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LIQUEFACTION SUSCEPTIBILITY BASED ON AN ARTIFICIAL NEURAL NETWORK

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Abstract

The traces of liquefaction were recognized in the area of Zagreb in the Sava valley in previous earthquakes and liquefaction can be expected in future earthquakes as well similar to the many cases which occurred in the Petrinja earthquake. Therefore, it is useful to have a tool allowing quick identification of susceptibility to liquefaction in larger areas.

CPTU testing covers many aspects of soil behaviour and enables the estimation of parameters needed in liquefaction susceptibility analysis. During the 2010-2011 series of earthquakes in Christchurch and Canterbury, New Zealand, a very rich dataset was collected that links soil data obtained by the CPTU, earthquake data, and on-site liquefaction manifestations – or lack of it. An artificial neural network was developed from these data. In addition to the description of location and time, the data contains CPTU measurements, earthquake magnitude, medial peak ground acceleration, its standard deviation, groundwater depth and classification of the manifestation of liquefaction on the ground surface.

The data collected after the Petrinja earthquake – obtained from CPTU tests and from analysis of the manifestations of liquefaction and the available data on the earthquake – are used in the developed artificial neural network.

Keywords: liquefaction, artificial neural networks, CPTU, Christchurch and Canterbury earthquakes

1. Liquefaction in Zagreb and Petrinja

It was found that during the 1880 Zagreb earthquake liquefaction occurred at several locations in the Sava valley [1], which means that liquefaction could be expected in future earthquakes in Zagreb again.

a  b  c 

Figure 1. Examples of liquefaction in Petrinja earthquake: a) ejecta in the field in Hrastelnica, b) cracks in the levee in Sisak along the Sava river (Galdovo), c) subsidence of the road in Petrinja (Drenčinina)

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The Petrinja earthquake in year 2020 [2] showed a vast array of various manifestations of liquefaction illustrating thus and reminding the citizens and engineers of Croatia that this phenomenon is to be taken in account seriously. An overview of geotechnical damages caused by Petrinja earthquake is given in the report led by Tomac and Zlatović for GEER [3]. The three characteristic damages caused by liquefaction are shown in Figure 1: a) liquefaction occurred in many fields in the area, and it was rather vast in the area of Hrastelnica; b) some of the levees protecting the area from the waters of the Kupa and Sava rivers got mostly longitudinal cracks due to liquefaction and lateral spreading as is seen here on the section in Galdovo; c) liquefaction in the villages caused cracking in several houses in the area, as well as subsidence of roads like one in this photograph and many of the wells in the area were filled with sandy soil.

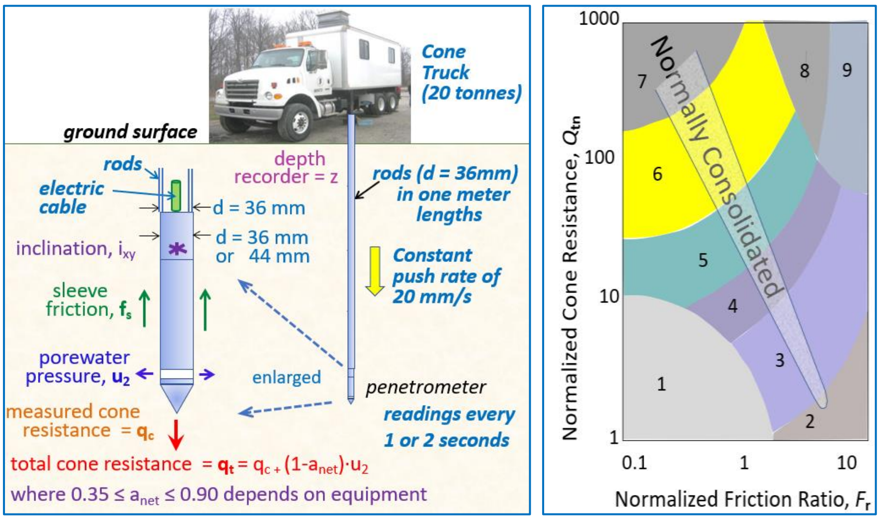
2. Predictions of liquefaction

Since the Alaska M9.2 earthquake and Niigata M7.5 earthquake, both in the year 1964, when tremendous damages were caused by liquefaction, there has been a great deal of effort input to the liquefaction research. It is quite clear that both the properties of the soil on the location - including the presence of groundwater, and the properties of the earthquake and its impact on the location, influence the onset of liquefaction [4]. The understanding of this phenomenon has been developing in the last 60 years, as well as the models used to make the necessary evaluations [5].

One of the investigation methods covering the most of soil characteristics is CPTU. Therefore, various soil properties are derived from the CPTU measurements, to be used in estimations of the hazards and in design. [6, 7, 8, 9, 10]. However, it is worth noting that each of these estimations carries its own uncertainties. Therefore, it seems it would be valuable to relate the liquefaction susceptibility directly to CPTU measurements.

3. Cone Penetration Testing

In the Cone Penetration Test (CPT), a cone on the end of a series of rods is pushed into the ground at a constant rate, and continuous measurements are made of the resistance to penetration of the cone and of a surface sleeve – separately – as shown in Figure 2. Additionally, very often recently, at the same time, pore water pressure is measured during the penetration (CPTU). [8] These tests give a very good overview of the subsoil, especially if they are combined with some borings and appropriate laboratory testing, and some geophysical investigation, to obtain a more complete picture. Robertson developed the interesting Sol Behaviour Type index which is derived from the CPT data, which is describing soil behaviour and defines partially the Soil Behaviour Type as shown in Figure 2 [8].



	Soil Behavior Type	I_c
1	Sensitive fine grained	N/A
2	Organic soils – clay	>3,6
3	Clays: clay to silty clay	2.95-3.6
4	Silt mixtures: clayey silt & silty clay	2.6-2.95
5	Sand mixtures: silty sand to sandy silt	2.02-2.6
6	Sands: clean sands to silty sands	1.31-2.05
7	Dense sand to gravelly sand	<1.31
8	Very stiff sand to clayey sand*	N/A
9	Very stiff fine-grained*	N/A

Figure 2. a) An overview of a Cone Penetration Test after ASTM D 5778 [11]. b) SBTn chart, where number corresponds to the Soil Behavior Type defined in c) I_c is the Soil Behavior Type index [8]

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4. Canterbury earthquakes and New Zealand Geotechnical Database

M7.1 earthquake with an epicentre 70 km East from Christchurch, the largest city in the South Island of New Zealand and the seat of the Canterbury Region, caused widespread liquefaction. It was followed by a series of aftershocks (21 earthquakes with magnitude 5 or more, less than 20km from the city centre), and liquefaction was often repeated in the same place over and over again [12, 13]. A vast amount of data, including seismologic, hydrologic, geospatial, and geotechnical measurements (mostly CPT) was collected and related to the liquefaction manifestation during and after these earthquakes, and offered to the researchers in the whole world [14, 15], the newest base being New Zealand Geotechnical Database [16]. Figure 3 presents the organization of data in this Database. The liquefaction manifestation has been shown in 7 classes listed in Figure 4.

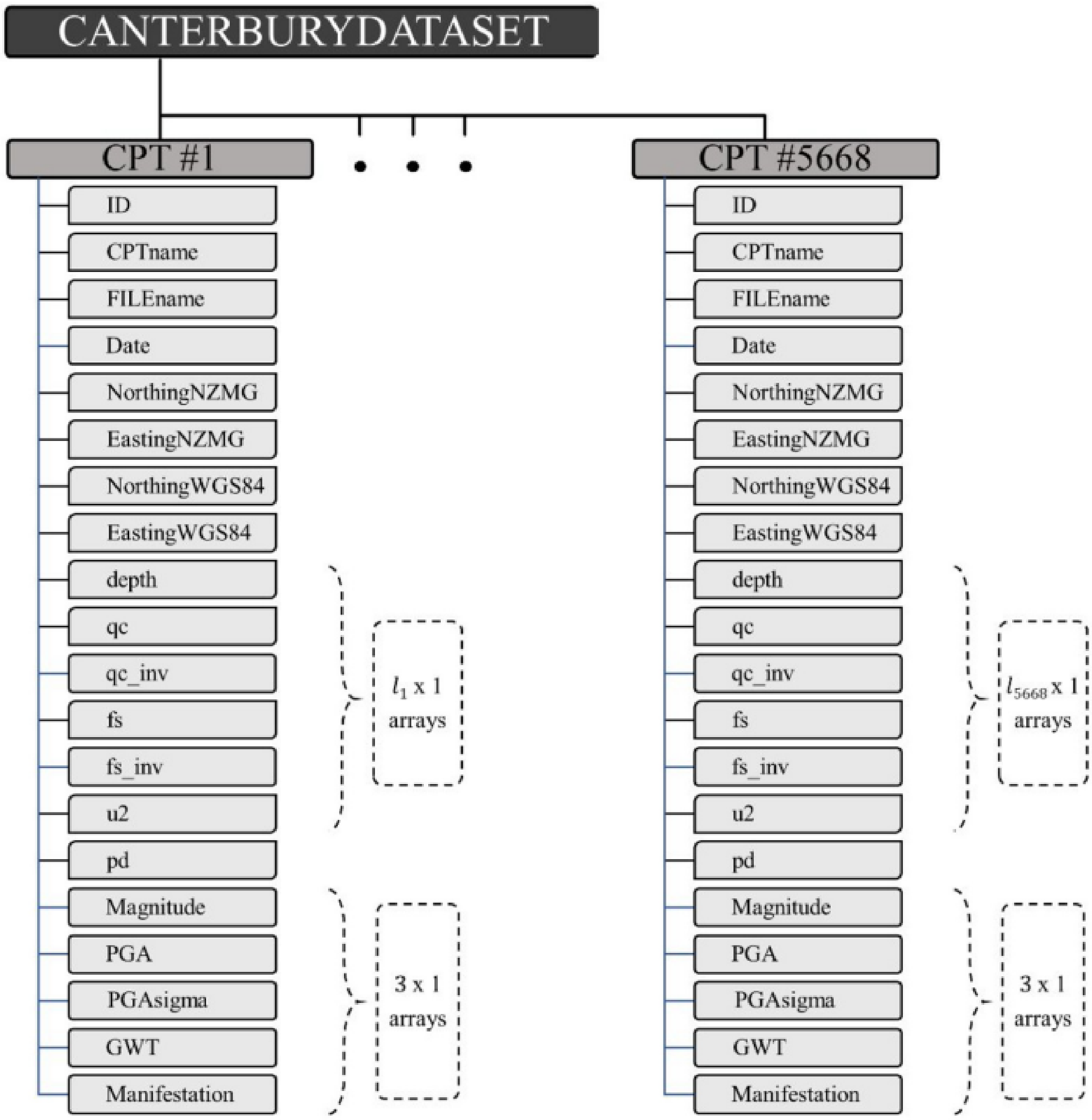

Figure 3. Depiction of the Canterbury case-history dataset structure array. [17].

Figure 4 presents a timeline of executed CPT measurements relative to the dates of the strongest earthquakes in Canterbury, from which the data of magnitude and peak ground acceleration (for the locations of the CPT measurements) were collected. Groundwater table depth at CPT locations was calculated from the data observed in numerous monitoring wells at the time of the mentioned earthquakes. Manifestations were collected from aerial footage and site reconnaissance.

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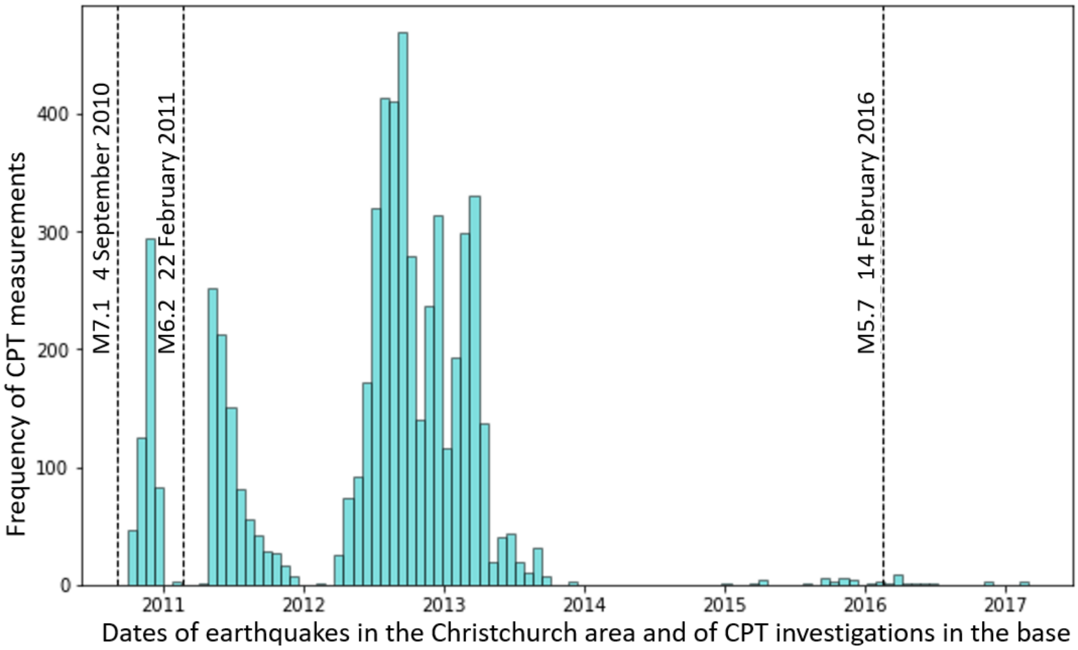

Figure 4. Frequency of CPT measurements through time and in relation to the dates of the strongest earthquakes in the Christchurch area

5. Artificial Neural Networks

Artificial Neural Networks are computational models which find solutions for input data after the so-called training in which a chosen set of examples is analysed. A network consists of thousands of simple processing nodes that are organized into layers and densely interconnected. To each of its incoming connections, a node assigns a number known as weight, with which it multiplies the input data coming from that node and then add a number known as bias. Adding those products together passes through activation function and yields a single number which is passed to the next layer. During training, the training examples are fed to the input layer, the data are multiplied and added, and sent to further layers, until the output layer. The weights and thresholds are continually adjusted until training data yield wished outputs in process known as backpropagation.

If the investigated phenomenon is too complicated, and each of the parameters carries a lot of uncertainty, it may be more feasible to use an Artificial Neural Network, developed on a well-chosen set of data, in other words: always considering if the training examples would fit the analysed problem.

This is why such an artificial neural network was developed to use raw data describing the location and the effect of earthquake and connect them directly to the liquefaction manifestation.

6. Developed Artificial Neural Network and Application to Petrinja Earthquake

The Artificial Neural Network for liquefaction prediction was developed using Python [18,19] by Matija Lozić during his last semester of the Polytechnic Professional Graduate Study at the Zagreb University of Applied Sciences [20].

For the training and validation, the New Zeland Geotechnical Database [16] was used.

First, the data were analized, and Figure 4 shows some data on the soil investigated [20].

The Artificial Neural Network was developed as a Multi-Layer Perceptron for classification. In total 5 models of Artificial Neural Network were developed; each model was fitted for specific data subset.

The individual parameters used are listed in Table 1, together with their boundaries, and listed by data subsets in Table 2.

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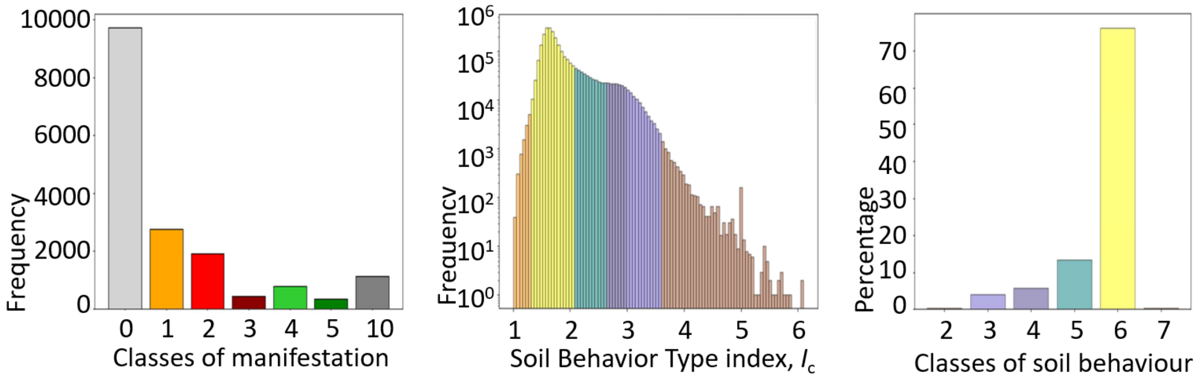

Figure 4. Data used for the network development. a) Frequency of examples by the classes of manifestation: 0 for no liquefaction; 1-3 for three levels of liquefaction intensity: minor, moderate and severe; 4 and 5 for lateral spreading and severe lateral spreading; 10 for cases with not enough of data. b) Frequency of measurements by the Soil Behaviour Type index, I_c after Robertson [8]. Colours show the class of soil behaviour as used in c) and in Figure 2b). c) Percentage of the measurements by the classes of soil behaviour after Robertson [8] as stated in Figure 2c). [20].

First data subset contains data of peak ground acceleration, cone tip resistance and cone sleeve friction. Second data subset contains earthquake magnitude, peak ground acceleration, maximal CPTu depth, depths of CPTu readings, depth of ground water table, cone tip resistance, cone sleeve friction, and measured pore pressure. Third data subset contains dana of normalized cone tip resistance and earthquake-induced cyclic stress ratio. Fourth data subset contains Robertson's Soil Behavior Type index and earthquake-induced cyclic stress ratio. Fifth data subset contains depths of CPTu readings, normalized cone tip resistance, normalized sleeve friction ratio and earthquake-induced cyclic stress ratio. All are further normalized according to simple min-max scaling, after removing some data outliers. Data boundaries are represented in Table 1. Further on, subset data were balanced according to equilibrium of binary classes of liquefaction manifestation.

Table 1 – Data boundaries for individual parameters

Parameter	Min	Max
Peak ground acceleration, a_{max} $[g]$	0.051	0.674
Cone tip resistance, q_c $[kPa]$	3.28	29994.02
Cone sleeve friction, f_s $[kPa]$	0.001	397
Earthquake magnitude, M	5.7	7.1
Depth of individual CPT measurement, $d_{CPT,max}$ $[m]$	5.08	34.94
Depths of CPT readings, d_{CPT} $[m]$	0	34.94
Ground water table depth, GWT $[m]$	0	6.78
Pore pressure measured behind cone u_2 $[kPa]$	-230	799.2
Normalized cone tip resistance, Q [1]	0.033	299.94
Earthquake induced cycling stress ratio, CSR [1]	0.529	1.009
Soil behavior type index, I_c [1]	1.008	6.094
Normalized friction ratio, F [%]	0	836.0

Table 2 – Parameters of data subsets

Data subset	Parameters
1	a_{max}, q_c, f_s
2	$a_{max}, M, d_{CPT,max}, d_{CPT}, GWT, q_c, f_s, u2$
3	Q, CSR
4	I_c, CSR
5	d_{CPT}, Q, F, CSR

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For each data subset, after data normalizing and classes balancing, Artificial Neural Network model was defined with optimized model hyperparameters. Optimized hyperparameters for each Artificial Neural Network model were chosen from iterative process observing model performances as shown in Table 3. Detailed descriptions of each of the parameters are given in [18,19].

Table 3 – Hyperparameters for each model

Hyperparameter	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
Input layer	2001	4004	2000	2000	4000
Hidden layer arhitecture	(100)	(100, 100)	(100, 100)	(100,100)	(100,100)
Backpropagation solver	'adam'	'adam'	'adam'	'adam'	'adam'
Activation function	'logistic'	'logistic'	'logistic'	'logistic'	'logistic'
Regularization coefficient	0.1	0.01	0.0001	0.0001	0.001
Initial learning rate	0.001	0.001	0.001	0.001	0.001
Maximal number of iterations	200	200	200	200	200
Shuffle	True	True	True	True	True
Tolerance	0.0001	0.0001	0.0001	0.0001	0.0001
Early stopping	True	True	True	True	True
Validation fraction in early stopping case	0.1	0.1	0.1	0.1	0.1
Initial weights value	0	0	0	0	0
Model accuracy on training data	0.863	0.869	0.756	0.776	0.740
Model accuracy on test data	0.836	0.834	0.745	0.750	0.725

After choosing hyperparameters for each model, models were trained on corresponding data subsets.

Trained models were used on collected data from locations affected by the Petrinja earthquake at locations Brest Pokupski, Galdovo, Krnjica and Palanjek, in total 61 measurements, already preproccesed by normalization and using data boundaries shown in Table 1. Collected CPTu data were analyzed and they were slightly different, difference being represented by Soil type behaviour index shown in Figure 5, where the frequency of the Soil Behaviour Index is shown for the 2 cm sections of CPT measurements. .

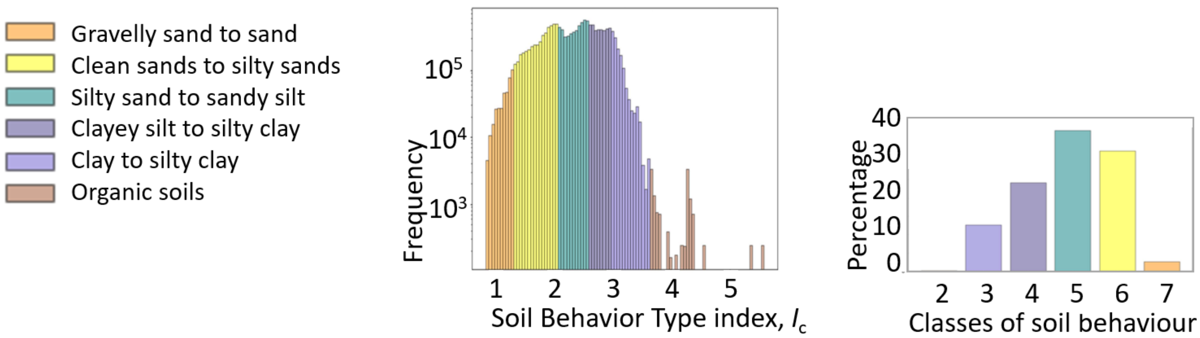

Figure 5. Data from the Petrinja area. a) Frequency of measurements by the Soil Behaviour Type index, I_c. b) Percentage of the measurements by the classes of soil behaviour. [20].

An overview of the main steps of the proces are shown in Figure 6. Pretprocessing was done on the Canterbury case-history dataset to obtain inputs for the 5 models of Artificial Neural Networks, and then on the data from Petrinja area, the developed models were used to predict liquefaction manifestation, i.e. its probability.

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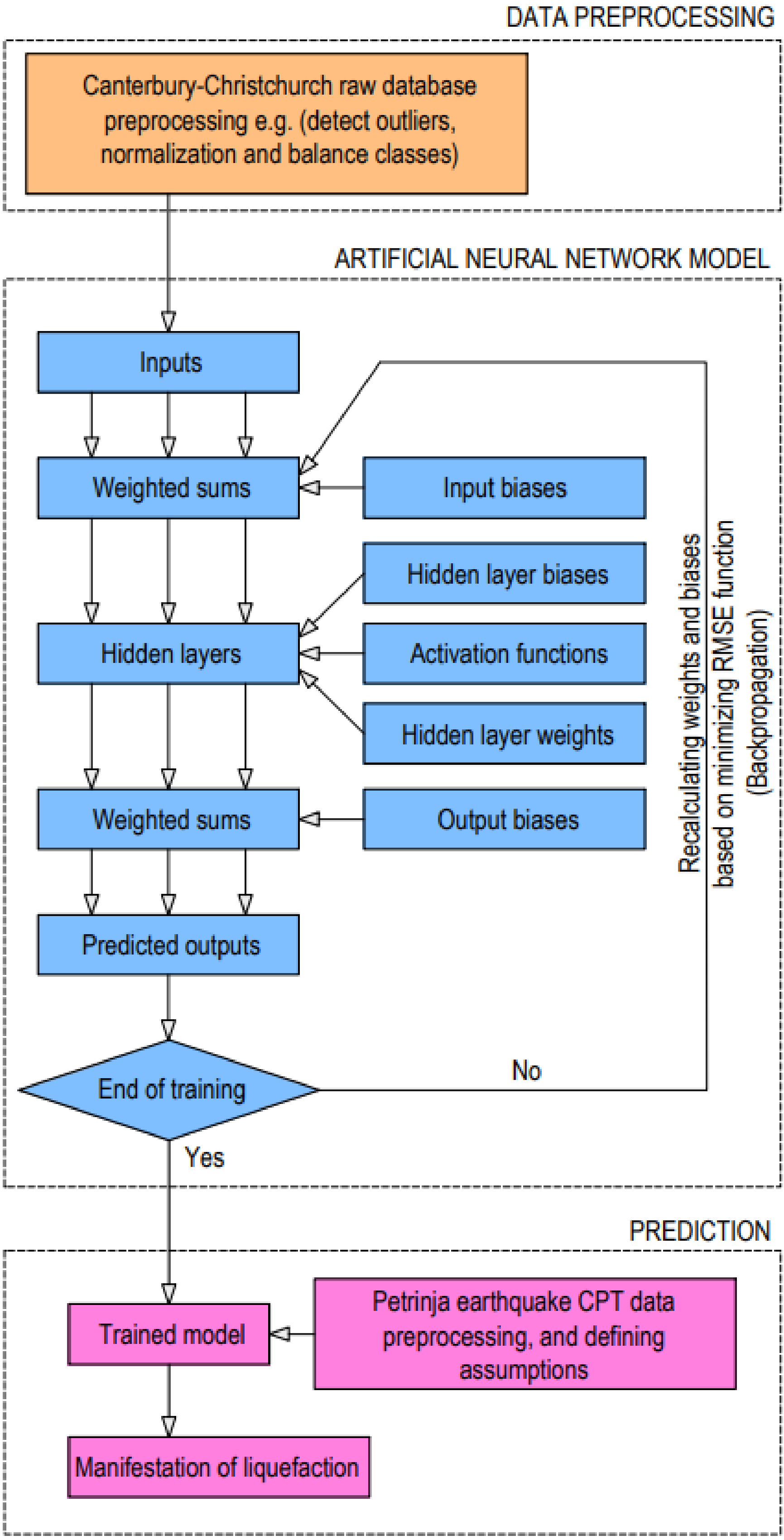

Figure 6. The three main steps of the development and application of the Artificial Neural Network

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Results of implementing defined models are shown in Table 4. for one location in Brest Pokupski – the corresponding CPTu results are given in Figure 6. All five models predicted liquefaction, as it was noted on the site, but with different probabilities.

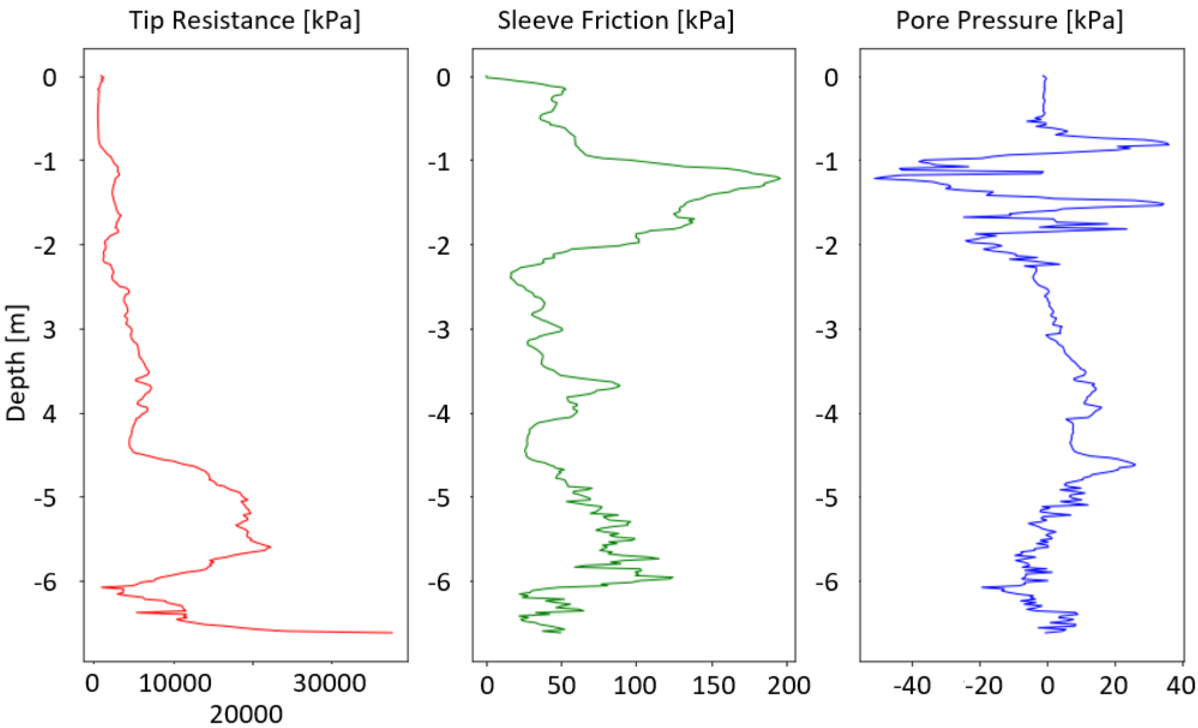

Figure 6. CPTu results for the chosen location in Brest Pokupski.

Table 4 – Results for C-13 in Brest Pokupski

		Assumptions		MODEL 1		MODEL 2		MODEL 3		MODEL 4		MODEL 5	
CPTu	M	a_{max}	GWT	Manifestation of liquefaction	Probability	Manifestation of liquefaction	Probability	Manifestation of liquefaction	Probability	Manifestation of liquefaction	Probability	Manifestation of liquefaction	Probability
Brest Pokupski C-13	6.4	0.2	1	Yes	0.76	Yes	0.98	Yes	0.63	Yes	0.67	Yes	0.96

These results show that on the tested soil location, the liquefaction could be expected according to all five models. Model 2 and model 5 show the most likely soil liquefaction susceptibility. Results correspond to site liquefaction manifestation in form of sand ejecta. Output from this neural network generally shows liquefaction susceptibility at the location of the CPT measurements, and does not specify the depth of the liquefaction.

7. Discussion

The earthquakes which caused liquefaction in Christchurch and its vicinity were of magnitudes 7.0 to around 5. The subsoil of Canterbury contains thick layers prone to liquefaction.

The Petrinja earthquake with M6.2 and some aftershocks caused liquefaction in some layers not more than a meter or so, several meters deep.

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The variety in results of different models suggests that it is good – in the training of the network, to use the training examples which correspond to the geological, geotechnical, seismological and hydrological conditions of the location in question. In such a way, it may be believed, the variety of influences will be accounted for.

Figure 7. One of many evidences of liquefaction in Brest Pokupski (Photo already published [2]).

8. Conclusions

The CPT measurements give valuable insight into the soil behaviour. The artificial neural network developed on the basis of the very rich New Zeland Geotechnical Database could be adjusted for the conditions on the investigated location to obtain the probability of liquefaction in various conditions.

References

[1] Veinović, Ž., Kovačević Zelić, B., Kvasnička, P., & Domitrović, D. (2008). Assessment of liquefaction potential of the Sava river plain near Zagreb. *Ulitsky, V.M., Kovalev, V.I. (ur.) Proceedings of the International Geotechnical Conference " Development of Urban Areas and Geotechnical Engineering"*

[2] Miranda, E.; Brzev, S.; Bijelic, N.; Arbanas, Ž.; Bartolac, M.; Jagodnik, V.; Lazarević, D.; Mihalić Arbanas, S.; Zlatović, S.; Acosta V..; Archbold, J.; Bantis, J.; Blagojevic, N.; Borozan, J.; Božulić, I.; Cruz, C.; Dávalos, H.; Fischer, E.; Gunay, S.; Hadzima-Nyarko, M.; Heresi, P.; Lignos, D.; Lin, T.; Marinkovic, M.; Messina, A.; Miranda, S.; Poulos, A.; Scagliotti, G.; Tomac, I.; Tomic, I.; Ziotopoulou, K.; Žugić, Ž.; Robertson, I. (2021) *PRJ-2959 | StEER-EERI: PETRINJA, CROATIA DECEMBER 29, 2020, Mw 6.4 EARTHQUAKE*. https://www.designsafe-ci.org/data/browser/public/designsafe.storage.published/PRJ-2959

[3] Tomac, I. (Co-Team Lead); Zlatovic, S. (Co-Team Lead) ; Athanasopoulos-Zekkos, A.; Bleiziffer, J.; Domitrovic, D.; Frangen, F.; Gjetvaj, V.; Govorcin, M.; Grilliot, M.; Gukov, I.; Herak, M.; Hrženjak, P.; Hutchinson, T; Hudyma, N.; Jagodnik, V.; Kalfatic, V.; Kinikles, D.; Kosovic, I.; Kovacevic-Zelic, B.; Lyda, A.; Matoš, B.; Maric, B.; Matešic, D.; Matos, B.; Mihaljevic, M.; Mijic, Z.; Miletic, M.; Monteiro de Silva, M.; Montgomery, J.; Oršulic, E.; Parlov, J.; Pavelic, D.; Pavicic, I.; Peric, D.; Pham, N.; Puz, G.; Burecic Šafran, M.; Salkovic, A.; Salkovic, I.; Šiša, P.; Sitar, N.; Terzic, J.; Vlahovic, I.; Vlahovic, Z.; Vucetic, M.; Vucenovic, J.; Wang, J.; Ziotopoulou, K.; Žderic, P.K. (2021) *2020 PETRINJA, CROATIA EARTHQUAKE*. https://geerassociation.org/index.php/component/geer_reports/?view=geerreports&layout=build&id=99

[4] Ishihara, K. (1993) Liquefaction and Flow Failure during Earthquake. *Géotechnique*, 43, 351-415

DOI: https://doi.org/10.5592/CO/2CroCEE.2023.88

[5] Youd,. T.L.; Idriss. I.M.; Andrus, R.D.; Arango, I.;.Castro, G.; Christian, J.T.; Dobry, R.; Finn, W.D.L.; Harder, L.F. Jr.;Hynes, M.E.; Ishihara K.; Koester, J.P.; Liao, S.S.C.; Marcuson, W.F. III; Martin G.R.; Mitchell, J.K.; Moriwaki, Y.; Power, M.S.; Robertson, P.K.; Seed, R.B.; Stokoe, K.H. II. 2001. *Liquefaction Resistance of Soils: Summary Report from the 1996 NCEER and 1998 NCEER/NSF Workshops on Evaluation of Liquefaction Resistance of Soils.* Vol.l. Journal of Geotechnical and Geoenvironmental Engineering 127(10).

[6] Boulanger, R. W. & Idriss, I. M. (2014) *CPT and SPT based liquefaction triggering procedures, Report No. UCD/CGM-14/01*, s.l.: Center for Geotechnical Modeling, Department of Civil & Environmental Engineering, College of Engineering, University of California at Davis.

[7] Robertson, P. (2016) *Cone penetration test (CPT)-based soil behaviour type (SBT) classification system — an update*, Gregg Drilling & Testing Canada Ltd., Canada.

[8] Robertson, P.K; Cabal, K. (2022) *Guide to Cone Penetration Testing*, Gregg Drilling LLC, Signal Hill, CA, USA

[9] Kovacevic, M. S., Gavin, K., Reale, C. & Libric, L., 2018. The use of neural networks to develop CPT correlations for soils in northern Croatia. F. P. &. J. P. M. A. Hicks, editors. *Cone Penetration.*

[10] Kovacevic, M. S., Gavin, K., Reale, C. & Libric, L., 2019. *Developing correlations between the soil fines content and CPT results using neural networks.* s.l., Proceedings of the XVII ECSMGE-2019 Geotechnical Engineering foundation of the future ISBN 978-9935-9436-1-3.

[11] Mayne, P. (2016) *Geocharacterization by Seismic Piezocone in the Year 2016 and Beyond*, Nonveiller Lecture, http://www.hgd-cgs.hr/nonveiller-lectures/14-nonveiller-lecture-odrzat-ce-professor-paul-w-mayne-5-10-2016

[12] Cubrinovski, M., Henderson, D., Bradley, B.A. (2012) Liquefaction impacts in residential areas in the 2010-2011 Christchurch earthquakes. Tokyo, Japan: *One Year after 2011 Great East Japan Earthquake: International Symposium on Engineering Lessons Learned from the Giant Earthquake*, 3-4 Mar 2012.

[13] Cubrinovski, M., Taylor, M., Henderson, D., Winkley, A., Haskell, J., Bradley, B.A., Hughes, M., Wotherspoon, L., Bray, J., O'Rourke, T. (2014) Key factors in the liquefaction-induced damage to buildings and infrastructure in Christchurch: Preliminary findings. Auckland, New Zealand: 2014 *New Zealand Society for Earthquake Engineering Conference (NZSEE)*, 21-23 Mar 2014. 9pp.

[14] Brandenberg, S. J.; P. Zimmaro, J. P. Stewart, D. Y. Kwak, K. W. Franke, R. E. Moss, K. O. Cetin, G. Can, M. Ilgaç, J. Stamatakos, T. Weaver i S. Kramer (2020) Next-generation liquefaction database,*Earthquake Spectra*, Vol. 36, No. 2, pp. 939-959

[15] Zimmaro P., Brandenberg S.J., Stewart J.P., Kwak D.Y., Franke K.W., Moss R.E.S., Cetin K.O., Can G., Ilgac M., Stamatakos J., Juckett M., Mukherjee J., Murphy Z., Ybarra S., Weaver T., Bozorgnia Y., Kramer S.L. (2019) *Next-Generation Liquefaction Database.* Next-Generation Liquefaction Consortium. DOI: 10.21222/C2J040.

[16] New Zeland Geotechnical Database (2020) https://www.nzgd.org.nz/

[17] Geyin M, Maurer BW, Bradley BA, Green RA, van Ballegooy S. (2021) CPT-based liquefaction case histories compiled from three earthquakes in Canterbury, New Zealand. *Earthquake Spectra*. 37(4) 2920-2945. doi:10.1177/8755293021996367

[18] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P, Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., Scikit-learn (2011) Machine Learning in Python, JMLR 12, pp. 2825-2830, available at https://jmlr.csail.mit.edu/papers/v12/pedregosa11a.html

[19] Géron, A. (2019) Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, O'Reilly Media, Inc.

[20] M. Lozić (2022) PRIMJENA UMJETNIH NEURONSKIH MREŽA NA PROCJENU LIKVEFABILNOSTI TLA KORIŠTENJEM STATIČKE SONDE CPT, Diploma work, Zagreb: Zagreb University of Applied Sciences