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Reliability-Based Liquefaction Triggering Assessment Framework: A Unified Approach for SPT-CPT-Vs

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Abstract. For longer than four decades, the current practice for liquefaction triggering engineering assessments have been dominated by case history-based deterministic and probabilistic models. The predictive model proposals have been constituted based on different sets of case histories concerning in-situ test indices, namely standard penetration test (SPT) N value, cone penetration test (CPT) q , and shear-wave velocity (V_s), etc. The present study uses the databases of Cetin et al., Moss et al., and Kayen et al. together to develop a unified liquefaction triggering predictive model within a probabilistic framework. The scope concentrates on the illustrative introduction of the proposed unified reliability-based framework along with the comparative presentation of model predictions. The unified model enables a joint assessment of liquefaction performance predictions at sites, where different in-situ test indices are used individually or jointly to characterize the soil resistance against liquefaction.

Keywords: Soil liquefaction, Seismic Hazard, In-situ tests, SPT, CPT, V_s

1 Introduction

As part of widely used seismic soil liquefaction triggering assessment models, the penetration resistances by either SPT or CPT; or shear wave velocity test are used as capacity terms. The simplified procedure introduced by Seed and Idriss [1] sets the basis for estimating cyclic stress ratio (CSR), which is usually adopted as a demand term. The liquefaction triggering performances, compiled from available well-documented case histories, were plotted in the capacity-demand [e.g., $N_{1,60}$ vs. Cyclic Shear Ratio (CSR)] domain, and deterministic liquefaction triggering boundary curves were proposed for varying contents of fines, as proposed by Seed et al. [2]. CSR, as estimated by simplified procedure, is given in Equation 1, where σ_v and σ'_v are the total and effective vertical stresses, a_{max} and g are the peak ground and gravitational accelerations, and finally r_d is the shear mass participation factor.

$$CSR_{\sigma'_{v,MW}} = 0.65 \cdot \frac{a_{max}}{g} \cdot \frac{\sigma_v}{\sigma'_v} r_d \quad (1)$$

Similarly, Figure 1 presents the pioneering liquefaction triggering boundary curves suggested by Seed et al. [2] with minor adjustment at low $N_{1,60}$ region by NCEER [3].

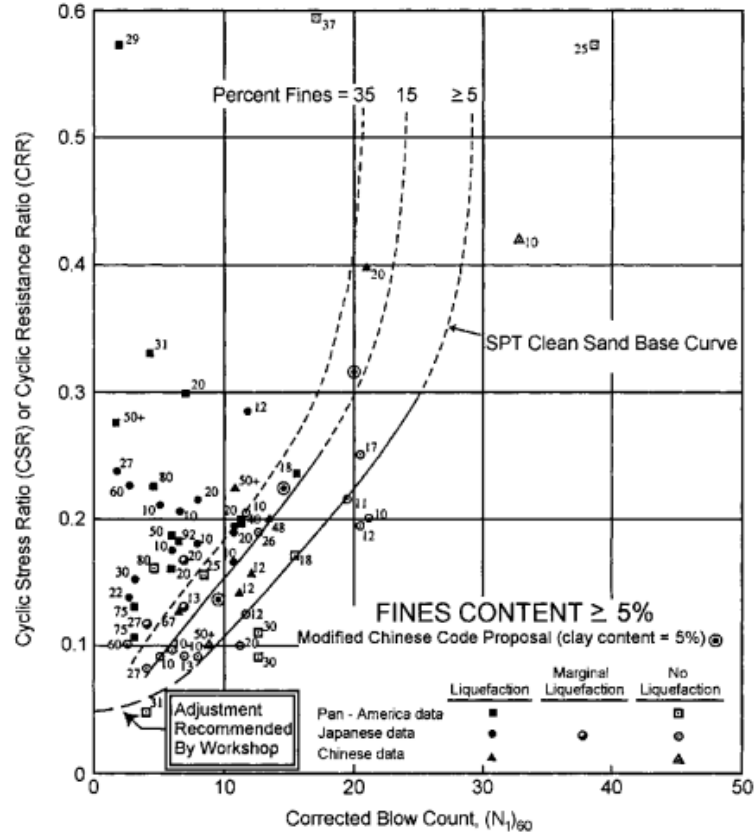


Fig. 1. Pioneering deterministic liquefaction triggering model of Seed et al. [2] as modified by NCEER [3]

As the figure implies, well-documented cases from higher shaking intensities (i.e.: from higher CSR) are scarce; hence the efforts were directed to extend the dataset with cases from recent large magnitude events, and more specifically, from high-intensity shaken sites. The intent behind these efforts is to develop more accurate performance predictions in this large demand region. [4-9].

On an alternative path, research efforts were also put to improve the accuracy and precision of demand terms, more specifically of CSR. As presented in Equation 1, the uncertainty in CSR is governed mostly by the uncertainties in the prediction of peak

ground acceleration (PGA) and shear mass participation factor (r_d). The r_d term simply models the seismic response of the flexible soil column. As an excellent starting point, Seed et al. [2] proposed a site-response-based r_d model given as a function of the soil column depth. Then, Liao and Whitman [10] fitted an empirical relationship to this curve for improved convenience in engineering use. Ishihara [11] again addressed that the r_d is governed by site response parameters i.e.: site stiffness, damping and seismic shaking input parameters. Idriss [12] suggested using an M_w -dependent r_d predictive model, which had been adopted by others [e.g., 8-9]. Alternatively, as part of Cetin and Seed [13], more than 2,000 site response analyses were performed to assess the variation of r_d with depth, soil stiffness, earthquake magnitude (duration), and PGA. Later, by using Cetin and Seed [13] r_d relationships, Cetin et al. [4-5], Moss et al. [6], and Kayen et al. [7] assessed the CSR terms to develop their recommended set of liquefaction triggering boundary curves corresponding to different probability levels. Figure 2 presents these widely used probabilistic liquefaction triggering models, exclusively developed by using SPT-, CPT-, or V_s -databases, respectively.

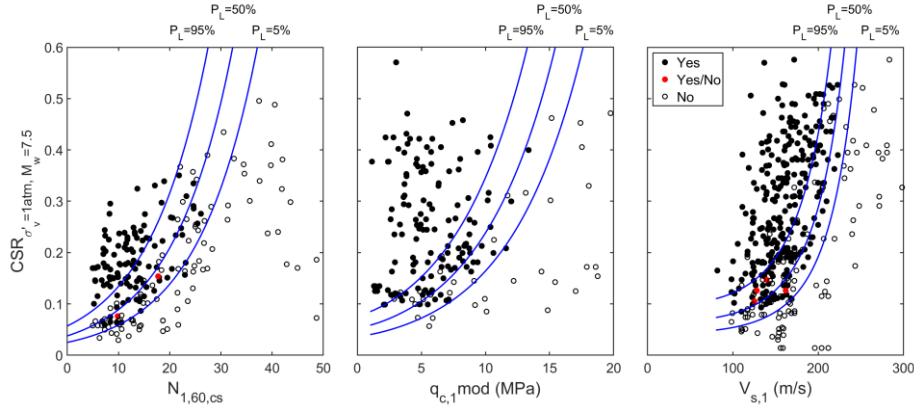


Fig. 2. Widely used probabilistic liquefaction triggering models: Cetin et al. [5]; Moss et al. [6]; Kayen et al. [7], respectively.

As the figures suggest, depending on the datasets and in-situ indices used, different sets of liquefaction triggering curves are suggested. Moreover, again depending on the dataset and in-situ indices used, different sets of magnitude (duration) K_{Mw} , overburden stress (K_σ) corrections to be applied on CSR (or cyclic resistance ratio, CRR), and fines corrections to be applied on penetration resistances, are proposed [e.g., 5-7, 14]. As a reminder, these correction factors are given in Equations 2 and 3. Note that the corrections given in Equations 2 and 3 are estimated based on Cetin et al [5] SPT-database, and a similar but different set of corrections is also proposed to be applied for CPT- and V_s -based assessments.

$CSR_{\sigma'_v=1atm,\alpha=0,M_w=7.5} = CSR_{\sigma'_v,\alpha,M_w} \cdot \frac{1}{K_\sigma} \cdot \frac{1}{K_{M_w}} \cdot \frac{1}{K_\alpha}$; $\lim: CSR_{\sigma'_v=1atm,\alpha=0,M_w=7.5} \leq 0.60$, where

$$K_\sigma = \left(\frac{\sigma'_v}{7.5}\right)^{-0.336}; \lim: 0.8 \leq K_\sigma \leq 1.6 \quad \text{and} \quad K_{M_w} = \left(\frac{M_w}{7.5}\right)^{-2.324}; \lim: 5.5 \leq M_w \leq 8.4 \quad (2)$$

$$N_{1,60,cs} = N_{1,60} + \Delta N_{1,60}; \text{ where } \Delta N_{1,60} = FC \cdot (0.00167 \cdot N_{1,60} + 0.089); \lim 5\% \leq FC \leq 35\% \quad (3)$$

Figure 3 presents the set of these correction factors available in the literature, which are observed to be significantly different.

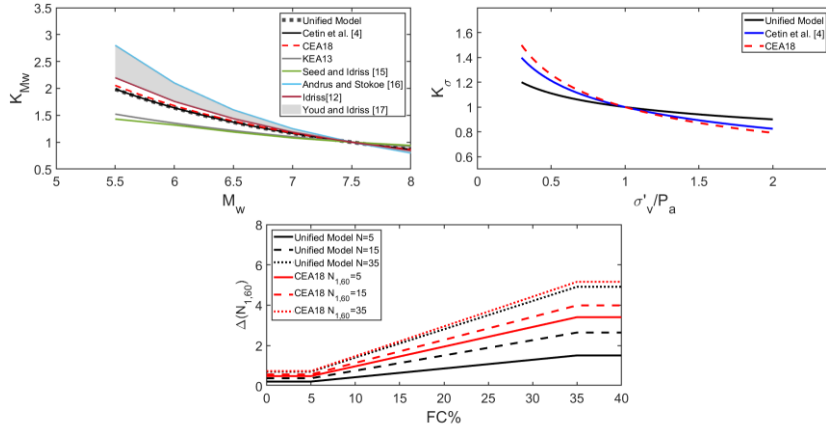


Fig. 3. Widely used correction factors.

To reduce the uncertainties in liquefaction triggering assessments and eliminate the need to use in-situ test-specific correction terms applied on CSR; SPT-, CPT-, and V_s -based liquefaction triggering databases are jointly assessed within a reliability-based framework. More specifically, the proposed framework will be illustratively applied to the joint assessment of SPT-, CPT-, and V_s -based databases of Cetin et al. [5], Moss et al. [6], and Kayen et al. [7] with the intent to constitute a unified probabilistic liquefaction triggering model. These databases will be referred to herein as CEA18, MEA06, and KEA13, respectively. SPT dataset is composed of a total of 210 case histories, 113 of which are liquefied, 2 marginals, and 95 non-liquefied field performances. Similarly, the CPT dataset has 182 case histories, including 139 liquefied and 43 non-liquefied cases. Finally, the V_s dataset has 415 case histories, where 217 are from liquefied sites and 124 from non-liquefied ones. Note that marginal liquefaction performances were observed only at 4 sites. Some important statistics of the databases are given in Table 1.

Table 1. Some important statistics of CEA18, MEA06, KEA13 databases

	CEA18		MEA06		KEA13	
	Mean	SD	Mean	SD	Mean	SD
$N_{1,60}$	15.13	3.09	-	-	-	-
FC%	16.57	4.16	-	-	-	-
q_{c1} (MPa)	-	-	6.33	1.58	-	-
Rf%	-	-	0.793	0.42	-	-
c	-	-	0.487	-	-	-
$V_{s,1}$ (m/s)	-	-	-	-	156.08	15.03
Critical depth (m)	4.93	0.55	4.29	-	4.89	-
a_{max} (g)	0.24	0.05	0.27	0.066	0.296	0.074
σ_v (kPa)	89.7	10.6	75.18	5.68	82.3	10.26
σ'_v (kPa)	60.62	5.62	51.83	3.59	51.8	6.08
r_d	0.911	0.057	0.76	0.073	0.788	0.087
M_w	7.09	-	7.11	0.11	7.10	0.12
$CSR_{\sigma'_v, M_w}$	0.208	0.05	0.249	0.0673	0.252	0.086

2 A Unified Reliability-based Limit State Model

CEA18, KEA13, and MEA06 implemented the MLE and/or Bayesian updating frameworks to assess the liquefaction triggering models. Bayesian updating enables to develop a joint liquefaction triggering assessment framework by considering both prior information with newly available case history-based data. The adopted probabilistic assessment model identifies the boundaries between liquefied and non-liquefied case history performances. For the purpose a limit state function, capable of defining this boundary is needed. Consistent within structural reliability conventions, the limit state function is formulated as load terms subtracted from the demand terms. The failure or liquefaction is expected to occur when the limit state function yields negative values. As a reminder, the limit state functions used by CEA18, KEA13, and MEA06 are given in Equations 4 through 6.

$$g(x, \theta) = N_{1,60}(1 + \theta_1 FC) - \theta_2 \ln(M_w) - \theta_3 \ln\left(\frac{\sigma'_v}{P_d}\right) + \theta_4 FC + \theta_5 - \theta_6 \ln(CSR_{\sigma'_v, \alpha, M_w}) + \varepsilon_{total} \quad (4)$$

$$g(x, \theta) = \theta_1 V_{s,1}^{\theta_2} + \theta_3 \ln(CSR) + \theta_4 \ln(M_w) + \theta_5 \ln(\sigma'_v) + \theta_5 FC + \varepsilon_{total} \quad (5)$$

$$g(x, \theta) = q_{c,1}(1 + \theta_1 R_f) + \theta_2 R_f + c(1 + \theta_3 R_f) - \theta_4 \ln(CSR) - \theta_5 \ln(M_w) - \theta_6 (\ln \sigma'_v) - \theta_7 + \varepsilon_{total} \quad (6)$$

As discussed earlier, these equations are composed of both capacity ($N_{1,60}$ and FC, or $V_{s,1}$, or $q_{c,1}$ and Rf) and demand terms (CSR, M_w , and σ'_v), as well as of the unknown model coefficients (θ). Note that despite the in situ-test based differences in the capacity terms, the demand terms of CSR, M_w , and σ'_v are common in all three models. The roles of M_w , and σ'_v terms in these expressions are to correct the field CSR terms for magnitude (duration) and effective stress variabilities, which are wide-

ly referred to as K_{Mw} and K_σ corrections. Inspired from the availability of common demand terms and after some re-arrangements, the limit state functions are jointly expressed as a single functional form given in Equation 7.

$$g(x, \theta) = -\ln(CSR) - \theta_{11} \ln(M_w) - \theta_{12} \ln\left(\frac{\sigma'_v}{P_a}\right) + \theta_{13} + \left\{ \begin{array}{l} \theta_1 \cdot N_{1,60} + \theta_2 \cdot N_{1,60} \cdot FC + \theta_3 \cdot FC + \varepsilon_{SPT} \\ \theta_4 \cdot q_{c,1}^{\theta_5} + \theta_6 \cdot q_{c,1} \cdot R_f + \theta_7 \cdot R_f + \theta_8 \cdot c \cdot R_f + \varepsilon_{CPT} \\ (\theta_9 \cdot V_{s,1})^{\theta_{10}} + \varepsilon_{VS} \end{array} \right\} \quad (7)$$

Capacity terms, $N_{1,60}$ (equipment corrected SPT-N values), $q_{c,1}$ (normalized tip resistance in MPa) and $V_{s,1}$ (normalized shear wave velocity in m/s) are used as defined in Cetin et al. [5], Moss et al. [6], and Kayen et al. [7]. FC and friction ratio (R_f) terms are expressed as a percentile in the proposed limit state function. Similarly, all necessary corrections other than the ones explicitly defined in Equation 7, are applied again consistent with their definitions given in the source databases.

Equation 7 assumes that these descriptive variables (i.e.: CSR, M_w , σ'_v , $N_{1,60}$ and FC, $V_{s,1}$, $q_{c,1}$ and R_f) fully explain the liquefaction triggering response, but some other variables (e.g.: drainage conditions, particle shape and size, strain history, etc.) exist. Moreover, the proposed limit state function may not have the ideal mathematical form. Hence, a normally distributed random model error term, ε , with zero mean and standard deviation [i.e.: $\varepsilon = N(0, \sigma_\varepsilon)$] is introduced to account for the influences of possible missing descriptive variables and the imperfect functional form. The model error terms (ε) defined in Equation 7 are assumed to be in-situ test dependent and this is designated with a subscript in ε . Alternatively, a single set of a model error term commonly valid for all three tests can also be defined. Predictive models with both in-situ test specific- and generalized-model error terms will be presented, along with a discussion regarding how the predictive curves vary.

Employing the unified limit state function given in Equation 7, and, assuming that the case histories are statistically independent for simplicity, the likelihood function is written as the product of individual liquefaction triggering performance probabilities of the case histories, as given in Equation 8.

$$L(\theta, \sigma_\varepsilon) = \prod_{i=1}^{\text{Num. of liquefied sites}} P[g(x_i, \varepsilon_i, \theta) \leq 0] \cdot \prod_{j=1}^{\text{Num. of non-liquefied sites}} P[g(x_j, \varepsilon_j, \theta) > 0] \cdot \prod_{k=1}^{\text{Num. of marginally liquefied sites}} P[g(x_k, \varepsilon_k, \theta) \cong 0] \quad (8)$$

Valid for the SPT-database, Suppose that $x_i = (N_{1,60,i}, CSR_{\sigma'_v, \alpha, M_{w,i}}, M_{w,i}, FC_i, \sigma'_{v,i})$ for each liquefaction field performance case history is exact, i.e., no measurement or estimation uncertainty is present. Then, noting that Equation 7 has the normal distribution with mean $\hat{g}(x_i, \theta)$ and standard deviation, σ_ε , the likelihood function Equation 8 can be written as given in Equation 9.

$$L(\theta, \sigma_\varepsilon) = \prod_{i=1}^{\# \text{ liq sites}} \Phi\left(-\frac{\hat{g}_i(x_i, \theta)}{\sigma_\varepsilon}\right)^{w_{liq}} \cdot \prod_{j=1}^{\# \text{ non-liq sites}} \Phi\left(\frac{\hat{g}_j(x_j, \theta)}{\sigma_\varepsilon}\right)^{w_{non-liq}} \cdot \prod_{k=1}^{\# \text{ marginal-sites}} \varphi\left(\frac{\hat{g}_k(x_k, \theta)}{\sigma_\varepsilon}\right) \quad (9)$$

As given in Equation 9, weighting factors are consistently applied in the likelihood function. As part of the Bayesian updating process, non-informative uniform distributions are employed, which allows the likelihood function to dominate the posterior distributions. However, note that the non-informative prior for σ_ε is $1/\sigma_\varepsilon$ [18].

In Equation 9 $\Phi[\cdot]$ and $\varphi[\cdot]$ are the standard normal cumulative function and the standard normal probability density functions, respectively. Also note that w_{liq} and w_{nonliq} are the sampling bias correction factors 0.8 and 1.2, respectively.

3 Results and Discussion

The unknown model coefficients are updated as part of a unified attempt to maximize the likelihood presented in Equation 9. The posterior model parameters are estimated by following the Bayesian statistics with Markov Chain Monte Carlo (MCMC) sampling procedure. As discussed earlier two alternative model error forms are tested: i) a set of three model error terms specific for each in-situ test (i.e.: ε_{SPT} , ε_{CPT} , or ε_{Vs}) ii) a single set of a model term constant for three in-situ tests (i.e.: $\varepsilon_{Unified}$). These predictive models will be separately discussed next.

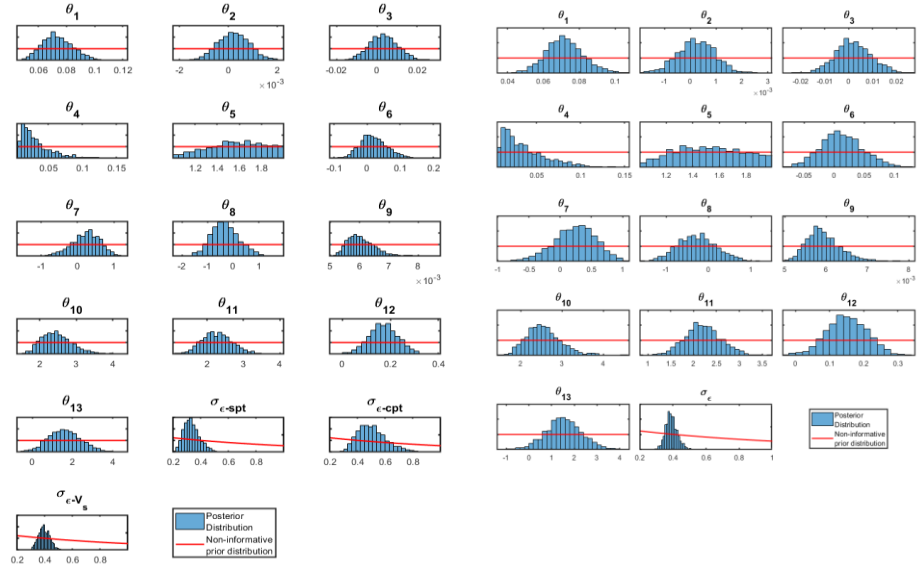
Tables 2 and 3 present the resulting medians, standard deviations, and correlation matrices for the unknown model coefficients, separately estimated for the models with in-situ test dependent or with generalized-unified model error terms, respectively. Similarly, Figure 3 shows non-informative prior and posterior distributions of these model coefficients.

Table 2. Posterior mean and standard deviation of model coefficients (model with in-situ-test-dependent model error)

[illegible]

Table 3. Posterior mean and standard deviation of model coefficients (model with a single-unified model error term)

	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	θ_{10}	θ_{11}	θ_{12}	θ_{13}	$\sigma_{\epsilon, \text{unified}}$
μ	0.0719	0.00023	0.0019	0.0367	1.52	0.013	0.24	-0.27	0.0059	2.57	2.21	0.151	1.53	0.39
SD	0.01	0.0007	0.0078	0.025	0.25	0.0351	0.33	0.46	0.0004	0.452	0.404	0.059	0.797	0.0354
Correlation Matrix														
θ_1	1	-0.68	0.64	0.4	-0.29	-0.067	0.045	0.16	0.038	0.029	0.172	-0.004	0.018	0.2
θ_2		1	-0.8	-0.22	0.154	0.039	0	-0.088	-0.426	0.38	-0.031	0.163	0.047	-0.05
θ_3			1	0.345	-0.247	-0.064	0.405	0.143	0.657	-0.597	-0.075	-0.148	-0.199	0.0101
θ_4				1	-0.96	-0.24	0.22	-0.21	48	-0.45	-0.039	0.026	-0.131	-0.032
θ_5					1	0.082	-0.09	0.145	-0.354	0.337	0.04	-0.048	0.109	0.045
θ_6						1	-0.91	0.73	-0.073	0.064	-0.008	0.055	-0.001	0.037
θ_7							1	-0.88	0.038	-0.036	0.009	-0.05	0.008	0.02
θ_8								1	0.205	-0.18	0.058	0.044	-0.04	-0.029
θ_9									1	-0.91	0.038	-0.017	-0.014	0.058
θ_{10}										1	0.03	-0.015	0.188	0.049
θ_{11}											1	-0.036	0.97	0.312
θ_{12}												1	-0.079	0.031
θ_{13}													1	0.287
σ_{ϵ}														1



(a) Model with in-situ test dependent model error term

(b) Model with generalized-unified model error term

Fig. 4. Non-informative prior and posterior distributions for model coefficients

The recommended relationships are presented in Equations 10-13, along with the probabilistic liquefaction triggering boundary curves shown in Figures 5 and 6.

$$P_L(N_{L60}, q_{c,1}, V_{s,1}, M_w, \sigma'_v, FC, P_L, R_f) = \Phi \left(\frac{-\ln(CSR) - 2.278 \ln(M_w) - 0.171 \ln\left(\frac{\sigma'_v}{P_L}\right) + 1.61 + \left\{ \begin{array}{c} 0.074 \cdot N_{L60} + 0.0002 \cdot N_{L60} \cdot FC + 0.0033 \cdot FC \\ 0.031 \cdot q_{c,1}^{1.57} + 0.0198 \cdot q_{c,1} \cdot R_f + 0.228 \cdot R_f + (-0.315) \cdot c \cdot R_f \\ (0.0061 \cdot V_{s,1})^{2.478} \end{array} \right\}}{\begin{array}{c} 0.33 \\ 0.51 \\ 0.40 \end{array}} \right) \quad (10)$$

$$CRR(N_{L60}, q_{c,1}, V_{s,1}, M_w, \sigma'_v, FC, P_L, R_f) = \exp \left[-2.278 \ln(M_w) - 0.171 \ln\left(\frac{\sigma'_v}{P_L}\right) + 1.61 + \left\{ \begin{array}{c} 0.074 \cdot N_{L60} + 0.0002 \cdot N_{L60} \cdot FC + 0.0033 \cdot FC \\ 0.031 \cdot q_{c,1}^{1.57} + 0.0198 \cdot q_{c,1} \cdot R_f + 0.228 \cdot R_f + (-0.315) \cdot c \cdot R_f \\ (0.0061 \cdot V_{s,1})^{2.478} \end{array} \right\} + \begin{array}{c} 0.33 \\ 0.51 \\ 0.40 \end{array} \right] \cdot \Phi^{-1}(P_L) \quad (11)$$

$$P_L(N_{L60}, q_{c,1}, V_{s,1}, M_w, \sigma'_v, FC, P_L, R_f) = \Phi \left(\frac{-\ln(CSR) - 2.21 \ln(M_w) - 0.151 \ln\left(\frac{\sigma'_v}{P_L}\right) + 1.53 + \left\{ \begin{array}{c} 0.0719 \cdot N_{L60} + 0.00023 \cdot N_{L60} \cdot FC + 0.0019 \cdot FC \\ 0.0367 \cdot q_{c,1}^{1.52} + 0.013 \cdot q_{c,1} \cdot R_f + 0.24 \cdot R_f + (-0.27) \cdot c \cdot R_f \\ (0.0059 \cdot V_{s,1})^{2.57} \end{array} \right\}}{0.39} \right) \quad (12)$$

$$CRR(N_{L60}, q_{c,1}, V_{s,1}, M_w, \sigma'_v, FC, P_L, R_f) = \exp \left[-2.21 \ln(M_w) - 0.151 \ln\left(\frac{\sigma'_v}{P_L}\right) + 1.53 + \left\{ \begin{array}{c} 0.0719 \cdot N_{L60} + 0.00023 \cdot N_{L60} \cdot FC + 0.0019 \cdot FC \\ 0.0367 \cdot q_{c,1}^{1.52} + 0.013 \cdot q_{c,1} \cdot R_f + 0.24 \cdot R_f + (-0.27) \cdot c \cdot R_f \\ (0.0059 \cdot V_{s,1})^{2.57} \end{array} \right\} + 0.39 \cdot \Phi^{-1}(P_L) \right] \quad (13)$$

Valid for the model with in-situ test specific- model error, the SPT-based liquefaction triggering predictive model has the smallest model error standard deviation. This suggests that SPT-database liquefaction triggering assessment produce the most precise prediction, followed by V_s -database- and CPT-database assessments, respectively. This statement should be carefully interpreted. The SPT should not be interpreted as favored over V_s or CPT for soil characterization. Instead, due to probably longer existence of it, SPT-liquefaction triggering database is naturally better filtered out for poor quality case histories. This results in a higher-quality, less scattered SPT liquefaction case history database, which produces a smaller model error standard deviation. Similarly, probably due to higher resolution characterization of thinner soil layers, identifying potential critical layers is more difficult and prone to uncertainties in CPT. This might have contributed to relatively larger scatter in the CPT-based database.

Figure 5 shows comparatively the resulting probability of liquefaction curves against the proposals of CEA18, MEA06, and KEA13. The shifts in the median curves are rather modest.

In Figure 6, the resulting probability of liquefaction curves by single-unified model error term are compared with the recommendations of CEA18, MEA06 and KEA13. Similarly, the shift in the median curves is modest against the earlier suggestions of CEA18, MEA06 and KEA13, so it can be said that the unified model outcomes are in good agreement with the existing models.

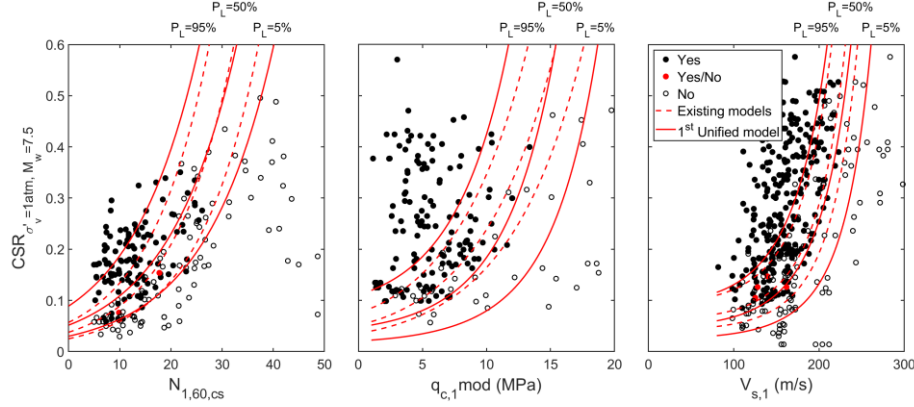


Fig. 5. Comparison of existing CEA18, MEA06, and KEA12 model probability of liquefaction triggering curves with the proposed models with in-situ-test-dependent error terms

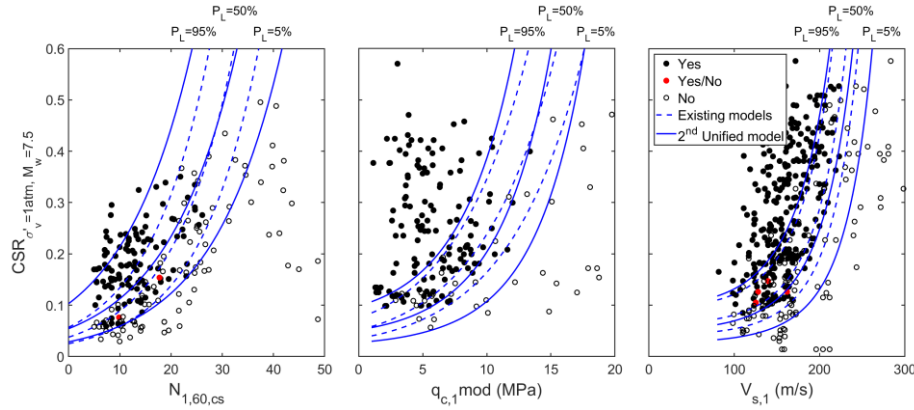


Fig. 6. Comparison of existing CEA18, MEA06, and KEA12 model probability of liquefaction triggering curves with the proposed models with a single generalized unified model error term

Ultimately, the resulting unified model is illustratively given in Figure 7, for a clean sand layer subjected to effective vertical stress of 1 atm, shaken by an $M_w=7.5$ event. Note that three different sets of capacity axes (i.e., $N_{1,60,cs}$, $q_{1,cs}$, $V_{s,1}$) are provided, and all case history data points coming from three different in-situ test based datasets are jointly assessed. The suggested median probability of liquefaction triggering curve is observed to fairly define the liquefied and non-liquefied regions valid for all three datasets despite the model's unified (more generalized) nature. The factor of safety (FS) values corresponding to different probabilities of liquefaction are also shown on the same figure. Depending on the target FS level these probabilistically defined liquefaction triggering boundary curves can be conveniently used for deterministic assessments. Note that, usually an FS value varying in the range of 1.0 to 1.20 is widely used in conventional deterministic liquefaction triggering assessments.

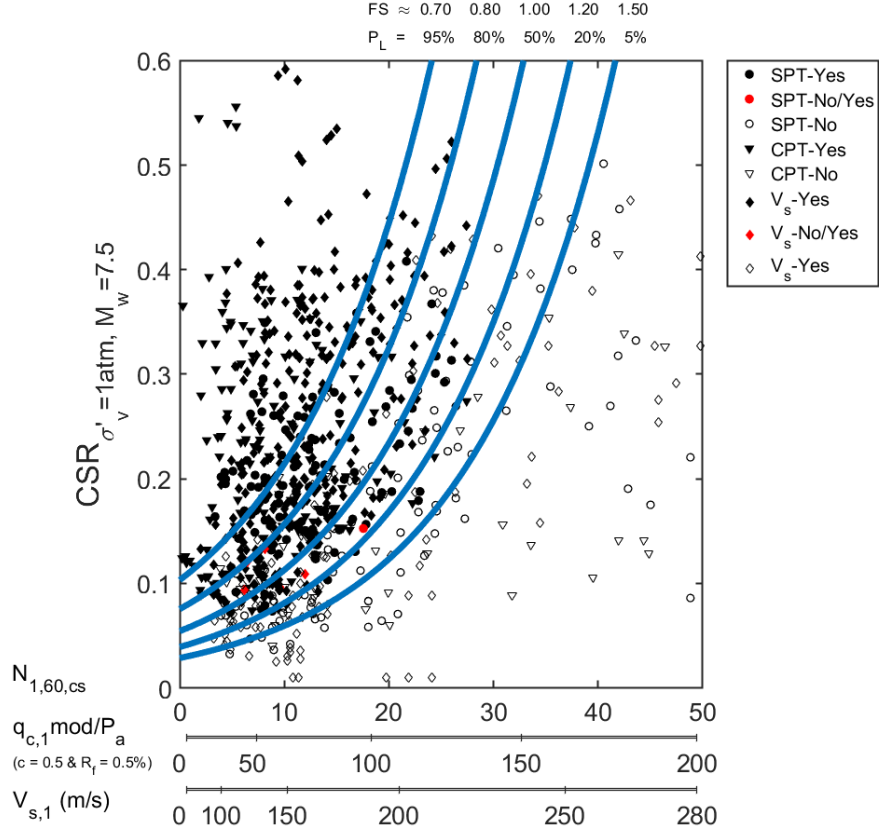


Fig. 7. Resulting unified model

The resulting unified model-based K_{Mw} , K_{σ} and fines corrections are shown in Figure 8 along with currently available correction proposals. These two expressions are defined by using Equations 11 and 12, which employed a single model error term.

$$K_{Mw} = \left(\frac{M_w}{7.5}\right)^{-\theta_{11}} = \left(\frac{M_w}{7.5}\right)^{-2.21} \quad (11)$$

$$K_{\sigma} = \left(\frac{\sigma'_v}{P_a}\right)^{-\theta_{12}} = \left(\frac{M_w}{7.5}\right)^{-0.151} \quad (12)$$

Again, the shifts in these correction factors as compared to earlier suggestions of CEA18, MEA06 and KEA13 are modest, and the resulting unified corrections agree well with currently available literature.

As the concluding remark, the comparisons with in-situ test based predictive models revealed that the unified liquefaction triggering model can a viable alternative by jointly assessing different in-situ based datasets, benefitting from the expanded data-

base sizes without losing much from over generalizations. Inspired from this, as part of their ongoing research studies within the Next Generation Liquefaction Project model developers' group, the updated and expanded liquefaction performance databases are to be used to develop a new set of unified probabilistic predictive models.

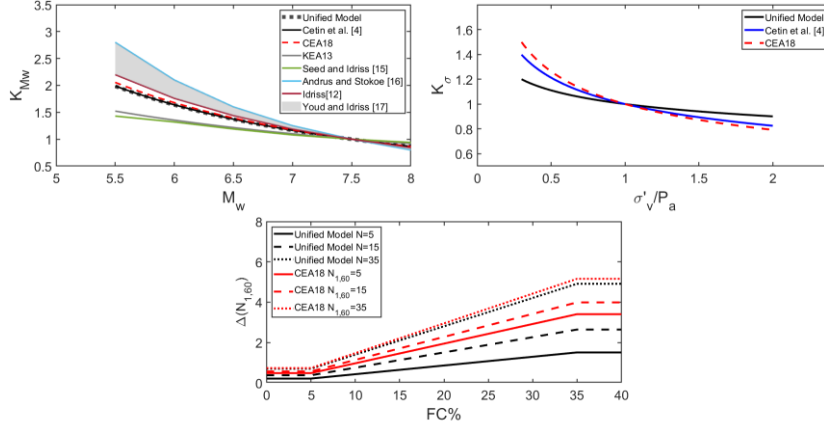


Fig. 8. Comparison of widely used correction factors with the proposed unified model

4 Summary and Conclusion

As part of liquefaction engineering assessments, predictive models developed based on historical liquefaction performance case history data are widely used. These models are commonly developed benefitting from datasets composed of a single set of in-situ test-based soil characterization parameters. Hence, the models are commonly referred to as SPT-based, CPT-based, V_s -based etc. The present study briefly introduces a reliability based unified SPT, CPT, and V_s liquefaction triggering assessment framework. CEA18, MEA06 and KEA13, SPT, CPT and V_s -based databases are jointly used for the purpose. A unified limit state functional form is introduced, and the likelihood function is defined under the assumption of the statistical independency of case histories. Bayesian updating framework is followed to estimate the posterior model parameters.

The resulting unified model is illustratively compared with earlier suggestions of CEA18, MEA06, and KEA13. These comparisons revealed that despite unified (and more generalized) nature of the model, the resulting median curves are observed to be not very different than in-situ test specific boundary curves. Similarly, the resulting unified (K_{Mw}) and overburden stress (K_σ) corrections are in good agreement with currently available recommendations. Despite the unified and more generalized nature of the proposed assessment framework, comparable predictions with available in-situ test-based frameworks suggest that the unified framework can be a viable alternative

to jointly assess different in-situ based datasets by benefitting from the expanded database sizes without losing much from over generalizations.

References

1. Seed, H.B. and Idriss, I.M.: Simplified procedure for evaluating soil liquefaction potential. *Journal of Soil Mechanics and Foundation Division* 97(9), 1249-1273 (1971).
2. Seed, H.B., Tokimatsu, K., Harder, L.F., and Chung, R.M.: The influence of SPT procedures in soil liquefaction resistance evaluations. *Journal of Geotechnical Engineering*, 111(12), 1425-1445 (1985).
3. National Center for Earthquake Engineering Research, (NCEER): Proceedings of the NCEER workshop on evaluation of liquefaction resistance of soils. Technical Report No: NCEER-97-0022, T.L. Youd and I.M. Idriss eds. (1997).
4. Cetin, K.O., Seed, R.B., Der Kiureghian, A., Tokimatsu, K., Harder, L.F., Kayen, R.E. and Moss, R.E.S.: Standard Penetration Test-Based Probabilistic and Deterministic Assessment of Seismic Soil Liquefaction. *Journal of Geotechnical and Geoenvironmental Engineering*, 130(12), 1314-1340 (2004).
5. Cetin, K.O., Seed, R.B., Kayen, R.E., Moss, R.E.S., Bilge, H.T., Ilgac, M. and Chowdhury, K.: SPT-based probabilistic and deterministic assessment of seismic soil liquefaction triggering hazard. *Soil Dynamics and Earthquake Engineering*, 115, 698-709 (2018).
6. Moss, R.E.S., Seed, R.B., Kayen, R.E., Stewart, J.P., Der Kiureghian, A. and Cetin, K.O.: CPT-based Probabilistic and Deterministic Assessment of In Situ Seismic Soil Liquefaction Potential, *Journal of Geotechnical and Geoenvironmental Engineering*, 132(8), 1032-1051 (2006).
7. Kayen, R.E., Moss, R.E.S., Thompson, E.M., Seed, R.B., Cetin, K.O., Der Kiureghian, A., Tanaka, Y. and Tokimatsu, K.: Shear-wave velocity-based probabilistic and deterministic assessment of seismic soil liquefaction potential. *Journal of Geotechnical and Geoenvironmental Engineering*, 139(3), 404-419 (2013).
8. Boulanger, R.W. and Idriss, I.M.: Probabilistic standard penetration test-based liquefaction-triggering procedure. *Journal of Geotechnical and Geoenvironmental Engineering*, 138(10), 1185-1195 (2012).
9. Boulanger, R.W. and Idriss, I.M.: CPT-based liquefaction triggering procedure. *Journal of Geotechnical and Geoenvironmental Engineering*, 142(2) 04015065 (2016).
10. Liao, S.S.C., and Whitman, R.V.: Catalogue of liquefaction and non-liquefaction occurrences during earthquakes. Report, Department of Civil Engineering, MIT, Cambridge (1986)
11. Ishihara, K.: Simple method of analysis for liquefaction of sand deposits during earthquakes. *Soils and Foundations*, 17(3), 1-17 (1977).
12. Idriss, I.M.: An update to the Seed-Idriss simplified procedure for evaluating liquefaction potential. (Publication No. FHWA-RD-99-165). In *Proceedings of TRB workshop on new approaches to liquefaction*, Federal Highway Administration (1999).
13. Cetin, K.O. and Seed, R.B.: Nonlinear shear mass participation factor, r_d for cyclic stress ratio evaluation. *Soil Dynamics and Earthquake Engineering*, 24(2), 103-113 (2004).
14. Boulanger, R.W.: High overburden stress effects in liquefaction triggering procedure. *Journal of Geotechnical and Geoenvironmental Engineering*, 129(12), 1071-1082 (2003).
15. Seed H.B. and Idriss, I.M.: Ground motions and soil liquefaction during earthquakes. *Earthquake Engineering Research Institute Monograph*, Oakland, Calif. (1982).

16. Andrus, R.D. and Stokoe, K.H.: Liquefaction resistance based on shear wave velocity. Proceeding NCEER Workshop on Evaluation of Liquefaction Resistance of Soils, State Univ. of New York, Buffalo, 89-128 (1997).
17. Youd T.L. and Idriss I.M.: Liquefaction Resistance of Soils: Summary Report from the 1996 NCEER and 1998 NCEER/NSF Workshops on Evaluation of Liquefaction Resistance of Soils. Journal of Geotechnical and Geoenvironmental Engineering, 127(4), 297-313 (2001).
18. Box, G.E.P. and Tiao, G.C.: Bayesian inference in statistical analysis. Wiley, New York (1992).