq. (4) with n = -2.56(Idriss, personal communication to T. L. Youd, 1995).

Figure 1 presents the CRR-V_{s1} curves defined by Eq. (3) for $M_w =$ 7.5. Also, presented are the 225 case history data points compiled by Andrus et al. (1999) for magnitude 5.3 to 8.3 earthquakes. Values in of CSR in each case history have been adjusted by dividing by Eq. (4) with n = -2.56. The data are limited to relatively level ground sites with average depths less than 10 m, uncemented soils of Holocene age, and ground water table depths between 0.5 m and 6 m.



Fig. 1. Case history data and liquefaction evaluation curves developed by Andrus et al. (1999).

ARTIFICIAL NEURAL NETWORK MODEL

Chen (1999) and Juang and Chen (2000) developed a sophisticated, multi-dimensional neural network model using the original database compiled by Andrus and Stokoe (1997). In this paper, their model is simplified and training of the neural network is repeated using the updated database given in Andrus et al. (1999) to permit direct comparison with the two-dimensional boundary curves shown in Fig. 1. The simplified ANN model takes the form:

$$LI = f_{LI}(V_{S1}, FCI, CSR_{7.5})$$
(5)

where LI is the liquefaction index with value of 1 for liquefaction cases or 0 for non-liquefaction cases, and FCI is the fines content index. Values of FCI are set as 1 for FC $\leq 5\%$, 2 for FC = 6% to 34%, and 3 for FC $\geq 35\%$. The objective of the training is to determine a set of coefficients so that the prediction from the ANN model for a given set of input matches the target (known) Ll value. Details of the trained model are not presented due to space limitations. They can be obtained by contacting the first author.

Figure 2 presents data generated by the trained ANN Model along with the case history data. The distribution of plotted ANN Model data exhibits small variation and is nearly linear for FC ≤ 5 %, as shown in Fig. 2a. This linear trend, indicated by the curve labeled "Best-fit ANN Model", may be explained by the little or no overlap of the plotted liquefaction and non-liquefaction case histories. For soils with FC > 5 %, however, the distribution of plotted ANN Model data exhibits large variation and is non-linear (see Figs. 2b and 2c). It appears that the ANN Model is a high-order function capable of tracking the irregular boundary separating individual liquefaction and non-liquefaction cases histories. This observation explains the better prediction of no liquefaction by ANN models (Juang and Chen, 2000) than by the smooth boundary curves shown in Fig. 1.

LOGISTIC REGRESSION MODELS

To develop the logistic regression models, V_{S1} values are adjusted to a clean soil (FC \leq 5 %) equivalent by:

$$V_{S1,CS} = K_{fc} V_{S1}$$
 (6)

where $V_{S1,CS}$ is the equivalent clean soil value of V_{S1} , and K_{fc} is a fines content correction to adjust V_{S1} values to a clean soil equivalent. Value of K_{fc} are approximated using the following preliminary equation:

$$K_{fc} = 1, \text{ for } FC \le 5\%$$
(7a)

$$K_{fc} = 1 + (FC-5) f(V_{S1}), \text{ for } FC = 6\% \text{ to } 34\%$$
 (7b)

$$K_{fc} = 1 + 30 f(V_{S1}), \text{ for FC} \ge 35\%$$
 (7c)

where

$$f(V_{s1}) = 0.009 - 0.0109 (V_{S1}/100) + 0.0038 (V_{S1}/100)^2$$
(8)

The case history data adjusted using Eqs. (6) and (7) are plotted in Figs 3 and 4 along with two simple logistic regression models described below.

Model 1

Logistic regression Model 1 is similar in form to the model used by Liao et al. (1988) for analyzing SPT-based case histories. The preliminary probability equation for Model 1 is given by ($R^2 = 0.58$):

$$ln[P_{\rm L}/(1-P_{\rm L})] = a_1 + a_2 V_{\rm S1,CS} + a_3 ln(\rm CSR_{7.5})$$
(9)



Fig. 2. Comparison of data generated by the trained ANN model and field case history data.



Fig. 3. Preliminary logistic regression Model 1 and case history data adjusted for fines content.

where P_L is the probability that liquefaction will occur, $a_1 = 14.8967$, $a_2 = -0.0611$, $a_3 = 2.6418$, and CSR_{7.5} is CSR adjusted to $M_w = 7.5$. From Fig. 3, Model 1 appears to provide reasonable P_L curves within the limits of most of the data. However, the P_L curves may be inappropriately too conservative at high values of V_{S1} (say > 200 m/s), since 210 m/s is considered equivalent to a corrected blow count of 30 in clean sands and liquefaction is generally assumed not possible above this value.

Model 2

To investigate the influence that the form of a regression equation might have on P_L curves, the analysis is repeated using a slightly different equation. The preliminary probability equation for Model 2 is defined by ($R^2 = 0.61$):

$$ln[P_{\rm L}/(1-P_{\rm L})] = b_1 + b_2 V_{\rm S1,CS} + b_3 ln(CSR_{7.5}) + b_4 [ln(CSR_{7.5})]^2$$
(10)

where $b_1 = 10.0155$, $b_2 = -0.0643$, $b_3 = -3.9534$, and $b_4 = -1.8381$. Figure 4 presents P_L curves defined by Eq. (10). These curves reach a peak CSR value of about 0.33. Above CSR of 0.33, the curves trend to the left, decreasing in $V_{S1,CS}$ with increasing CSR. Nevertheless, the results clearly show that P_L curves depend on the form of the regression equation. However, one would expect P_L curves to slope towards higher values of V_{S1} with increasing CSR rather than be vertical, as suggested by the dashed lines in Fig. 4.

BAYESIAN MAPPING MODEL

A common way to express the potential for liquefaction is in terms of a factor of safety. The factor of safety, F_s , against liquefaction can be defined by:



Fig. 4. Preliminary logistic regression Model 2 and case history data adjusted fines content.

$$F_{\rm S} = CRR/CSR \tag{11}$$

Liquefaction is predicted to occur when $F_s \le 1$, and not to occur when $F_s > 1$.

Juang et al. (1999) pioneered an approach for mapping F_s to P_L . In their approach, values of F_s are determined using a deterministic evaluation curve, such as the SPT-based curve by Seed et al. (1985) or the V_s-based curve by Andrus et al. (1999) shown in Fig. 1. Values of P_L are then estimated from the probability density functions of F_s for liquefaction and non-liquefaction case histories using Bayes' theorem. Figure 5 presents the Bayesian Mapping Model based on the case history data and evaluation curves developed by Andrus et al. (1999), which is defined by:

$$P_L = 1/[1 + (F_s/0.78)^{3.5}]$$
(12)

In Eq. (12), a F_s value of 1 corresponds to the deterministic evaluation curves. Thus, on average, the Andrus et al. (1999) curves are characterized with a P_L value of 30 % based on the Bayesian Mapping Model.

Equation (12) provides an important link between the probabilistic and deterministic methods. By combining Eqs. (3), (11) and (12), one can obtain the P_L curves shown in Fig. 6. These curves exhibit convergence to a V_{S1} value of 215 m/s, the assumed value of V_{S1}^*

for clean soils, at high values of CSR. It is important to note that similar results were obtained by Juang and Jiang (2000) for the SPT-based procedure, where P_L curves converge to a correct blow count of 30. Also, Juang et al. (2000) found that the SPT-based boundary curve recommended by the 1996 NCEER Workshop (Youd et al., 1997) is characterized with an average P_L value of 31 %. These findings suggest that the V_{S} - and SPT-based evaluation curves exhibit similar conservatism on average.

4



Fig. 5. Relationship between P_L and F_S based on Bayes' Theorem.



Fig. 6. Bayesian Mapping Model along with case history data adjusted for fines content.

COMPARISON OF MODELS

Figure 7 compares the ANN, logistic regression, and Bayesian mapping models with the boundary curve proposed by Andrus et al. (1999) for soils with $FC \le 5$ %. The curve by Andrus et al. lies between the two logistic regression curves for $P_L = 30$ % below a V_{S1} value of about 140 m/s and above a V_{S1} value of about 205 m/s. The best-fit ANN model for clean soils is very similar to logistic regression Model 1. Between V_{S1} values of 140 m/s and 205 m/s, the Andrus et al. curve bounds the other curves. These results support the Bayesian Mapping Model, which provides an overall P_L value of 30% for the Andrus et al. curve.



Fig. 7. Comparison of ANN, logistic regression, and Bayesian models with the CRR-V_{S1} curve proposed by Andrus et al. (1999) for clean soils.

As shown in the probability analyses presented above, it is possible that liquefaction could occur outside the region of predicted liquefaction shown in Fig. 7. The acceptable value of F_s for a particular site will depend on several factors, including the type and importance of structure and the potential for ground deformation. The Building Seismic Safety Council (1997, page 158) suggests a factor of safety of 1.2 to 1.5 is appropriate when applying the Seed-Idriss simplified procedure in engineering design. From Fig. 5, F_s values of 1.2 to 1.5 correspond to P_L values of 20 % to 10 %, respectively.

CONCLUSIONS

Presented in this paper are three preliminary probability-based models and one artificial neural network model for the Vs-based case history data compiled by Andrus et al. (1999). The ANN model exhibits a remarkable ability to track the irregular boundary separating liquefaction and no liquefaction cases. This finding explains the better predictions of no liquefaction by ANN models than by the Andrus et al. curves. The best-fit ANN model for soils with FC \leq 5 % is similar to logistic regression Model 1 with P_L = 30 %. The preliminary logistic regression and Bayesian models indicate that the liquefaction evaluation curves developed by Andrus et al. are characterized with PL of about 30 %. The Bayesian model (Fig. 6) is believed to be better than the logistic regression models, and is suggested for engineering design. The Bayesian mapping function (Fig. 5) provides a method for making risk-based design decisions using deterministic procedures. Caution should be exercised when applying the Bayesian model to sites where conditions are different from the database. The database is limited to level ground sites with depth less than 10 m, uncemented soils of Holocene age, and shallow ground water tables (<6 m). Additional well-documented case histories with all soil types are needed to further validate the procedure.

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REFERENCES

Andrus, R.D. and K.H. Stokoe, II [1997]. "Liquefaction resistance based on shear wave velocity," NCEER Workshop on Evaluation of Liquefaction Resistance of Soils, Tech. Rep. NCEER-97-0022, (T.L. Youd and I.M. Idriss, eds.) Nat. Ctr. for Earthquake Engrg. Res., Buffalo, N.Y., 89-128.

Andrus, R.D. and K.H. Stokoe, II [in press]. "Liquefaction resistance of soils from shear wave velocity," J. Geotech. and Geoenvironmental Engrg., ASCE.

Andrus, R.D., K.H. Stokoe, II and R.M. Chung [1999]. "Draft guidelines for evaluating liquefaction resistance using shear wave velocity measurements and simplified procedures," NISTIR 6277, Nat. Inst. of Standards and Technology, Gaithersburg, MD.

Building Seismic Safety Council [1997]. "NEHRP recommended Provisions for seismic regulations for new buildings and other structures, Part 2: Commentary," FEMA 303, Federal Emergency Management Agency, Washington, D.C.

Chen, C.J. [1999]. "Risk-based liquefaction potential evaluation using cone penetration tests and shear wave velocity measurements," Ph.D. Dissertation, Clemson Univ., Clemson, SC.

Dobry, R., K.H. Stokoe, II, R.S. Ladd and T.L. Youd [1981]. "Liquefaction susceptibility from S-wave velocity," Proc. In Situ Tests to Evaluate Liquefaction Susceptibility, ASCE Nat. Convention, 27 Oct., St. Louis, MO.

Juang, C.H. and C.J. Chen [2000]. "A rational method for development of limit state for liquefaction evaluation based on shear wave velocity," Int. J. Numerical and Analytical Methods in Geomechanics, 24, pp. 1-27.

Juang, C.H. and T. Jiang [2000]. "Assessing probability methods for liquefaction potential evaluation," Soil Dyn. and Liquefaction, Geotech. Special Publ., ASCE, GeoDenver 2000 Conference.

Juang, C.H., D.V. Rosowsky and W.H. Tang [1999]. "A reliability-based method for assessing liquefaction potential of sandy soils," J. Geotech. and Geoenvironmental Engrg., ASCE, 125(8), pp. 684-689.

Juang, C.H., C.J. Chen, T. Jiang and R.D. Andrus [2000]. "Riskbased liquefaction potential evaluation using SPT," Can. Geotech. J. (assigned to the December issue).

Liao, S.C.C., D. Veneziano and R.V. Whitman [1988]. "Regression models for evaluating liquefaction probability," J. Geotech. Engrg., ASCE, 114(4), pp. 389-411.

Robertson, P.K., D.J. Woeller, W.D.L. Finn [1992]. "Seismic cone penetration test for evaluating liquefaction potential under cyclic loading," Can. Geotech. J., 29, pp. 686-695.

Seed, H.B. and I.M. Idriss [1971]. "Simplified procedure for evaluating soil liquefaction potential," J. Soil Mech. and Found. Div. ASCE, 97(SM9), pp. 1249-1273.

Seed, H.B, I.M. Idriss and I. Arango [1983]. "Evaluation of liquefaction potential using field performance data," J. Geotech. Engrg., ASCE, 109(3), pp. 458-482.

Seed, H.B., K. Tokimatsu, L.F. Harder and R.M. Chung [1985]. "Influence of SPT procedure in soil liquefaction resistance evaluation," J. Geotech. Engrg., ASCE, 111(12), pp. 1425-1445.

Stokoe, K.H., II and S. Nazarian [1985]. "Use of Rayleigh waves in liquefaction studies," Measurement and Use of Shear Wave Velocity for Evaluating Dyn. Soil Properties, (R.D. Woods, ed.) ASCE, 1-17.

Sykora, D.W. [1987]. "Creation of a data base of seismic shear wave velocities for correlation analysis," Geotech. Lab. Misc. Paper GL-87-26, U.S. Army Engineer Waterways Exp. Station, Vicksburg, MS.

Tokimatsu, K. and A. Uchida [1990]. "Correlation between liquefaction resistance and shear wave velocity," Soils and Found, Japanese Soc. of Soil Mech. and Found. Engrg., 30(2), pp. 33-42.

Youd, T.L. and S.K. Noble, [1997]. "Liquefaction criteria based on statistical and probabilitistic analyses," NCEER Workshop on Evaluation of Liquefaction Resistance of Soils, Tech. Rep. NCEER-97-0022, (T.L. Youd and I.M. Idriss, eds.) Nat. Ctr. for Earthquake Engrg. Res., Buffalo, N.Y., pp. 201-215.

Youd, T.L. and I.M. Idriss, eds. [1997]. "NCEER Workshop on Evaluation of Liquefaction Resistance of Soils," Tech. Rep. NCEER-97-0022, Nat. Ctr. for Earthquake Engrg. Res., Buffalo, NY.

Youd, T.L., I.M. Idriss, R.D. Andrus, I. Arango, G. Castro, J.T. Christian, R. Dobry, W.D.L. Finn, L.F. Harder, Jr., M.E. Hynes, K. Ishihara, J.P. Koester, S.S.C. Liao, W.F. Marcuson, III, G.R. Martin, J.K. Mitchell, Y. Moriwaki, M.S. Power, P.K. Robertson, R.B. Seed and K.H. Stokoe, II [1997]. "Summary report," NCEER Workshop on Evaluation of Liquefaction Resistance of Soils, Tech. Rep. NCEER-97-0022, (T.L. Youd and I.M. Idriss, eds.) Nat. Ctr. for Earthquake Engrg. Res., Buffalo, N.Y., pp. 1-40.