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Model uncertainty of SPT-based method for evaluation of seismic soil liquefaction potential using multi-gene genetic programming

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Abstract

In this paper, the model uncertainty of the developed standard penetration test (SPT)-based model for evaluation of liquefaction potential of soil is estimated within the framework of the first-order reliability method (FORM). First, an empirical model to determine the cyclic resistance ratio (*CRR*) of the soil is developed, based on the post-liquefaction SPT data using an evolutionary artificial intelligence technique, multi-gene genetic programming (MGGP). This developed resistance model along with an existing cyclic stress ratio (*CSR*) model forms a limit state function for reliability-based approach for liquefaction triggering analysis. The uncertainty of the developed limit state model is represented by a lognormal random variable, in terms of its mean and the coefficient of variation, estimated through an extensive reliability analysis following a trial and error approach using Bayesian mapping functions calibrated with a high quality post-liquefaction case history database. A deterministic model with a mapping function relating the probability of liquefaction (P_L) and the factor of safety against liquefaction (F_s) is also developed for use in absence of parameter uncertainties. Two examples are presented to compare the present MGGP-based reliability method with the available regression-based reliability method.

Keywords: Standard penetration test; Liquefaction index; Multi-gene genetic programming; Probability of liquefaction; Bayesian mapping function; Reliability index; Notional probability

1. Introduction

The first and perhaps the most important step toward mitigating liquefaction-induced damage is the evaluation of the liquefaction potential of a soil subjected to seismic loading. Though, different approaches like cyclic strain-based, energy-based and cyclic stress-based approaches are in use, the stress-based approach is the most widely used method for the evaluation of the liquefaction potential of soil (Kramer, 1996). Seed and Idriss (1971) pioneered the stress-based simplified method and the procedure has been modified and improved by Seed et al. (1983, 1985) using standard penetration test (SPT)-based field performance data. The National Center for Earthquake Engineering Research (NCEER) workshop, 1998, published the reviews of in-situ test-based simplified method with recommendations for the evaluation of liquefaction potential of soil (Youd et al., 2001). Deterministic methods were discussed, which allow the liquefaction potential of soil to be evaluated in terms of the factor of safety against liquefaction (F_s), defined as the ratio of cyclic resistance ratio (*CRR*) to the cyclic stress ratio (*CSR*). However, due to parameter and model uncertainties, $F_s > 1$ may not always indicate non-liquefaction cases, and similarly, $F_s \leq 1$ may not always correspond to liquefaction (Juang et al., 2000). The boundary curve that separates liquefaction and non-liquefaction

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Abbreviations

AAE	average absolute error
CDF	cumulative distribution function
COV	coefficient of variation
CRR	cyclic resistance ratio
$CSR_{7.5}$	cyclic stress ratio adjusted to a benchmark earthquake of moment magnitude of 7.5
FORM	first order reliability method
FOSM	first order second moment method
GP	genetic programming
LI	liquefaction index
MAE	maximum absolute error
MGGP	multi-gene genetic programming
MSF	magnitude scaling factor
PDF	probability density function
RMSE	root mean square error

Symbols

C_B	correction for borehole diameter
C_E	correction for hammer energy efficiency
C_N	factor to normalize N_m to a common reference effective overburden stress
C_R	correction for "short" rod length
C_S	correction for non-standardized sampler configuration
E	Nash–Sutcliffe coefficient of efficiency
E_f	error function
f	MGGP functions defined by the user
F	liquefaction index function
FC	fines content in percentage
F_s	factor of safety against occurrence of liquefaction
g	acceleration due to gravity
G_{max}	maximum number of genes
K_σ	overburden correction factor
L	liquefied cases
LI	liquefaction index
M_w	earthquake magnitude on moment magnitude scale
N_{gen}	number of generations
NL	non-liquefied cases
n	number of terms of target expression
N_m	measured SPT blow count
$N_{1,60}$	corrected SPT blow count (i.e., corresponds to the N_m value after correction for overburden, energy, equipment and procedural effects in SPT method)
$N_{1,60,cs}$	the equivalent clean-sand overburden stress corrected SPT blow count
P_L	probability of liquefaction
R	correlation coefficient
Z	performance function
σ'_v	effective vertical stress at the depth under consideration
σ_v	total vertical stress at the depth under consideration
a_{max}	peak horizontal ground surface acceleration
r_d	stress reduction factor
d_{max}	maximum depth of gene
c_0	bias
μ_z	mean of performance function
σ_z	standard deviation of performance function
β	reliability index
p_f	probability of failure
$\mathbf{\Phi}(\cdot)$	CDF of standard normal variable
c_{mf}	model factor
μ_{cmf}	mean of c_{mf}
β_1	reliability index without considering model uncertainty
β_2	reliability index considering model uncertainty

cases in the deterministic methods is considered as a performance function or "limit state function" and is generally biased toward the conservative side by encompassing most of the liquefied cases. The degree of conservatism, however, is not quantified (Juang et al., 2000). In order to overcome the above mentioned difficulties in the deterministic approach, a probabilistic evaluation of liquefaction potential has been performed where liquefaction potential is expressed in terms of the probability of liquefaction (P_L). Few attempts have been made by researchers to quantify the unknown degree of conservatism associated with the limit state function and to assess liquefaction potential in terms of the probability of liquefaction using statistical or probabilistic approaches. Haldar and Tang (1979) carried out second moment statistical analyses of the SPT-based test data using the limit state function introduced by Seed and Idriss (1971) to estimate the P_L. Lio et al. (1988), Youd and Nobble (1997) and Toprak et al. (1999) used logistic regression analyses of post-liquefaction field performance data to develop empirical equations for assessing P_L. These models are all data-driven as they are based on statistical analyses of the databases of post-liquefaction case histories. The calculation of P_L using these empirical models requires only the mean values of the input variables, whereas the uncertainty in the parameters and the model is excluded from the analysis. Thus, resulting P_L is subject to error if the effect of the parameter or the model uncertainty is significant. These difficulties can be overcome by adopting a reliability-based probabilistic analysis of liquefaction, which considers both model and parameter uncertainties. Juang et al. (1999) used the advanced first-order second moment (AFOSM) method to determine the reliability index (β) for liquefaction and non-liquefaction cases and developed a relationship between β and P_L using a Bayesian mapping function based on post-liquefaction CPT data. They used the ellipsoid method (Low and Tang, 1997) to determine the reliability index. Juang et al. (2000) developed a simplified method based on a post-liquefaction SPT database using the Bayesian mapping function approach to relate F_s with P_L. Juang et al. (2002) found that the Bayesian mapping function approach is better than the logistic regression approach for the site-specific probability of