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# PROBABILISTIC EVALUATION OF FIELD LIQUEFACTION POTENTIAL USING RELATIVE STATE PARAMETER INDEX ($\xi_R$)

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## ABSTRACT

From the earliest studies of soil behavior under cyclic loading, it is found that the cyclic stress required for liquefaction onset is strongly affected by the relative density ($D_r$) and initial effective overburden pressure of the soil. In this paper, relative state parameter index ($\xi_R$), which accounts for both relative density and effective stress, is used to evaluate the likelihood of liquefaction initiation in field condition. Two comprehensive databases of field case histories based on SPT and CPT are incorporated in the analyses. Logistic regression method is employed to derive a probabilistic expression that yields the probability of liquefaction initiation in terms of $\xi_R$. The most advantage of this expression is its consistency with both field SPT and CPT data. In addition, relative state parameter index has been evolved from dilatancy concept which has a reasonable consistency with liquefaction phenomenon. The boundary curve that obtains 20% likelihood of liquefaction initiation is found to be the most conservative boundary and is recommended as a deterministic $\xi_R$-based liquefaction criterion. Finally, a relationship is proposed to correlate liquefaction probability to the factor of safety against liquefaction triggering.

## INTRODUCTION

Earthquake is one of the most catastrophic phenomena that could have direct and indirect effects on structures. Liquefaction can resulted in a great impact on structure's foundation and lead to considerable settlements. Thus, evaluating liquefaction potential and considering the liquefaction effects in design procedure is crucial. Use of field and laboratory tests for the assessment of liquefaction is prevalent but cyclic laboratory testing on granular materials include some limitation such as sample disturbance. Accordingly, employing simplified method that was originally proposed by Seed and Idriss (1971) based on empirical evaluation of field observations has been state of the practice in liquefaction evaluation. This procedure that was frequently updated by researchers (e.g. Youd et al. 2001; Cetin et al. 2004; and Moss et al. 2006) is the most accepted approach among geotechnical engineers.

Common field tests for liquefaction evaluation could be divided into four major categories including Standard Penetration Test (SPT), Cone Penetration Test (CPT), Shear Wave Velocity (Vs) and Becker Penetration Test. Among these site characterizing techniques, SPT and CPT-based correlations are the most popular due to their simplicity and also the larger number of case histories. These methods that have been proposed and modified by various researches are based on the relation between liquefaction resistance of the soil (i.e. penetration resistance) and seismic demand (i.e. representative of earthquake loading action). Although earliest SPT and CPT based correlations of liquefaction assessment were deterministic, more recent studies have include probability in their analyses.

As an accepted deterministic approach, Youd et al. (2001)'s deterministic criterion has been recommended in different codes and guidelines. Although, the probabilistic approaches are still out of the mainstream of standard practice, developing of this procedure in the recent years is appealing. Use of probabilistic concept for the assessment of liquefaction firstly recommended by Liao et al. (1988) for SPT based data through logistic regression model. Using a larger database, Youd and Nobel (1977) and Topark et al. (1999) employed the same method and also considered the effect of fines content to propose other relations. The same logistic regression methodology was carried out by Lai et al. (1990), Topark et al. (1999), Juang et al. (2002), and Lai et al. (2006) for developing CPT based probabilistic models. Furthermore, some other researchers such as Cetin et al. (2004) and Moss et al. (2006) implemented a higher-order probabilistic tool (Bayesian Updating) and developed new correlations respectively for SPT and CPT. Although they indicated that the new approach greatly reduce overall uncertainty, it possesses its own disadvantages and limitations, like any analytical and statistical method.

A probabilistic model can be affected by probabilistic regression method, number and quality of data, and also method of interpretation (i.e. choice of representative variable for regression). In the present paper, relative state parameter index ($\xi_R$) is employed in place of SPT and CPT data in order to achieve a larger database. Relative state parameter index ($\xi_R$) that was gradually introduced by Been and Jeffries (1985), Bolton (1986), and Boulanger (2003) has been found to be useful for this purpose because this parameter can be obtained using the existing correlations between soil relative density and standard or cone penetration resistances. Therefore, use of this parameter improves the sufficiency condition of the database and can obtain a more generalized probabilistic model. On the other hand, $\xi_R$ considers the effect of relative density and initial overburden stress at the same time because it was derived from dilatancy concept that has close consistency with liquefaction phenomenon. This can be an important advantage of a $\xi_R$–based probabilistic model over the previously proposed probabilistic SPT and CPT based models that consider initial overburden pressure statistically. Two comprehensive and high quality field databases of SPT and CPT based liquefaction case histories reported by Cetin et al. (2004) and Moss et al. (2006) have been used to derive the $\xi_R$-based probabilistic model. Logistic regression method has been employed because of its frequent usage in field liquefaction assessment and wide popularity among researchers.

## LOGISTIC REGRESSION

Logistic regression is a statistical procedure which allows assigning degrees of belief (i.e. probability levels) in a multi-dimensional space of independent variables (explanatory), by means of a derived empirical model.

The scope of logistic regression is to establish an expression for conditional probability of liquefaction ($P_L$) as a function of explanatory variables ($X$), which are factors that affect the occurrence of liquefaction, by identifying the best-fitting for regression model to describe the unknown relationship between an outcome variable and a set of variables. Explanatory variable vector ($X$) should represent seismic loading, soil properties and in-situ stresses. The $P_L$ function is derived from binary or dichotomous regression analyses because each case in liquefaction catalog is represented by a binary variable which indicates whether or not liquefaction is occurred (0 for non-liquefaction, 1 for liquefaction).

Logistic regression may be preferred over other distribution functions available for analyzing dichotomous outcome variables due to its simplicity, flexibility and interpretability (e.g. Cox and Snell 1989; Hosmer and Lemeshow 2000). Liao et al. (1988) initially applied logistic regression framework to consider the uncertainties involved in deterministic criteria and to estimate the likelihood of liquefaction triggering in terms of SPT resistance and the other factors implemented in the simplified shear stress-based method.

The probability function that should be fitted by employing field observation data can be defined as follows (Cox 1970 and Liao et al. 1988):

$$P_L = \frac{\exp[\beta_0 + \beta_1 x_1 + ... + \beta_n x_n]}{1 + \exp[\beta_0 + \beta_1 x_1 + ... + \beta_n x_n]} = \frac{1}{1 + \exp\left[-\left(\beta_0 + \sum_{i=1}^{n} \beta_i x_i\right)\right]} \quad (1)$$

Where $P_L$ = likelihood of liquefaction occurrence and $0 \le P_L \le 1$, $n$ = total number of explanatory variables, $X = [x_1\ , x_2,\ .\ .\ .\ .\ , x_n]$ = vector of explanatory variables, $\beta = [\beta_0\ , \beta_1,\ .\ .\ .\ .\ , \beta_n]$ = regression coefficients that are determined from logit analysis.

$P_L$ can be mapped into $Q_L$ so that $Q_L$ varies from $-\infty$ to $\infty$ while $P_L$ varies from 0 to 1 (Liao et al. 1988, Lai et al. 2006):

$$Q_L = \log it[P_L] = \ln\left[\frac{P_L}{1-P_L}\right]$$

$$= \beta_0 + \beta_1 x_1 + \ .\ .\ .\ .\ + \beta_n x_n \tag{2}$$

Eqs. (1) and (2) are the basis of a logistic regression analysis.

## ESTIMATION OF REGRESSION COEFFICIENTS

Least squares regression or maximum likelihood of estimation can be utilized to determine the vector of regression coefficients, $\beta = [\beta_0\ , \beta_1,\ .\ .\ .\ .\ , \beta_n]$, by fitting the probability function to field observation data. Method of maximum likelihood is one of the best methods to estimate a point estimator of a parameter and has received more attention among statisticians due to its desirable advantages. As the name implies, the estimators are the values that maximizes the likelihood function and are known as maximum likelihood estimators (i.e. $\beta$ vector). The likelihood function for $m$ independent observations that correlates explanatory variable vector $X$ with $\beta$ vector is:

$$L(X;\beta) = \prod_{j=1}^{m} [P_L]^{y_j} \left[1-P_L\right]^{(1-y_j)} \tag{3}$$

Where $L(X;\beta)$ =likelihood function with explanatory variable vector $X$ that is maximized with respect to $\beta$ vector, $y_j$ =binary indicator for case $j$, which is 1 in liquefied and 0 in non-liquefied cases, and $m$ =total number of cases. The vector of maximum likelihood estimators ( $\beta$ ) corresponding to the maximum of the likelihood function is the best fit of $P_L$. Maximum likelihood estimators would be found by equating the first partial derivatives of likelihood function to zero and solving the resulting system of equations. To avoid the computations of large values and large amount of multiplications, the first derivatives of the natural logarithm of the likelihood function, $\ln[L(X;\beta)]$, are computed instead of $L(X;\beta)$ .

As indicated by Liao et al. (1988) and Lai et al. (2006), one of the procedures that can be used to evaluate the adequacy of a binary regression model and determine its goodness-of-fit is the modified likelihood ratio index (MLRI) proposed by Horowitz (1982). The MLRI was denoted by $\rho^2$ as follows:

$$\rho^2 = 1 - \frac{L(\hat{\beta}) - (m+1)/2}{L(0)} \tag{4}$$

Where $L(\hat{\beta})$ = the log-likelihood function evaluated using the values of maximum likelihood estimators, $\beta$ ; $L(0)$ = value of the maximum likelihood function assuming $\beta_i = 0$ ; and $m$ =total number of explanatory variables. In theory, values of $\rho^2$ vary between 0 and 1 and a regression model is said to be sufficiently well fitted when $\rho^2$ is larger than 0.4 (Hensher and Johnson 1981).

More details about the logistic regression can be found in Liao (1986) and Liao et al. (1988).

## MODEL DEVELOPING

Development of a probabilistic model for liquefaction assessment needs the following steps:

1) Collecting a suitable database

2) Selecting explanatory variable

3) Analyzing the binary data with selected explanatory variables

The mentioned procedure is presented as follows.

<u>Data base</u>

As mentioned above, quality and sufficiency of input data has a great impact on the generalization of a probabilistic model. In fact, a model with poor generalization cannot obtain reasonable estimation for the future unseen data. Cetin et al. (2004) and Moss et al. (2006) presented two dependable liquefaction case history catalogs, respectively, based on SPT and CPT data recorded in the field condition. They performed a reasonable procedure to classify numerous data based on their quality and compiled the final databases (201 SPT and 188 CPT data) with the data possessing the greater ranks.

In this study, thanks to use of relative state parameter index, both of these databases have been employed and therefore the number of data has been duplicated.

In the database, liquefied cases are significantly more than non-liquefaction cases and may affect the result by producing an undesirable bias in logistic regression. Similar to the countermeasure used in Mayfield (2007), Moss et al. (2006), and Cetin et al. (2004), this bias is reduced by a prior probability assigned to each liquefied or non-liquefied class such as the proportion of class's population in the database.

Explanatory variable

An explanatory variable in a logistic regression would be considered as a qualified variable if satisfy certain presumptions. Statisticians, however, have no complete agreement on the details of these presumptions. For example, Anderson (2003) and Johnson and Wichern (2002) described that all explanatory variables in a statistical analysis of classification must be independent of each other, normally distributed, linearly dependent with the expected value, and the expected value [i.e., $P_L(X)$ in Eq. (1)] must be normally distributed. In addition, Johnson and Wichern (2002) suggested that even though $P_L(X)$ is not normally distributed, the logistic transformation of $P_L(X)$ (i.e., $Q_L(X)$ in Eq. (2)) still must be normally distributed and there must be a linear relationship between $Q_L(X)$ and the explanatory variables. On the other hand, Garson (2003) declared that the expected value in a logistic regression analysis should neither be strictly normally distributed nor be linearly dependent with the expected value, however its distribution must still be within the domain of the family of exponential distributions, such as normal, Poisson, binomial, or gamma distributions (Lai et al. 2006).

In summary, the current feeling among many statisticians is that logistic regression is more versatile and better suited for most situations than the other analyses method because it does not assume that the independent variables are normally distributed. However, this fact should be considered that selecting explanatory variable with normal distribution could lead to more logical results.

To be introduced in logistic regression, some explanatory variables that satisfy the mentioned statistical properties and suitably represent soil characteristics should be selected. Since, this study is presented based on the simplified method, the seismic disturbance induced by earthquakes is represented as equivalent cyclic stress ration ($CSR_{eq}$). On the opposite side, soil characteristics is captured by relative state parameter index ($\xi_R$), which accounts for both relative density and effective stress. The reduction of liquefaction resistance with increasing initial effective overburden at constant $CSR$ is directly considered by $\xi_R$. Thus, the common laboratory based correction for overburden pressure ($K_\sigma$) is not necessary to be considered in this study.

Relative density of each case history in both SPT and CPT databases should be determined to calculate their corresponding $\xi_R$. For this purpose, existing relations between $D_r$ and penetration resistance (i.e. $N_{1,60}$ and $q_{c1n}$) have been used. Because of increasing uncertainties in determining the relative densities of sands containing high fractions of fines content, this study is only limited on clean sands and silty sands having up to 15% silts.

Boulanger and Idriss (2006) indicated that mixed soils with plasticity index less than 7 (i.e. $PI < 7$) exhibit sand-like behavior. Therefore, it is reasonable to expect that sand sample containing up to 15% fines exhibit sand-like behavior even though they contain a small fraction of clay.

Regression model consists of 3 variables including $\xi_R, CSR_{eq}$ and $M_w$ (moment magnitude) that represent measures of soil properties and seismic loading. All of these parameters are described as follows.

Relative state parameter index ($\xi_R$) From the earliest studies of soil behavior under cyclic loading condition, it has been deduced that the cyclic stress required to develop liquefaction are profoundly influenced by the relative density ($D_r$) of the soil (Seed 1979). Convenient determination of $D_r$ for sands and silty sands in laboratory and also its reasonable consistency with the field SPT and CPT tests are the most important advantages of this parameter that has been widely used to correlate laboratory and field studies (e.g. Yoshimio et al. 1994 and Suzuki et al. 1995). On the other hand, several researchers showed the influence of initial effective confining pressure on liquefaction resistance (e.g. Lee and Seed 1967). At a given small effective confining pressure, dense sands show dilative response under shearing while loose sands behave contractively. Increasing initial effective confining pressure can reverse the dilative behavior of the dense sand to contractive behavior. Been and Jeffries (1985) indicated that properties of sands cannot be expressed in terms of relative density alone and a description of effective stress level must also be included. As they showed, sands and silty sands behave similarly if test conditions assure an equal initial proximity to the steady state line. This proximity was identified by Been and Jeffries (1985) as the "state parameter", which was defined as the difference between the initial and steady state void ratios at the same mean effective stress (Eq. 5). This parameter appropriately reflects the combined effects of density and confining pressure in granular materials.

$$\xi = e - e_{cs} = (e_{\max} - e_{\min})(D_{r,cs} - D_r) \qquad (5)$$

Where $e$ = void ratio of the soil, $e_{cs}$ = void ratio of the soil on critical state line at the same effective stress, $e_{\max}$ and $e_{\min}$ = maximum and minimum void ratios, $D_{r,cs}$ = relative density on critical state line at the same effective stress, and $D_r$ = relative density.

Bolton (1986) studied an extensive database including the strength and dilatancy of 17 sands at different densities and confining pressures and introduced relative density index as a measure to reflect dilatancy potential of granular soils with reasonable accuracy:

$$I_R = D_r(Q - \ln\frac{100p'}{P_a}) - 1$$
(6)

Where, $D_r$ =relative density, $p'$=mean effective confining pressure, $(1+2k_0)\sigma'_{v0}/3$, $P_a$ = atmospheric pressure, and $Q$ =an empirical constant dependent to the mineralogy and breakage of soil (for example $Q = 10$ for quartz sands).

Since $I_R = 0$ describes critical state condition, relative density at this condition can be obtained as follows:

$$D_{r,cs} = \frac{1}{Q - \ln(\frac{100p'}{P_a})} \quad (7)$$

Eq. (7) can be substituted into Eq.(5) to obtain ξ value for any given granular soil. Konrad (1988) and Boulanger (2003) normalized the state parameter ($\xi$), Eq. (5), with respect to $e_{max} - e_{min}$ and proposed relative state parameter index ($\xi_R$) as a parameter that is more useful and applicable than $\xi$ in the field condition. Konrad (1988) indicated that the normalization of state parameter is required because a given negative $\xi$ may correspond closely to the densest state in a uniform well-rounded soil, whereas it would only explain the behavior of a well-graded angular sand in a medium-dense state. The need for such normalization of $\xi$ was also recognized by Been and Jefferies (1986). Konrad (1988), also, reevaluated the data of several sands presented by Been and Jefferies (1985) and found that peak dilation rate ($d\varepsilon_v / d\varepsilon_a$) shows more proportionality to $\xi_R$ than $\xi$. Accordingly, relative state parameter index ($\xi_R$) is obtained as:

$$\xi_R = \frac{1}{Q - \ln\frac{100p'}{P_a}} - D_r \quad (8)$$

It is suggested that $\xi_R$ can be a useful parameter reflecting liquefaction resistance of soils, since it inherently considers the influence of both void ratio and initial effective stress.

For determining $\xi_R$ of field SPT and CPT data, correlations between penetration resistance and $D_r$ have been used. Over the past decades, several researchers have tried to correlate field penetration resistance (i.e. SPT and CPT resistances) to relative density of granular soils. The common form of the relationship between $N_{1,60}$ and $D_r$ is:

$$N_{1,60} = C_d \times D_r^2 \quad (9)$$

Skempton (1986) suggested $C_d$ values equal to 44 for relative densities varying between 30% and 90%. Cubrinouski and Ishihara (1999) proposed a more comprehensive recommendation for $C_d$ and indicated its dependence on basic properties of soil. Idriss and Boulanger (2004) proposed that considering $C_d = 46$ for clean sands can be more realistic because it obtains a relative density of 81% for a corrected SPT blow counts of 30 ($N_{1,60} = 30$). In the present study, Skempton (1986)'s recommendation is used that yields a reasonable $D_r$ of 80% at $N_{1,60} = 30$. Using Skempton (1986)'s recommendation, Eq. (8) is rearranged in terms of $N_{1,60}$:

$$\xi_R = \frac{1}{Q - \ln(\frac{100p'}{P_a})} - \sqrt{\frac{N_{1,60}}{44}}$$
(10)

Boulanger (2002) and Idriss and Boulanger (2004) summarized Salgado et al. (1997a,b) works on CPT and proposed the following equation to obtain $D_r$ from corrected values of CPT tip resistance ($q_{C1N}$) for clean sands:

$$D_r = 0.478 \times q_{C1N}\text{-}1.063$$
(11)

This relationship can be used to result in a relative density of about 80% at the limiting value of $q_{C1N}$ of 175 ($(q_{C1N})_{lim} = 175$).

Eq. (11) was proposed for clean sands that can quickly dissipate the excess pore water pressure developed during sounding. Carraro et al. (2003) studies on calibration chambers, however, shows that the sounding procedure of cone remains in drained condition even by increasing silts content up to 15%. Accordingly, application of Eq. (11) is generalized to silty sands containing up to 15% silts. The following equation is resulted by substituting Eq. (11) into Eq. (8).

$$\xi_R = \frac{1}{Q - \ln(\frac{p'}{P_a})} - 0.478 q_{C1N}{}^{0.264} - 1.063 \quad (12)$$

In order to be in conservative side, the value of $Q$ in Eqs. (10) and (12) is assumed to be equal to 10 according to Boulanger (2003)'s assumption.

Cyclic Resistance Ratio (CSR) For considering the earthquake action, cyclic stress ratio ($CSR_{eq}$) has been used as recommended in the simplified shear stress approach.

$$CSR_{eq} = \left(\frac{a_{\max}}{g}\right).\left(\frac{\sigma_v}{\sigma'_v}\right).(r_d) \tag{13}$$

Where $a_{\max}$ = peak horizontal ground acceleration, $\sigma_v$ and $\sigma'_v$ = total and effective vertical overburden stress and $r_d$ = depth reduction factor.

To account the random nature of earthquake excitation, Duration Weighting Factor has been introduced through laboratory studies and based on this factor, equivalent CSR has been recommended as follows:

$$CSR^*_{eq} = CSR_{eq} / DWF_m \tag{14}$$

Whereas, in some probabilistic recommendations such as Cetin et al. (2004) and Moss et al. (2006), earthquake magnitude is considered as an explanatory variable beside $CSR_{eq}$.

The proposed model

The experiences gathered during previous studies (e.g. Liao et al. 1988; Cetin et al. 2004; and Moss et al. 2006) reveals that $\ln(CSR_{eq})$ is more naturally distributed than $CSR_{eq}$. Thus, in this study, $\xi_R$, moment magnitude, $M_w$, and natural logarithm of $CSR_{eq}$, i.e. $\ln(CSR_{eq})$, are selected as explanatory variables.

The following expression is obtained by fitting $P_L$ function to the 202 SPT and CPT data:

$$P_L = \frac{1}{1+\exp\left\{-[-2.562 + 1.835\mathrm{M_w} + 4.704\ln(CSR^*_{eq}) + 26.393\xi_R{}^3]\right\}}$$

(15)

Moreover, the $\xi_R$-based cyclic resistance ratio for a given liquefaction probability is obtained as:

$$CRR_{\xi_R} = \exp\left(\frac{\ln(\frac{1}{P_L} - 1) + 1.835\mathrm{M_w} + 26.393\xi_R{}^3 - 2.562}{-4.704}\right)$$

(16)

Where; $CRR_{\xi_R}$ stands for cyclic resistance ratio at various levels of liquefaction risk.

Figure 1 shows probabilistic five family curves that are produced by Eq. (16) and denote on the contours of equivalent liquefaction probability at $M_w = 7.5$. In contrast to the limit state curves obtained from deterministic approach, any probabilistic curve individually reflects a uniform level of risk. Eqs. (15) and (16) can be used to evaluate probabilistic liquefaction potential of sands and silty sands (up to 15% silt) in terms of $\xi_R$ parameter. This $\xi_R$-based probabilistic criterion has been originated from critical state concept and considers the influence of SPT and CPT resistances together with effective overburden pressure. According to Fig. 10, the boundary curve representing 20% probability of liquefaction is sufficiently conservative and is suggested to be considered as a deterministic boundary curve that guarantees required safeties.

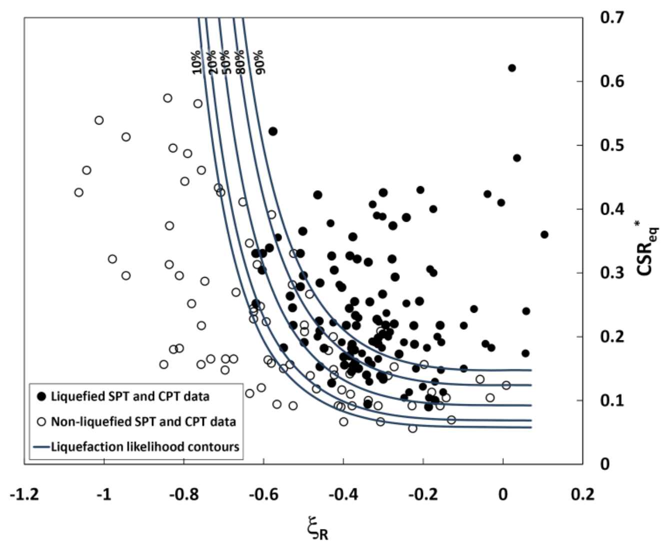


*Fig. 1. Probabilistic $\xi_R$ -based liquefaction criterion developed by logistic regression method applied on SPT and CPT data, only for clean and silty sands containing up to 15% silts*

RELATIONSHIP BETWEEN SAFETY FACTOR AND PROBABILITY OF LIQUEFACTION

The conventional factor of safety ($F_s$) is considered as a reliability index (Juang et al. 2006, Lai et al. 2006) to obtain a probability-safety factor relationship for estimating liquefaction probability for a given factor of safety. This relationship provides a proper estimation of the level of uncertainty behind the factor of safety that is obtained from deterministic analysis. The factor of safety against liquefaction is obtained by dividing cyclic resistance ratio at 20% liquefaction probability $CRR_{\xi_R,20\%}$ by $CSR^*_{eq}$. Figure 3 illustrates probability of liquefaction (obtained from Eq. 15) versus conventional factor of safety for all the SPT and CPT cases. This relation indicates that increase in factor of safety does not decrease the probability of liquefaction linearly. The following relationship is derived by nonlinear regression and Fig. 2 shows how it fits the field data:

$$P_L = \frac{1}{1+5.13F_s^{\ 4.735}}$$
(17)

Figure 11 also compares Eq. (17) with the relations proposed by Juang et al. (2000) for SPT data and Lai et al. (2006) for CPT data. Note that these researchers considered $P_L = 50\%$ as liquefaction failure (i.e. $F_s = 1$), as seen in Fig. 11. The trend of the proposed S-type curve is logical and has consistency with the previous suggestion but the proposed curve is more conservative.

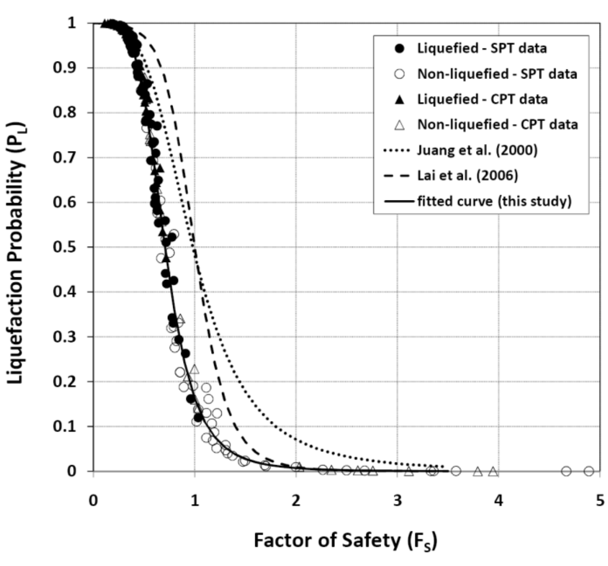


*Fig. 2. Factor of safety versus liquefaction probability and the fitted curve*

CONCLUSION

Probabilistic model for evaluating field liquefaction potential based on relative state parameter index is developed. The advantage of this parameter is considering relative density and effective stress at the same time. Logistic regression is used for proposing the probabilistic model. It has been found that using of $\xi_R^{\ 3}$ leads to a better logistic model rather than $\xi_R$. The resulted probabilistic capacity curves have a logical trend and enough consistency with the previous studies. It has been shown that the probabilistic curve corresponding to 20% probability ($P_L$=20%) provides required conservatism and shows successful behavior in the classification of liquefied and non-liquefied data to be proposed as a deterministic curve. Finally, a relation between safety factor against liquefaction and liquefaction probability is proposed.

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