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Prediction of Liquefaction Susceptibility of Subsoil Layers Using Artificial Neural Networks

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Abstract. In the recent past, more focus has been given to the practical utilization of Artificial Neural Networks (ANN) in solving diverse geotechnical engineering prob- lems. The present study mainly aims to evaluate liquefaction potential for Visakha- patnam city based on IS 1893 Part-1 2016 method using an artificial neural network. Earlier researchers have developed back propagation artificial neural networks to predict the liquefaction potential of subsoil and concluded that modeling of any com- plex relationship between seismic, soil parameters and liquefaction potential is possi- ble with neural networks. These models are reported to be simpler and more reliable than conventional methods of evaluating liquefaction potential.

In the above context, an attempt has been made on a total of 10 boreholes data in the city premises of Visakhapatnam at different locations, which spreads over the coast- line. The most critical input parameter identified in the modelling of the network is the Standard Penetration N-Value. The data set in the model was trained, validated, and tested in the ratio of 60:20:20. The final results showed that neural networks are a powerful tool in predicting the occurrence of liquefaction potential. These predictions are almost 90 % similar with an acceptable confidence level to the IS 1893 Part-1 2016 method.

Keywords: Liquefaction, Artificial Neural Networks, saturated sands, Earthquakes, SPT NValue.

1 INTRODUCTION

Liquefaction is a phenomenon that mainly occurs when saturated fine sands and silts are subjected to earthquake or dynamic loading. During this phenomenon, the saturated cohesion less soils lose their strength completely due to increased pore water pressure rapidly [1-4]. The phenomenon has been widely observed worldwide after the Niigata 1964 and Alaska 1964 earthquakes in Japan. Liquefaction causes devastating effects on infrastructure projects like foundation and settlement-related problems, lateral spreading of embankments, sand boils and ground oscillations, etc. Since the 1970s, various researchers have conducted much research and proposed methods to forecast the occurrence of liquefaction based on field and Laboratory test data. It was found that there are certain limitations to using laboratory test data in predicting the liquefaction potential of soils. One of the main drawbacks of laboratory test results is that the results do not take into consideration of actual soil properties like fabric, soil structure, past strain history and over consolidation [5]. Another major drawback is that laboratory equipment is too costly, tedious and time-consuming. Analytical techniques such as the finite element method are often hampered because these techniques need a lot of parameters to accurately model complex geotechnical engineering problems such as liquefaction [6]. These drawbacks are overcome by using the field test data from the SPT test, CPT test, and other field tests that are often quite commonly used for analyzing the liquefaction potential of soils. Seed and Idriss method [7] was the most popular method proposed based on field data and they suggested a simplified method that considers all factors that influence the liquefaction. Iwasaki et al. [8] proposed a technique based on liquefaction resistance and potential factor for the evaluation of liquefaction susceptibility of the soils. Idriss and Boulanger [9] presented several potentially significant correlations and recommendations associated with seismic-induced soil liquefaction. But still, these empirical and semi-empirical methods also have some limitations due to the complexity of the issue and uncertainty in soil parameters.

To overcome above-said limitations and constraints, artificial neural networks (ANNs) techniques have been evolved. Within a short time, ANN's applications have widened across all disciplines of science and engineering. These techniques are more reliable than traditional empirical and statistical methods for certain reasons. The Artificial Neural Networks train and learn from the data given to them as input and build a strong relationship among them to get a precise output even though the fundamental relationships are unknown. The use of ANNs in the field of geotechnical engineering commenced in the early 1990s by Goh [10] and Ghaboussi and Sidarta [13]. Afterward, ANN has received significant attention worldwide from many researchers to solve complex geotechnical problems.

Initially, Goh [10] prepared ANN Model based on SPT test data gathered from different places in different countries, and later, this work extended to CPT test data [11] for evaluation of liquefaction susceptibility of soils. Afterward, many of the researchers Ural and Saka [14], Hanna et al. [15], Tung et al. [16], Baziar and Nilipour [17], also used ANNs models for the prediction of liquefaction occurrence in soils. Farrokhzad et al. [18] prepared the liquefaction microzonation map for the Babol city based on Seed and Idris's (1983) method using ANN based on field tests of 30 borholes. Some studies were done based on laboratory test results in ANN to predict liquefaction [20, 22]. Kim Young-su [20] used the ANN model to estimate the liquefaction CSR of sandy soils by experimental laboratory data.

2 ARTIFICIAL NEURAL NETWORKS

Neural Networks is a tool allows for solving problems that are complex and unsolved [6-7]. Neural networks work in the same as manner as human brains by taking past experiences and measurements to solve issues and face situations. Neural networks develop a system called neurons. Neural Networks are basically divided into two types supervised and unsupervised. A supervised network develops models that help diagnose patterns, assume predictions and implement decisions based on the inputs taken and present outputs that have been learned. There are many types of supervised networks, namely Back propagation networks, Generalized Regression Neural Network and Probabilistic neural networks. An unsupervised network categorizes a set of patterns without displaying how to classify them in advance. This network system works based on Clustering Patterns. An example of an unsupervised network is Kohonen Networks. None of the supervised or unsupervised networks gives an accurate or correct answer when the patterns are incomplete, and data is deficient.

In general, the simple neural network contains three different layers. The first layer is called the Input layer, which receives the data from outside as input parameters. The layer which gives output in the form of classifications and predictions is called the output layer. The layer between the input and output layers is termed as a hidden layer. Sometimes the hidden layers are more than one based on the requirement. A typical neural network diagram is shown in Fig.1. Basically, a neural network operation has done in two phases, the first one is the training or learning phase and the second one is the recall or retrieval phase. In the first phase, the data is supplied to the network to train or learn, and the learning phase is highly time-consuming yet seeks the best performance. The retrieval phase can be rapid once the network is trained because processing can be distributed. The network "learns" by adjusting the interconnection weights between layers.

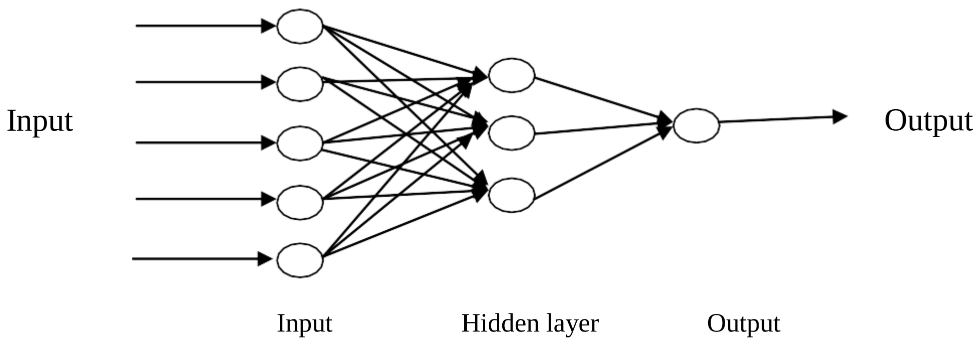

Fig.1 Artificial Neural network

3 DATASET & PRE-PROCESSING

A proper data set plays a vital role in solving any complex problem precisely using ANN. The data set should consist of the characteristics namely (1) reliability and (2) sufficient data covers all affected parameters [17]. In the present study 10 selected study areas are considered in the region of Visakhapatnam city in Andhra Pradesh state, India. Visakhapatnam is a coastal city comprising of saturated fine sands and silts at shallow depths. The data set required to constitute any ANN model should account for various factors that affect and complexity of the relationship among them. Hence study area, depth of soil, SPT N value, earthquake zone (Z2, Z3, Z4 &Z5), and earthquake magnitude intensity (5M, 5.5M, 6M &6.5M) are the parameters used as data set to develop a model in the present study. The data set is imported into the model as a dot CSV file and 592 data points are used for the study.

Any model in ANN needs to have the training, validation and testing from the same data set. In the present study, the data is divided in 60:20:20 proportions, which means 60% data is used in training and 20% of data is used in validation and 20% data is used in testing for predication. After grouping the information, the data is pre-processed to avoid the dimensional dissimilarities [19] of different input parameters and to get better results. As the data set shall be wholly numerical, liquefaction is indicated with 1, and non-liquefaction is indicated with 0.

4 RESULTS AND DISCUSSIONS

ANN model is created using Python with Keras deep learning technique. The proposed network in the study is a single-layer feed-forward artificial network. The data is fed to the network by five input nodes/neurons and the output is represented by a single node. Generally, the number of nodes in the hidden layer is the average of nodes in the input and output layers. In this network number of epochs is 100. In each epoch, the whole training set is fed through the network and used to adjust the network weights. The input parameters considered for this study are study area, depth, SPT N value, zone, and earthquake intensity Magnitude. At the end of the training and validation process, 20% of data (randomly splitted from input data) is used for testing, and the results are presented in Table1. From the total input of 592 data points, 119 points are tested. Out of which 26 points are from study area1 and 6,6,11,12,5,9,21,14,8 points form remaining study areas respectively for different conditions. In Table 1, the detailed tested data and comparisons of predicted and observed results are presented.

Table1.Comparion of model tested data with IS 1893 part-1 (2016)

S.No	Study Area	Depth	(N1)60	Zone	Earthquake Magnitude	IS 1893 part-1 (2016)	ANN Predicted
1	SA-1	3	8	Z2	5.5	Non Liquefiable	Non Liquefiable
2	SA-1	3	8	Z3	6	Liquefiable	Liquefiable
3	SA-1	3	8	Z3	6.5	Liquefiable	Liquefiable
4	SA-1	3	8	Z5	5	Liquefiable	Liquefiable
5	SA-1	4.5	11	Z2	5	Non Liquefiable	Non Liquefiable
6	SA-1	4.5	11	Z4	5	**Liquefiable**	**Non Liquefiable**
7	SA-1	4.5	11	Z4	6.5	Liquefiable	Liquefiable
8	SA-1	4.5	11	Z5	6.5	Liquefiable	Liquefiable
9	SA-1	6	18	Z2	5.5	Non Liquefiable	Non Liquefiable
10	SA-1	6	18	Z4	6.5	Liquefiable	Liquefiable
11	SA-1	6	18	Z5	5.5	Liquefiable	Liquefiable
12	SA-1	6	18	Z5	6.5	Liquefiable	Liquefiable
13	SA-1	7.5	14	Z3	5	Non Liquefiable	Non Liquefiable
14	SA-1	9	12	Z2	5	Non Liquefiable	Non Liquefiable
15	SA-1	9	12	Z2	5.5	Non Liquefiable	Non Liquefiable
16	SA-1	9	12	Z3	5	Non Liquefiable	Non Liquefiable
17	SA-1	9	12	Z3	5.5	Non Liquefiable	Non Liquefiable
18	SA-1	9	12	Z4	5	Non Liquefiable	Non Liquefiable
19	SA-1	9	12	Z5	5	Liquefiable	Liquefiable
20	SA-1	10.5	10	Z3	5	Non Liquefiable	Non Liquefiable
21	SA-1	10.5	10	Z5	5	Liquefiable	Liquefiable
22	SA-1	12	12	Z2	5.5	Non Liquefiable	Non Liquefiable
23	SA-1	12	12	Z3	5	Non Liquefiable	Non Liquefiable
24	SA-1	12	12	Z3	6	Non Liquefiable	Non Liquefiable
25	SA-1	12	12	Z4	5.5	Liquefiable	Liquefiable
26	SA-1	12	12	Z5	6	Liquefiable	Liquefiable
27	SA-2	4.5	14	Z2	6.5	Non Liquefiable	Non Liquefiable
28	SA-2	4.5	14	Z5	5	Liquefiable	Liquefiable
29	SA-2	6	18	Z3	6.5	**Non Liquefiable**	**Liquefiable**
30	SA-2	6	18	Z4	5	Non Liquefiable	Non Liquefiable
31	SA-2	6	18	Z4	6	Liquefiable	Liquefiable
32	SA-2	6	18	Z5	5.5	Liquefiable	Liquefiable
33	SA-3	2	13	Z2	5.5	Non Liquefiable	Non Liquefiable
34	SA-3	2	13	Z2	6.5	Non Liquefiable	Non Liquefiable

35	SA-3	2	13	Z3	6.5	**Non Liquefiable**	**Liquefiable**
36	SA-3	2	13	Z5	5	Liquefiable	Liquefiable
37	SA-3	2	13	Z5	5.5	Liquefiable	Liquefiable
38	SA-3	3.5	17	Z5	5	**Non Liquefiable**	**Liquefiable**
39	SA-3	3.5	17	Z5	6.5	Liquefiable	Liquefiable
40	SA-4	3.5	8	Z2	5	Non Liquefiable	Non Liquefiable
41	SA-4	3.5	8	Z2	6	Non Liquefiable	Non Liquefiable
42	SA-4	3.5	8	Z4	6.5	Liquefiable	Liquefiable
43	SA-4	5	11	Z2	6	Non Liquefiable	Non Liquefiable
44	SA-4	5	11	Z2	6.5	Non Liquefiable	Non Liquefiable
45	SA-4	5	11	Z5	6	Liquefiable	Liquefiable
46	SA-4	5	11	Z5	6.5	Liquefiable	Liquefiable
47	SA-4	3.5	12	Z3	5	Non Liquefiable	Non Liquefiable
48	SA-4	6.5	12	Z3	6	Non Liquefiable	Non Liquefiable
49	SA-4	6.5	12	Z3	6.5	Non Liquefiable	Non Liquefiable
50	SA-4	6.5	12	Z5	5	Liquefiable	Liquefiable
51	SA-5	3.5	8	Z2	5.5	Liquefiable	Liquefiable
52	SA-5	3.5	8	Z2	6	Non Liquefiable	Non Liquefiable
53	SA-5	3.5	8	Z5	5.5	Non Liquefiable	Non Liquefiable
54	SA-5	5	11	Z2	5.5	Liquefiable	Liquefiable
55	SA-5	5	11	Z3	5	Non Liquefiable	Non Liquefiable
56	SA-5	5	11	Z3	5.5	Non Liquefiable	Non Liquefiable
57	SA-5	5	11	Z5	6.5	Non Liquefiable	Non Liquefiable
58	SA-5	6.5	12	Z2	5	Liquefiable	Liquefiable
59	SA-5	6.5	12	Z2	6	Non Liquefiable	Non Liquefiable
60	SA-5	6.5	12	Z3	5	Non Liquefiable	Non Liquefiable
61	SA-5	6.5	12	Z3	6.5	Non Liquefiable	Non Liquefiable
62	SA-5	6.5	12	Z4	5	**Non Liquefiable**	**Liquefiable**
63	SA-6	3	13	Z3	5	Non Liquefiable	Non Liquefiable
64	SA-6	3	13	Z3	6.5	Non Liquefiable	Non Liquefiable
65	SA-6	3	13	Z5	6.5	**Non Liquefiable**	**Liquefiable**
66	SA-6	4.5	15	Z3	5	Liquefiable	Liquefiable
67	SA-6	4.5	15	Z3	6.5	Non Liquefiable	Non Liquefiable
68	SA-7	1.5	2	Z2	6.5	**Non Liquefiable**	**Liquefiable**
69	SA-7	1.5	2	Z3	6	**Liquefiable**	**Non Liquefiable**
70	SA-7	1.5	2	Z4	5.5	Liquefiable	Liquefiable
71	SA-7	1.5	2	Z5	5.5	Liquefiable	Liquefiable

72	SA-7	2.5	4	Z2	6.5	Liquefiable	Liquefiable
73	SA-7	2.5	4	Z5	5.5	**Liquefiable**	**Non Liquefiable**
74	SA-7	4.5	4	Z3	6	Liquefiable	Liquefiable
75	SA-7	4.5	4	Z4	5.5	**Liquefiable**	**Non Liquefiable**
76	SA-7	4.5	4	Z5	6.5	Liquefiable	Liquefiable
77	SA-8	3	11	Z3	6.5	Liquefiable	Liquefiable
78	SA-8	3	11	Z4	6	**Non Liquefiable**	**Liquefiable**
79	SA-8	4.5	10	Z2	6	Liquefiable	Liquefiable
80	SA-8	4.5	10	Z2	6.5	Non Liquefiable	Non Liquefiable
81	SA-8	4.5	10	Z3	6	Non Liquefiable	Non Liquefiable
82	SA-8	4.5	10	Z4	6	Non Liquefiable	Non Liquefiable
83	SA-8	4.5	10	Z5	5	Liquefiable	Liquefiable
84	SA-8	4.5	10	Z5	5.5	Liquefiable	Liquefiable
85	SA-8	6	7	Z2	6.5	Liquefiable	Liquefiable
86	SA-8	6	7	Z3	6.5	Non Liquefiable	Non Liquefiable
87	SA-8	6	7	Z4	6	Liquefiable	Liquefiable
88	SA-8	6	7	Z5	6	Liquefiable	Liquefiable
89	SA-8	8	9	Z4	5.5	Liquefiable	Liquefiable
90	SA-8	8	9	Z4	6	**Non Liquefiable**	**Liquefiable**
91	SA-8	8	9	Z5	6.5	Liquefiable	Liquefiable
92	SA-8	10	12	Z3	5.5	Liquefiable	Liquefiable
93	SA-8	10	12	Z3	6.5	Non Liquefiable	Non Liquefiable
94	SA-8	10	12	Z4	5	**Non Liquefiable**	**Liquefiable**
95	SA-8	10	12	Z4	6	Non Liquefiable	Non Liquefiable
96	SA-8	10	12	Z4	6.5	**Non Liquefiable**	**Liquefiable**
97	SA-8	10	12	Z5	5.5	Liquefiable	Liquefiable
98	SA-9	1.5	12	Z3	6	Liquefiable	Liquefiable
99	SA-9	1.5	12	Z3	6.5	**Liquefiable**	**Non Liquefiable**
100	SA-9	1.5	12	Z4	6	Liquefiable	Liquefiable
101	SA-9	1.5	12	Z5	5	Liquefiable	Liquefiable
102	SA-9	3	18	Z5	5	Liquefiable	Liquefiable
103	SA-9	3	18	Z5	5.5	**Non Liquefiable**	**Liquefiable**
104	SA-9	3	18	Z5	6.5	Liquefiable	Liquefiable
105	SA-9	4	3	Z2	6.5	Liquefiable	Liquefiable
106	SA-9	4	3	Z3	6	Liquefiable	Liquefiable
107	SA-9	4	3	Z3	6.5	Liquefiable	Liquefiable
108	SA-9	4	3	Z4	5	Liquefiable	Liquefiable

109	SA-9	6	19	Z3	6.5	Liquefiable	Liquefiable
110	SA-9	6	19	Z4	5	**Non Liquefiable**	**Liquefiable**
111	SA-9	6	19	Z5	5.5	**Non Liquefiable**	**Liquefiable**
112	SA-10	1.5	7	Z4	6	Liquefiable	Liquefiable
113	SA-10	3	6	Z3	5.5	Liquefiable	Liquefiable
114	SA-10	3	6	Z4	6	Liquefiable	Liquefiable
115	SA-10	6	7	Z2	6.5	Liquefiable	Liquefiable
116	SA-10	6	7	Z3	5.5	Non Liquefiable	Non Liquefiable
117	SA-10	6	7	Z3	6.5	Liquefiable	Liquefiable
118	SA-10	6	7	Z5	5.5	Liquefiable	Liquefiable
119	SA-10	7.5	8	Z5	6	Liquefiable	Liquefiable

Table2: Summary of observed and predicted values of selected study areas

Study Areas	Observed Values by IS 1893 part 1 (2016) (Non-Liquefaction-0 /Liquefaction-1)	ANN Predicted Non Liquefaction	ANN Predicted Liquefaction
SA-1 (26)	0	13	0
	1	1	12
SA-2(6)	0	2	1
	1	0	4
SA-3(6)	0	2	2
	1	0	2
SA-4(11)	0	6	0
	1	0	5
SA-5(12)	0	9	1
	1	0	2
SA-6(5)	0	2	2
	1	0	1
SA-7(9)	0	0	0
	1	3	6
SA-8(21)	0	6	4
	1	0	11
SA-9(14)	0	0	3
	1	1	10
SA-10(8)	0	1	0
	1	0	7
Total	0	41	13
	1	5	60

From Table 2, it is observed that the model predicted 41 non-liquefaction points as non-liquefaction points and 13 non liquefaction points as liquefaction points. Similarly, five liquefaction points as non-liquefaction points, and 60 liquefaction points as liquefaction points. Five liquefaction points predicted as non-liquefaction points are noticed as critical among all predictions. From Table 2, the percentage accuracy of ANN predictions for all study areas are represented in Fig.2. From the results, it is observed that for study areas 4 and 10, the observed and predicted results are 100% similar and for study areas 1 and 5 the prediction accuracy is observed to be greater than 95%. For remaining areas the accuracy of prediction varied from 67% to 90% due to less training and testing data fed to the network.

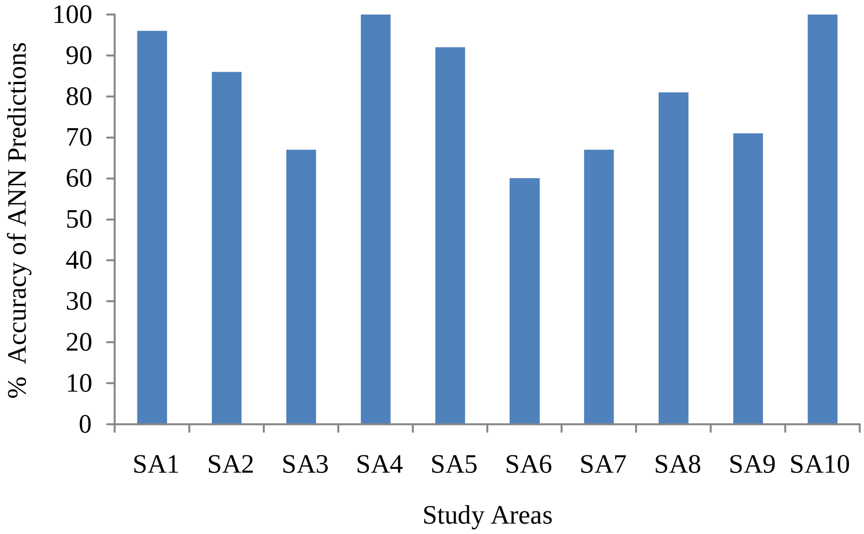

Fig.2. Plot between % Accuracy of ANN predictions and Study Areas.

5 SUMMARY AND CONCLUSIONS

From the output results, it is observed that the developed model is capable enough to predict the liquefaction susceptibility of subsoil layers in Visakhapatnam city region. The input parameters viz. depth, SPT N value, seismic zone, and earthquake intensity Magnitude formed a strong correlation and effectively predicted the liquefaction potential of soils. The efficiency and accuracy of the prediction model is almost 90% and it can be further improved by feeding more input data. The predicted results are compared with standard simplified procedures and the predictions are within acceptable confidence level to the IS 1893 Part-1 (2016) method. Hence ANN models can be used as simpler and more reliable over the conventional methods of evaluation the liquefaction potential of subsoil layers.

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