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A STUDY OF CPT BASED LIQUEFACTION ASSESSMENT USING ARTIFICIAL NEURAL NETWORKS

Deniz ÜLGEN [1] and H. Kürşat ENGİN[2]

ABSTRACT

The assessment of liquefaction potential can be defined by using actual cone penetration test (CPT) field data. The complex interaction between CPT results and liquefaction potential can be modeled by Artificial Neural Networks (ANN). In this study an ANN Model has been implemented for predicting liquefaction susceptibility of sandy soils. The large database for training the network is obtained using Robertson and Wride (1998) CPT based liquefaction evaluation procedure. A practical liquefaction assessment tool is developed using ANN model. The performance of this network is measured and the results are compared with a real case history.

Keywords: Liquefaction, CPT, Sandy Soil, Artificial Neural Networks

INTRODUCTION

Soil liquefaction is a complex phenomenon mostly for saturated sandy soils. It can cause substantial damage to structures during earthquakes. Therefore, recent studies focus on the assessment of liquefaction susceptibility. Laboratory and field tests are applied for evaluating the liquefaction resistance of soil (Cyclic Resistance Ratio, CRR). Due to difficulties during undisturbed sampling, field tests are mostly preferred by geotechnical earthquake engineers. Field tests commonly used for the evaluation of liquefaction resistance are standard penetration test (SPT), cone penetration test (CPT), shear-wave velocity (V_s) measurements.

In recent years, increased field performance data have become available at liquefaction sites investigated with CPT. These data have facilitated the development of CPT-based liquefaction resistance correlations. These correlations allow direct calculation of CRR, rather than through conversation of SPT measurements to equivalent SPT blow counts and then applying SPT criteria, a technique that was commonly used in the past (Youd, 1996).

The first CPT–based methods for liquefaction evaluation were essentially a conversion from the SPT–based methods using empirical SPT–CPT correlations (Olsen, 1984; Roberson and Campanella, 1985; Seed and Alba, 1986 (cited in Juang et al., 1999a)). Robertson and Wride (1998) provided an updated method to evaluate cyclic liquefaction using CPT. In this method, it is possible to estimate grain characteristics such as apparent fines content and grain size from CPT data and incorporate this directly into the evaluation of liquefaction potential.

[1] PhD Student, Department of Civil Engineering, Middle East Technical University, Turkey,
Email: udeniz@metu.edu.tr
[2] PhD Student, Department of Civil Engineering, Middle East Technical University, Turkey ,
Email: hkengin@metu.edu.tr

Recently, artificial neural networks (ANNs) have become a popular solution tool for a variety of geotechnical engineering problems. In consideration of the high complexity and multiparameter dependence of soil response, relatively simple, but robust, feed-forward neural network models trained by back-propagation (BP) algorithms have found wide usage in geotechnical engineering (Young-Su and Byung-Tak, 2006). Goh (1996) examined the feasibility of using BP neural networks for assessing liquefaction potential from actual CPT field data. The study indicated that neural networks can successfully model the complex relationship between seismic parameters, soil parameters and the liquefaction potential. Afterwards, Juang et al. (1999a, 1999b, 2002, 2003) proposed modified ANN models by using larger database of real case histories.

In this study, ANN Model has been implemented for predicting liquefaction susceptibility of sandy soils using Robertson and Wride (1998) CPT based liquefaction evaluation procedure. The performance of this network is measured and the results are compared with 1999 Chi-Chi, Taiwan earthquake liquefaction data.

ARTIFICIAL NEURAL NETWORKS

ANN is an informational system simulating the ability of a biological neural network by interconnecting many simple neurons (Figure 1). The neuron accepts inputs from a single or multiple sources and produces outputs by simple calculations, processing with a predetermined non-linear function (Jeng et. al. 2003). Like the human brain, the structure and processing sequence of an artificial neural network are parallel. It has a strong learning ability and can provide a method to solve problems involving complex systems. Flood and Kartam (1994) stated that artificial ANN is a powerful tool for modeling problems in which functional relationships between dependent and independent variables are poorly understood, subject to uncertainty. Such kind of problems are very common in civil engineering area.

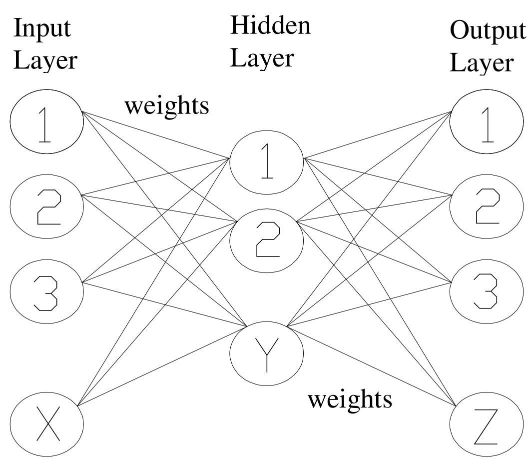

Figure 1. Structure of Artificial Neural Network Model

Back-propagation (BP) neural network

BP Neural Network is the most widely applied network to several civil engineering problems due to its simplicity. It is slow compared to other learning algorithms but it is great at prediction and classification.

A BP neural network is a fully connected, layered, feed-forward neural network trained using an error BP algorithm. A typical BP neural network usually has at least 3 layers of neurons each of which is connected to neurons in the next layer. The network starts out with a random set of connection weights and learns by adjusting the interconnection weights. Inputs are propagated forward through each layer of the network to emerge as outputs. The outputs that network produces are repeatedly compared with the desired outputs, and each time the connection weights are adjusted in the direction of the desired outputs. Consequently, it converges to a solution by minimizing the errors between the outputs and desired outputs.

LIQUEFACTION ASSESSMENT USING CPT

Robertson and Wride (1998) described the phenomena of soil liquefaction and provided an update on techniques to evaluate the cyclic liquefaction using CPT. They proposed a method to estimate the grain characteristics directly from the CPT and to use it for evaluating cyclic resistance. The recommended procedure in order to estimate the cyclic resistance can be summarized as follows:

1) Cone penetration resistance (q_c) is corrected for overburden stress and normalized with approximately one atmospheric pressure. The dimensionless normalized cone penetration (q_{c1N}) can be given by

$$q_{c1N} = (\frac{q_c}{P_{a2}})(\frac{P_a}{\sigma'_{v0}})^{0.5} \tag{1}$$

where P_a and P_{a2} are approximately 1 atm pressure (100kPa or 0.1MPa) in the same units with effective overburden stress (σ'_{vo}) and cone penetration resistance (q_c).

2) Grain characteristics can be estimated directly from CPT results and soil type behavior index, I_c can be calculated using the following equations

$$I_c = [(3.47 - \log Q)^2 + (1.22 + \log F)^2]^{0.5} \tag{2}$$

where

$$Q = [(q_c - \sigma_{vo})/P_a][(P_a/\sigma'_{vo})^n] \tag{3}$$

and

$$F = [f_s/(q_c - \sigma_{vo})] \times 100\% \tag{4}$$

Q is the normalized CPT penetration resistance (dimensionless) and the exponent n is typically equal to 1.0; F is the normalized friction ratio; f_s is the CPT sleeve friction stress and σ_{vo} is the total overburden stress.

3) K_c is the correction factor for grain characteristics, and used to calculate the clean sand equivalent normalized cone penetration resistance $(q_{c1N})_{cs}$.

$$(q_{c1N})_{cs} = K_c q_{c1N} \tag{5}$$

where, K_c is defined by the following equations

For $I_c \leq 1.64$ $K_c = 1.0$ (6a)
For $I_c > 1.64$ $K_c = -0.403\ I_c^4 + 5.581\ I_c^3 - 21.63\ I_c^2 + 33.75\ I_c - 17.88$ (6b)

4) Cyclic resistance ratio (for M_w=7.5) $CRR_{7.5}$ for clean sands can be estimated by using the following simplified equations

if $(q_{c1N})_{cs} < 50$ $CRR_{7.5} = 0.833[(q_{c1N})_{cs}/1000] + 0.05$ (7a)
if $50 \leq (q_{c1N})_{cs} < 160$ $CRR_{7.5} = 93[(q_{c1N})_{cs}/1000]^3 + 0.08$ (7b)

Robertson and Wride (1998) presented the flow chart illustrating the application of the CPT method of evaluating cyclic resistance ratio (CRR) in sandy soils (See Appendix A).

ESTIMATION OF CYCLIC RESISTANCE RATIO BY NEURAL NETWORKS

ANN model is constructed to estimate the CRR using the method proposed by Robertson and Wride (1998). For this purpose, two different neural network algorithms, namely back-propagation (BP) and generalized regression neural networks (GRNN) are employed by using the software MATLAB (version 7.01). BP algorithm is slower, however better results were obtained during training and testing process. Hence, BP was implemented for predicting CRR values. To train and test the network, a random database was created for the parameters depth (d), cone penetration resistance (q_c), total overburden stress (σ_{vo}), effective overburden stress(σ'_{vo}), sleeve friction (f_s). The ranges of these parameters are selected in order to represent real case histories for sandy soils (Table 1). Totally, 1150 random cases are used in the ANN model, 1000 of these cases are for training and the remaining 150 cases are for testing.

Table 1. Ranges of parameters

d(m)	σ_{vo} (kPa)	σ'_{vo} (kPa)	q_c (MPa)	f_s (kPa)
0 – 24	20 – 380	10 – 370	0 – 20	0 – 800

A number of neural network models were performed for different input parameter sets (Table 2). ANN model with the input layer constructed with set number 4 (q_{c1N}, σ_{vo}, σ'_{vo}, I_c) gave the best performance. The network implemented in this study is illustrated in Figure 2. The input layer, hidden layer and the output layers consist of four, eight and one neurons, respectively.

Table 2. Input sets for ANN

Set #	Inputs
1	q_{c1N}
2	q_{c1N}, σ_{vo}, σ'_{vo}
3	q_{c1N}, σ_{vo}, σ'_{vo}, f_s
4	q_{c1N}, σ_{vo}, σ'_{vo}, I_c

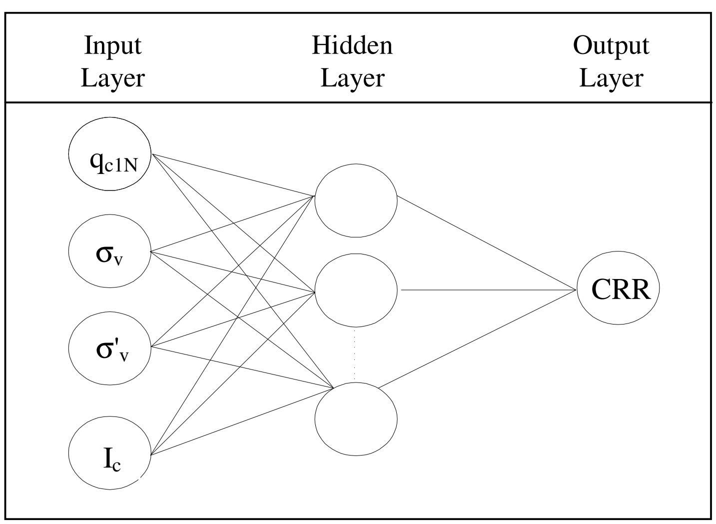

Figure 2. Illustration of implemented ANN model

The training and testing performances of ANN are shown in Figure 3 & 4, respectively. In these figures, the desired CRR values are plotted against the CRR values that network produces. As can be observed from these figures, BP neural network is very sufficient to estimate the CRR values predicted by Robertson and Wride (1998) procedure.

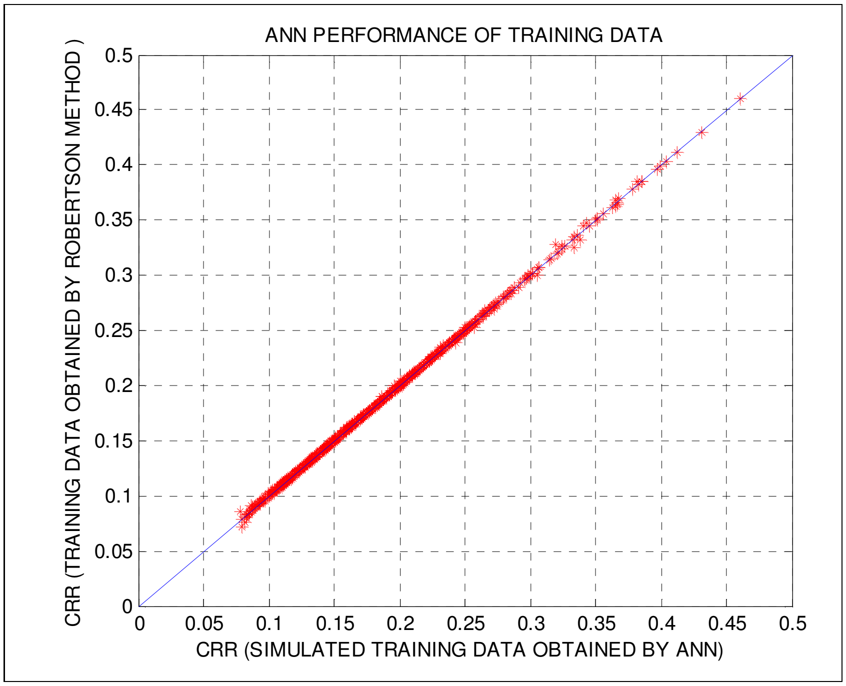

Figure 3. Performance of ANN model trained for 1000 cases

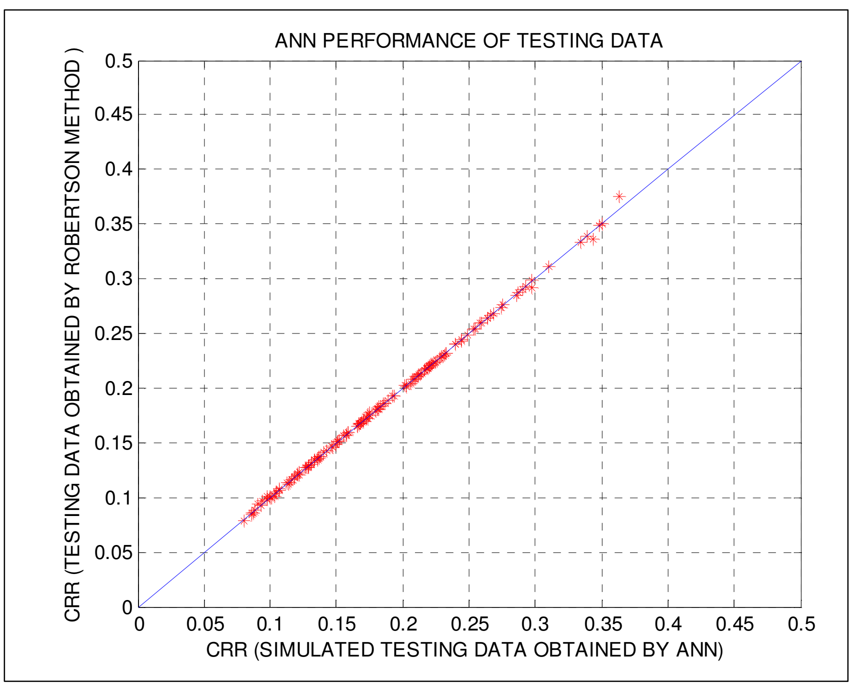

Figure 4. Performance of the ANN model by tested for 150 cases

VALIDATION OF ROBERTSON METHOD BY 1999 CHI-CHI EARTHQUAKE LIQUEFACTION DATA

Validation of ANN model created for Robertson and Wride (1998) was performed by the real case liquefaction data (See Appendix B) obtained from 1999 Chi-Chi, Taiwan earthquake. The validation procedure for Taiwan earthquake is summarized in the following steps:

i) Prediction of CRR values and verification of ANN model.
ii) Calculation of cyclic resistance ratio (CSR) values.
iii) Assessment of liquefaction by considering factor of safety (FS) values.
iv) Presentation of Robertson method performance

i) Real CRR values are predicted with Robertson method by hand calculations. Besides, real case data were simulated to estimate the CRR values by the constructed ANN model.. Performance of ANN model is verified by plotting real CRR values against estimated CRR values (Figure 5). As can be seen from the Figure 5 CRR values of real cases are well predicted by ANN model.

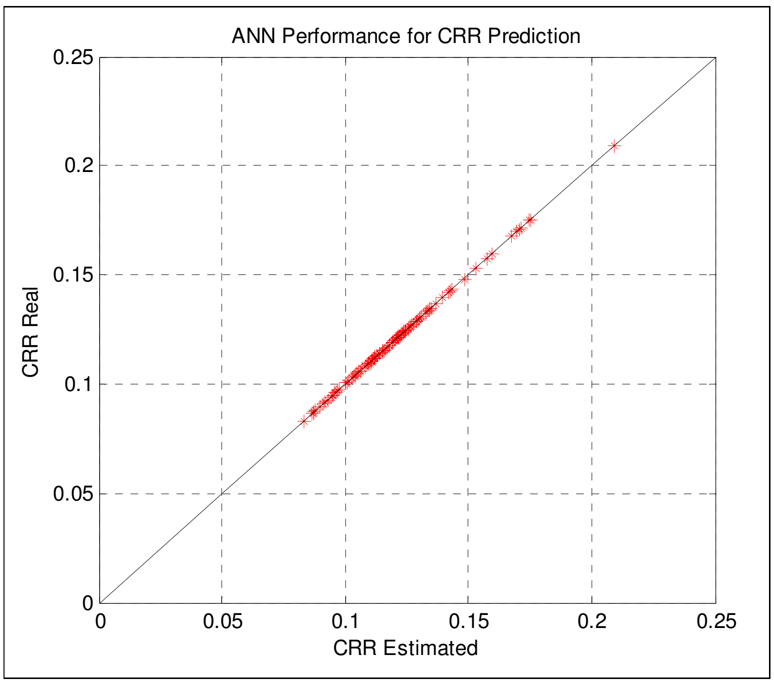

Figure 5. ANN Performance for CRR prediction of real cases

The CRR values are estimated for an earthquake with a magnitude (M_w) of 7.5. Therefore, these values have to be corrected for Taiwan earthquake having a magnitude of M_w= 7.6. The estimated CRR values are corrected with magnitude scale factor (MSF) for earthquake magnitude M_w by the following equations:

$$CRR\ (M_w) = CRR_{7.5} \times MSF \quad (8)$$

$$MSF = (M_w / 7.5)^{-3.3} \quad \text{(Andruss \& Stokoe (1997), cited in Youd (1996))} \quad (9)$$

ii) Cyclic stress ratios (CSR) for the real case data were calculated by Equation 10. The value for stress reduction coefficient, r_d is calculated from Equation 11 (Liao and Whitman (1986), cited in Youd (1996)).

$$CSR = 0.65 \times \left(\frac{\sigma_{VO} a_{\max}}{\sigma'_{VO}} \right) r_d \qquad (10)$$

where,

σ_{vo}, σ'_{vo} : total and effective overburden stresses

a_{max} : peak horizontal acceleration at ground surface.

$$r_d = 1.0\text{-}0.00765 \times z \qquad z \leq 9.15\text{m}$$
$$r_d = 1.174\text{-}0.0267 \times z \qquad 9.15\text{m} < z \leq 23 \text{ m} \qquad (11)$$

where,

z : depth below ground surface in meters.

iii) Liquefaction potential is defined by the factor of safety (FS),

$$FS = CRR / CSR \qquad (12)$$

for FS > 1 liquefaction is not expected

for FS ≤ 1 liquefaction is expected

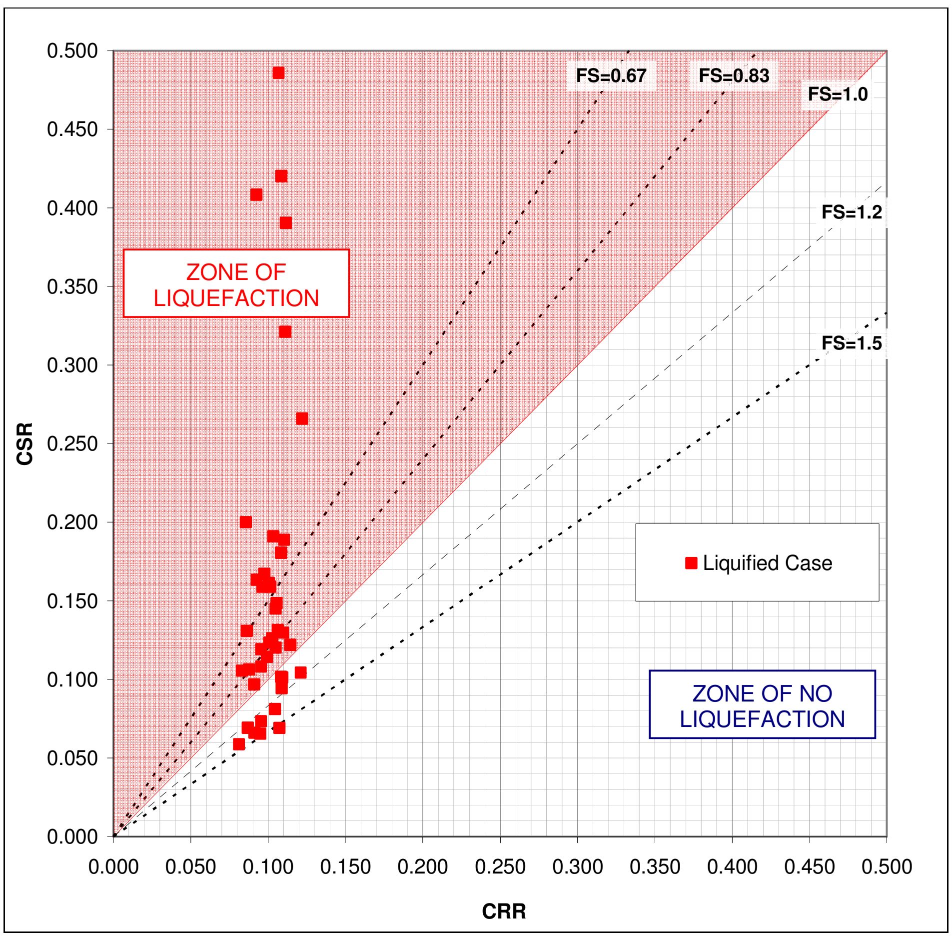

Figure 6. Performance of Robertson procedure for predicting liquefied cases

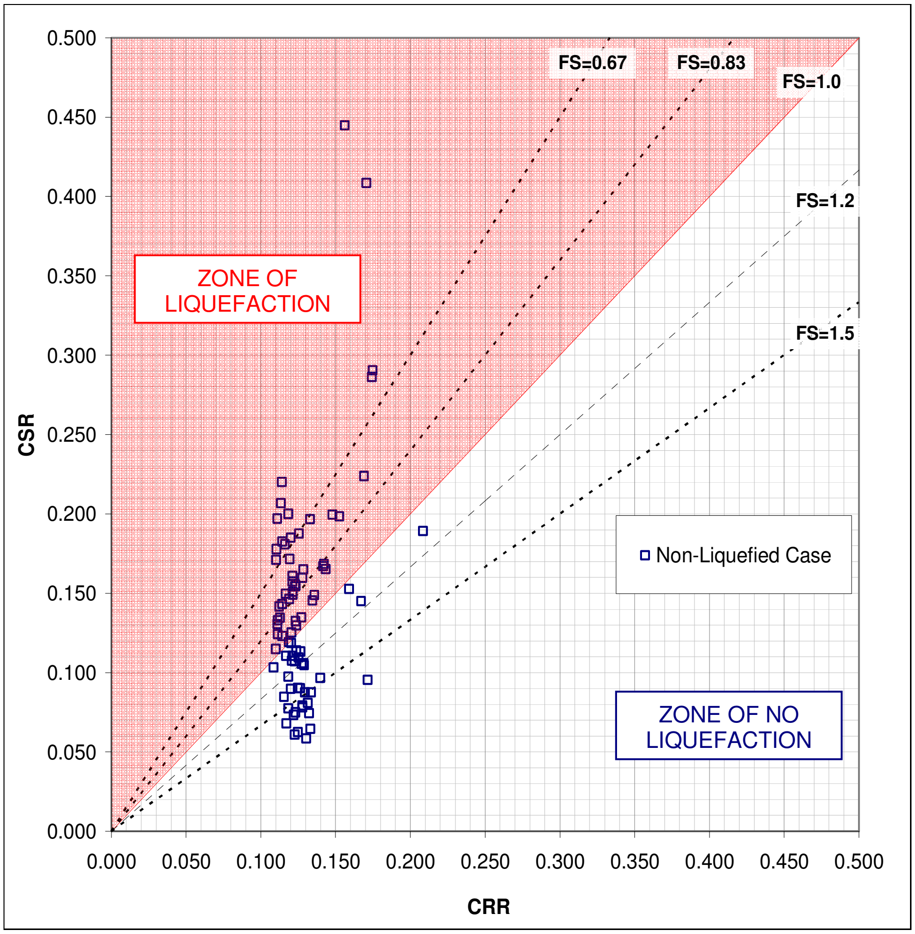

Figure 7. Performance of Robertson procedure for predicting non-liquefied cases

iv) In Figures 6 & 7, performance of Robertson and Wride (1998) method is presented for liquefaction assessment. In these figures horizontal axis represents estimated CRR values and vertical axis represents calculated CSR values for the considered case history. There are two regions separated by FS = 1.0 line; namely, zone of liquefaction and no-liquefaction, indicating the regions FS < 1.0 (upper region) and FS > 1.0 (lower region), respectively. Considering the uncertainty and variations in estimating critical stress ratios (CSR), safety margins are defined by factor of safeties to observe the order of approximation Therefore, on the same figure, factor of safety curves for 0.67, 0.83, 1.2 and 1.5 are shown with dotted lines. In Figure 6, performance of Robertson method is investigated for liquefied cases and 30 of 41 liquefied cases are predicted correctly. In Figure 7, performance of Robertson method is investigated for non-liquefied cases and 36 of 84 non-liquefied cases are predicted correctly. As can be seen from the results Robertson method gives better estimates for the liquefied cases. To summarize, Robertson method is on the conservative side in the assessment of liquefaction potential.

DISCUSSION AND CONCLUSION

Robertson and Wride (1998) method for estimating cyclic resistance ratio (CRR) was examined by artificial neural networks using a created database. Results indicate that this method is well adopted. Implemented ANN model was used to estimate the CRR values for the liquefaction assessment of a real case history (1999 Chi-Chi, Taiwan earthquake). Considering the uncertainty and variations in estimating critical stress ratios (CSR), safety margins are defined by factor of safeties to observe the order of approximation. In this point of view, Robertson and Wride (1998) method gives conservative results in estimating liquefaction potential. Presently, no doubt that assessment of liquefaction with only Robertson and Wride (1998) method is not completely sufficient; however, it is a good starting point for the preliminary design. Consequently, the constructed ANN model has shown a potential to be used as a practical tool for the liquefaction susceptibility of sandy soils.

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APPENDIX A

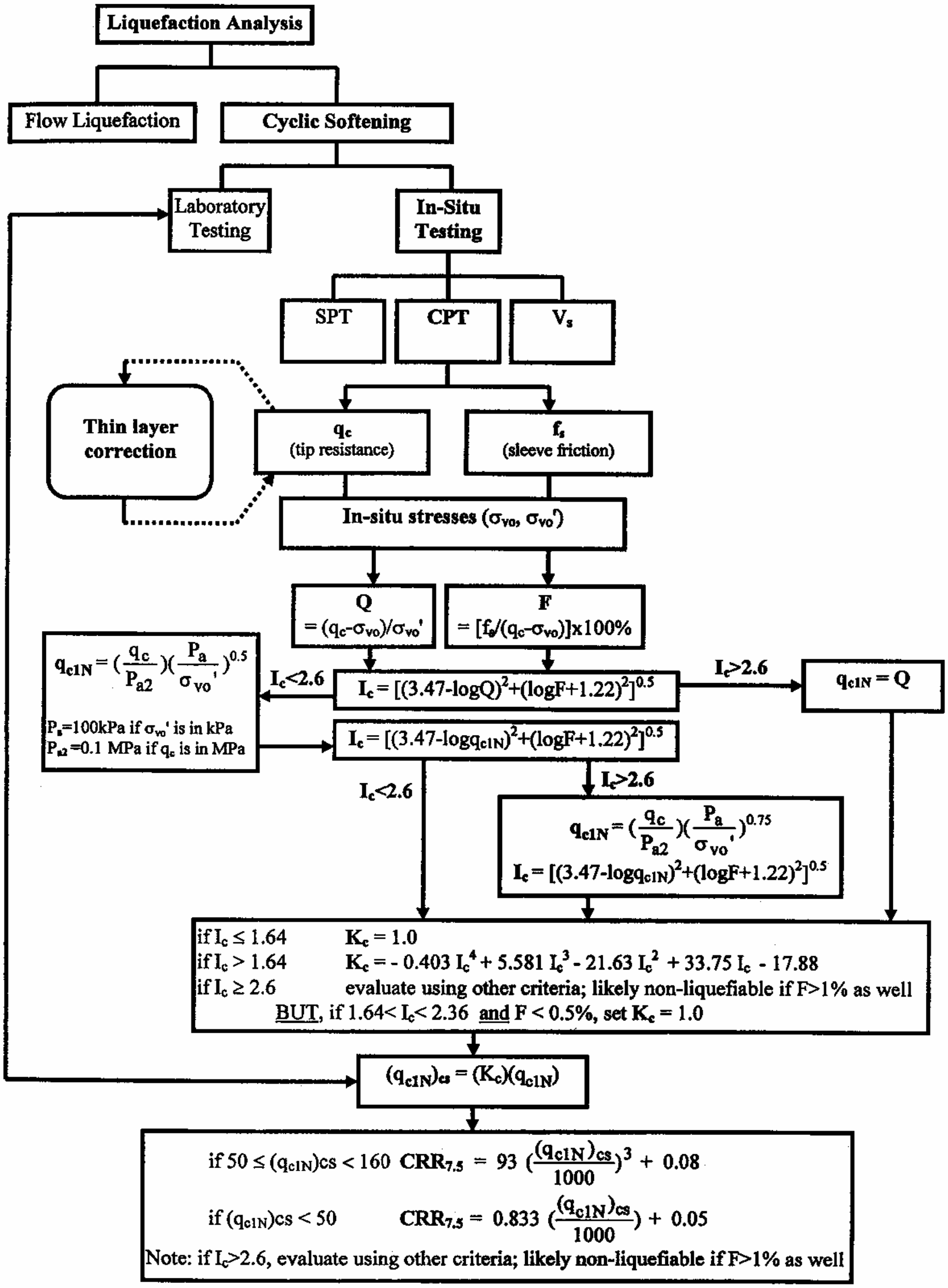

Figure A.1. Flow chart illustrating the application of the integrated CPT method of evaluating cyclic resistance ratio (CRR) in sandy soils (After Robertson and Wride, 1998)

APPENDIX B

Table B.1. Field liquefaction cases in the 1999 Chi-Chi, Taiwan Earthquake (Juang et al. 2002)

Boring ID	q_c (MPa)	f_s (kPa)	σ_{vo} (kPa)	σ'_{vo} (kPa)	a_{max} (g)	Liq?	Boring ID	q_c (MPa)	f_s (kPa)	σ_{vo} (kPa)	σ'_{vo} (kPa)	a_{max} (g)	Liq?
C-K1-NT	0.94	22.4	46.3	41.3	0.43	Yes	C-K2-YL	2.78	20.7	96.2	48.3	0.19	Yes
C-K1-NT	1.47	24.6	64.8	49.8	0.43	Yes	C-K2-YL	2.69	28.8	120.3	65.3	0.19	Yes
C-K1-NT	11.32	114.0	191.5	108.0	0.43	No	C-K2-YL	3.05	32.5	138.8	73.8	0.19	Yes
C-K5-NT	11.56	170.0	68.5	49.8	0.43	No	C-K2-YL	14.67	9.8	249.8	124.8	0.19	No
C-K5-NT	12.89	138.8	170.2	96.5	0.43	No	C-K2-YL	10.61	19.2	268.3	133.3	0.19	No
C-2-NT	3.86	24.3	64.8	49.8	0.43	Yes	C-K2-YL	14.74	26.2	286.8	141.8	0.19	No
C-2-NT	6.01	27.2	83.3	58.3	0.43	Yes	C-K2-YL	13.65	17.6	305.3	150.3	0.19	No
C-2-NT	16.30	130.1	249.8	134.8	0.43	No	C-LW-A1	1.28	8.8	63.0	43.0	0.12	Yes
C-7-NT	1.41	4.9	57.4	46.4	0.43	Yes	C-LW-A1	0.64	9.9	84.6	51.0	0.12	Yes
C-7-NT	0.90	9.0	75.9	54.9	0.43	Yes	C-LW-A1	5.46	45.9	136.8	74.2	0.12	No
C-7-NT	11.96	162.2	185.0	105.0	0.43	No	C-LW-A1	5.16	62.0	237.6	119.0	0.12	No
C-15-NT	1.87	23.6	74.0	49.0	0.43	Yes	C-LW-A2	3.26	9.5	48.6	35.0	0.12	Yes
C-15-NT	5.77	25.0	148.0	83.0	0.43	Yes	C-LW-A2	2.65	9.3	66.6	43.0	0.12	Yes
C-1-DC	8.27	0.2	231.3	121.3	0.19	No	C-LW-A2	7.40	30.3	120.6	67.0	0.12	No
C-2-DC	2.54	11.9	57.4	41.4	0.19	Yes	C-LW-A2	7.04	30.0	138.6	75.0	0.12	No
C-3-DC	7.46	35.8	189.0	99.0	0.19	No	C-LW-A2	7.47	34.8	156.6	83.0	0.12	No
C-3-DC	7.62	27.9	207.0	107.0	0.19	No	C-LW-A2	7.68	58.7	228.6	115.0	0.12	No
C-4-DC	2.70	32.4	68.5	46.5	0.19	Yes	C-LW-A2	6.54	49.8	246.6	123.0	0.12	No
C-5-YL	8.03	2.6	138.8	78.8	0.19	No	C-LW-A3	6.64	36.9	111.6	63.0	0.12	No
C-5-YL	6.80	37.2	231.3	121.3	0.19	No	C-LW-A3	5.59	21.8	138.6	75.0	0.12	No
C-5-YL	7.02	24.3	249.8	129.8	0.19	No	C-LW-A3	7.58	44.6	228.6	115.0	0.12	No
C-7-YL	6.67	14.2	166.5	91.5	0.19	No	C-LW-A3	6.85	59.1	246.6	123.0	0.12	No
C-9-YL	7.72	15.5	186.9	100.9	0.19	No	C-LW-A5	6.68	41.2	124.0	70.3	0.12	No
C-10-YL	7.68	60.8	314.5	159.5	0.19	No	C-LW-A5	5.21	28.8	142.5	78.8	0.12	No
C-19-YL	2.22	23.4	92.5	57.5	0.19	Yes	C-LW-A5	6.12	30.6	161.0	87.3	0.12	No
C-19-YL	6.23	1.7	138.8	78.8	0.19	No	C-LW-A5	7.18	45.5	179.5	95.8	0.12	No
C-19-YL	12.50	0.3	259.0	134.0	0.19	No	C-LW-A7	5.91	28.0	138.6	75.0	0.12	No
C-22-YL	2.54	23.0	46.3	36.3	0.19	Yes	C-LW-A7	5.38	26.1	156.6	83.0	0.12	No
C-22-YL	2.62	11.0	64.8	44.8	0.19	Yes	C-LW-A7	6.62	37.0	174.6	91.0	0.12	No
C-22-YL	8.15	37.0	218.3	115.3	0.19	No	C-LW-A7	7.99	43.3	210.6	107.0	0.12	No
C-22-YL	10.08	22.0	231.3	121.3	0.19	No	C-LW-A7	7.38	42.9	228.6	115.0	0.12	No
C-22-YL	12.43	28.2	259.0	134.0	0.19	No	C-LW-A7	7.41	58.9	246.6	123.0	0.12	No
C-22-YL	16.89	44.0	268.3	138.3	0.19	No	C-LW-A9	7.03	36.1	120.6	67.0	0.12	No
C-24-YL	1.62	15.5	46.3	36.3	0.19	Yes	C-LW-A9	6.73	49.2	156.6	83.0	0.12	No
C-24-YL	2.45	17.1	64.8	44.8	0.19	Yes	C-LW-A9	6.49	55.2	192.6	99.0	0.12	No
C-24-YL	6.70	46.9	205.4	109.4	0.19	No	C-LW-A9	5.47	63.3	228.6	115.0	0.12	No
C-24-YL	9.19	33.0	231.3	121.3	0.19	No	C-LW-A9	6.32	61.5	246.6	123.0	0.12	No
C-24-YL	13.65	21.8	259.0	134.0	0.19	No	C-LW-A10	0.92	18.9	48.6	35.0	0.12	Yes
C-24-YL	17.08	69.1	268.3	138.3	0.19	No	C-LW-A10	1.50	24.4	6.6	43.0	0.12	Yes
C-25-YL	2.66	19.2	59.2	42.2	0.19	Yes	C-LW-A10	0.64	27.5	84.6	51.0	0.12	Yes
C-25-YL	1.82	22.8	83.3	53.3	0.19	Yes	C-LW-A10	6.05	43.3	145.8	78.2	0.12	No
C-25-YL	8.25	70.6	194.3	104.3	0.19	No	C-LW-A10	6.76	64.9	174.6	91.0	0.12	No
C-25-YL	7.41	55.5	212.8	112.8	0.19	No	C-LW-C1	2.49	10.0	68.5	44.8	0.12	Yes
C-31-YL	2.54	12.8	92.5	57.5	0.19	Yes	C-LW-C1	2.01	5.1	87.0	53.3	0.12	Yes
C-31-YL	8.30	12.7	231.3	121.3	0.19	No	C-LW-C1	1.89	6.7	105.5	61.8	0.12	Yes
C-31-YL	12.77	22.8	259.0	134.0	0.19	No	C-LW-C1	1.54	5.8	124.0	70.3	0.12	Yes
C-32-YL	1.18	11.4	48.1	37.1	0.19	Yes	C-LW-C1	7.43	57.7	179.5	95.8	0.12	No
C-32-YL	2.96	21.1	92.5	57.5	0.19	Yes	C-LW-C1	7.72	62.6	218.3	113.6	0.12	No

C-35-ST	1.73	25.8	83.3	53.3	0.19	Yes	C-LW-C2	6.61	41.5	93.6	55.0	0.12	No
C-36-YL	8.00	26.8	249.8	129.8	0.19	No	C-LW-C2	7.12	50.7	120.6	67.0	0.12	No
C-36-YL	8.01	20.9	268.3	138.3	0.19	No	C-LW-C2	6.08	31.7	192.6	99.0	0.12	No
C-36-YL	8.74	41.0	286.8	146.8	0.19	No	C-LW-C2	7.76	53.9	228.6	115.0	0.12	No
C-36-YL	10.05	46.1	346.0	172.3	0.19	No	C-LW-C2	9.48	86.1	336.6	163.0	0.12	No
C-36-YL	11.26	35.5	364.5	180.8	0.19	No	C-LW-D1	0.20	3.7	68.5	44.8	0.12	Yes
C-42-ST	6.83	24.5	212.8	112.8	0.21	No	C-LW-D1	5.93	54.4	96.2	57.5	0.12	No
C-42-ST	7.52	30.9	231.3	121.3	0.21	No	C-LW-D1	7.94	45.1	124.0	70.3	0.12	No
C-43-YL	2.61	23.5	74.9	49.4	0.19	Yes	C-LW-D1	7.57	41.4	142.5	78.8	0.12	No
C-43-YL	6.61	26.0	148.0	83.0	0.19	No	C-LW-D2	0.23	0.9	50.0	36.3	0.12	Yes
C-43-YL	8.30	43.3	249.8	129.8	0.19	No	C-LW-D2	0.18	0.6	68.5	44.8	0.12	Yes
C-44-YL	8.32	27.1	216.5	112.8	0.19	No	C-LW-D2	7.24	41.4	116.6	66.9	0.12	No
C-44-YL	11.58	29.5	257.2	133.2	0.19	No	C-LW-D2	6.21	24.8	161.0	87.3	0.12	No
C-K2-YL	3.00	7.4	46.3	31.3	0.19	Yes	C-LW-D2	8.83	57.7	235.0	121.3	0.12	No
C-K2-YL	2.09	8.2	64.8	39.8	0.19	Yes							

REFERENCES

Flood, I., and Kartam, N. “Neural Networks in Civil Engineering. I: Principles and Understanding,” J. Comp. in Civ. Engrg., Volume 8, Issue 2, pp. 149-162 ,1994.

Goh A.T.C. "Neural network modeling of CPT Seismic Liquefaction data," Journal of Geotechnical Engineering, Vol 122, No. 1 pp.70-73, 1996.

Jeng, D.-S., Cha, D. H. and Blumenstein, M. “Application of Artificial Neural Network in Civil Engineering problems,” International Internet-Processing-Systems-Interdisciplinaries (IPSI-2003), Sveti Stefan, Montenegro (CD ROM), 2003.

Juang, C. H., Chen C. J. and Tien, Y-M. “Appraising cone penetration test based liquefaction resistance evaluation methods: artificial neural network approach,” Canadian Geotechnical Journal, Vol 36, pp. 443-454, 1999a.

Juang, C.H. & Chen “CPT-Based Liquefaction Evaluation Using Artificial Neural Networks,” Computer-Aided Civil and Infrastructure Engineering, Vol 14(3), pp. 221-229, 1999b.

Juang, C. H., Yang, H., Yuan, H., Lee, D.H., and Andrus, R.D. “CPT-based liquefaction triggering analysis with an emphasis on the 1999 Chi-Chi, Taiwan, earthquake,” Proceedings, Turkey-Taiwan NSF-TUBITAK Grantee Workshop, Turkey,2002.

Juang, H., Yuan H., Lee D-H., and Lin P-S. “Simplified Cone Penetration Test-based Method for Evaluating Liquefaction Resistance of Soils,” Journal of Geotechnical and Geoenvironmental Engineering, Vol. 129, No. 1, 2003.

MATLAB version 7.01 Neural Network Toolbox Manual.

Robertson, P.K. and Wride, C.E. "Evaluating Cyclic Liquefaction Potential Using the Cone Penetration Test", Canadian Geotechnical Journal, Vol. 35 (3), pp. 442-459, 1998.

Youd, T.L., Preliminary Report from the NCEER Workshop on Evaluation of Liquefaction Resistance of Soils: Proceedings, 4th Caltrans Seismic Research Workshop, Sacramento, Calif., 1996.

Young-Su K. and Byung-Tak K. “Use of Artificial Neural Networks in the Prediction of Liquefaction Resistance of Sands.” Journal of Geotechnical and Geoenvironmental Engineering, Vol. 132, No. 11, pp. 1502-1504, 2006