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HAZARD ESTIMATION OF EXISTING BUILDINGS IN THE CITIES OF KOCAELI AND ADAPAZARI DUE TO LOCAL SOIL CONDITIONS

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Abstract

This study is based on determining critical inputs to investigate the effect of structural components and seismic parameters on the damage of existing buildings, following 1994 Northridge earthquake for the forthcoming earthquakes. Data derived from ATC 38 report - Database on the Performance of Structures Near Strong-Motion Recordings: 1994 Northridge, California Earthquake (ATC, 2000) is used in the analysis. After the 1994 Northridge earthquake, engineers inspected more than 500 buildings located in a range within 1000 feet of 30 strong motion recording stations. An artificial intelligence tool, the Artificial Neural Network (ANN) method is used to determine the damage potential of the buildings. ANN can be used to build a complex relationship between input and output, or to find patterns in data. Neural networks have the ability to model complex nonlinear relationships between input and output. Once trained, neurons are able to make new decisions, classifications, and forecasts. The complexity of building a relationship between input and output data was well handled with neural network methodology in civil engineering related problems such as slope stability, settlement analysis, prediction of pullout capacity of ground anchors, pile capacity determination, predicting of foundation settlement, evaluation of liquefaction.

The input parameters utilized include plan irregularities, peak ground acceleration, epicentral distance, modified Mercalli intensity scale, number of basement floors and structural damage is the output data. Based on this artificial intelligence analysis, the important parameters and corresponding sensitivities affecting the structural damage which occurred during the Northridge earthquake is presented.

Keywords: Northridge earthquake, artificial neural network, soil structure interaction

1. Introduction

After latest earthquakes in urban area which caused significant damage to structures, the importance of seismic geotechnical safety thus seismic damage assessment of structures has attracted attention by the governmental authorities.

Soil related earthquake damages depend on many parameters such as seismic conditions, geotechnical parameters, structural conditions, topography etc. and also more complex phenomenon such as cyclic softening, liquefaction. This paper focuses on determining critical inputs to investigate the effect of seismic and soil related parameters on the performance of existing buildings for the 1994 Northridge earthquake for the forthcoming earthquakes in the region.

Data derived from ATC 38 report - Database on the Performance of Structures Near Strong-Motion Recordings: 1994 Northridge, California Earthquake - (ATC, 2000) is used in the analysis. Within the context of this after earthquake investigation, teams of licenced engineers inspected more than 500 buildings located in a range within 1000 feet of 30 strong motion recording stations after the 1994 Northridge earthquake.

Artificial Neural Network (ANN) method is used for this preventive risk analysis study. ANN can be used to build a complex relationship between highly nonlinear input and output as well as to find patterns in data and to overcome limitations of the classical statistical methods. Neural networks have the ability to model complex nonlinear relationships between input and output. Once trained, neurons are able to make new decisions, classifications, and forecasts. The complexity of building a relationship between input and output data was well handled with neural network methodology in civil engineering related problems such as slope stability, settlement analysis, prediction of pullout capacity of ground anchors, pile capacity determination, predicting of foundation settlement, evaluation of liquefaction.

The input parameters utilized include plan irregularities, peak ground acceleration, epicentral distance, number of basement floors and structural damage is the output data. Based on this artificial intelligence analysis, the important parameters and corresponding sensitivities affecting the structural damage which occurred during the Northridge earthquake is presented.

This study suggests a procedure that might help in predicting damage/no-damage spatial distributions in buildings in Los Angeles area for the future earthquakes.

In conclusion regression analysis and ANN analysis showed acceptable results.

Artificial neural network (ANN) is used in many disciplines as well as in geotechnical branch of Civil Engineering. Slope stability, settlement analysis, soil classification, soil behavior modeling, prediction of pullout capacity of marquee ground anchors, predicting settlement of shallow foundations, and even earthquake prediction are other studies already investigated with ANN

The method of back-propagation neural networks (BPNN) was employed to develop a model for estimating the consolidation settlements caused by transient or long-term groundwater drawdown along the main Red line sections of Kaohsiung mass rapid transit, Taiwan by S. M. T. Kerh, Y.G. Hu, C.H. Wu.The available on-site boring test data including soil void ratio, groundwater drawdown depth and total unit weight of soil were taken as the input parameters. Three neural networks models of back-propagation Networks with different combinations of these inputs were examined, which showed that the groundwater drawdown depth was the dominating factor to affect the consolidation settlement. The estimated results were compared with theoretical results, and statistical t-tests were performed to enhance the reliability of neural networks model. Only one of the neural networks models, which uses three parameters for the input gave the best result where four sections have the coefficient value over 0.9, and R^2=0.8755 in average for all sections.

M.H. Baziar, A. Ghorbani (2005) used a software called STATISTICA, a neural network model developed to predict the horizontal ground displacement in both ground slope and free face conditions due to liquefaction-induced lateral spreading. In total, 2002 data set from procured from 10 different sites has been used. the moment magnitude of the earthquake (M), the nearest distance to the seismic energy source (R), the cumulative thickness of saturated granular layers with corrected blow counts of SPT less than 15 (T15), the average fines content for granular materials included within T15 (F15), the average mean size for granular materials within T15 (D5015), the ground slope (S) and the free-face ratio (W). The results obtained in this study indicate that the model has ability to predict the lateral spreading with an acceptable degree of accuracy (R^2=0.92, RMSE= 0.7 m) for displacements ranging from 0.01 to 10.16 m. [2]

Pradeep U. Kurup, and Nitin K. Dudani (2002) used and trained three feed-forward, back-propagation ANN models using actual PCPT records from test sites around the world. The models are validated using new PCPT data (not used for training), and by comparing model predictions with reference OCR values obtained from oedometer tests The network used gave very reliable OCR estimates. [8]

Y.R. Chen, S.C. Hsieh, J.W. Chenb, C.C. Shih (2005) presented a seismic wave energy-based method with back-propagation neural networks to assess the liquefaction. A database consisting of 82 cases, 59 of them are liquefied cases and the other 23 cases are non-liquefied cases. [4]

G. W. Ellis, C. Yao, R. Zhao, D. Pneumadu evaluated a fundamentally different approach of using artificial neural network (ANN) to model the material behavior directly from the experimental data. In this research a sequential ANN was trained on 46 undrained triaxial test results for eight different sands varying different size distributions for both normally and over consolidated states. The ANN simulated the trained data well the simulation curves were in good agreement with the real test curves. [10]

Shahin et al. stated that there are also several areas of geotechnical engineering in which the feasibility of ANNs has yet to be tested, such as bearing capacity prediction of shallow foundations, capacity of bored piles, design of sheet pile walls and dewatering among others. [10]

2. Soil Structure Interaction Studies for Northridge Earthquake

Trifunac and Todorovska conducted a study called ‘Damage distribution during the 1994 Northridge, California, earthquake relative to generalized categories of surficial geology’. They have used pipe breaks as damage indicator, they have concluded in their study that that there is no simple correlation between damage patterns and surficial geology the San Fernando Valley and Los Angeles-Santa Monica regions. Single family wood-frame buildings were damaged less when built on fine silt and clay (0–3 m thick) from the late Holocene. [7]

There are correlation studies conducted following Northridge earthquake by using ATC38 database as well. Ramirez and Miranda used a probabilistic approach, Monte Carlo simulation, to obtain most probable values of the response parameters, then they were paired with reported damage stage for different group of buildings. In the study called ‘Survey of Damage to Historic Adobe Buildings after January 1994 Northridge Earthquake’ correlation was done indicate that the most severe damage is usually concentrated in areas with soft soil, many of areas of concentrated damage are underlain by Holocene deposits and alluvial basins.[9]

King et al. (2005) developed motion-damage relationships using the ATC-38 project as well as other similar datasets to create lognormal fragility curves and damage probability matrices for . Spectral acceleration and interstory drift ratio, the latter estimated by using spectral displacement and using a method proposed by Miranda [5] were used as structural response parameters to develop these fragility functions. Motion-damage relationships in the form of lognormal fragility curves and damage probability matrices have been developed for wood frame, steel moment frame, and concrete frame buildings – building types for which there are enough samples in the database to warrant statistical analysis. The ground motion parameters that were found to exhibit relatively higher correlations with building performance were used in the analysis. Building performance is characterized in terms of damage states and performance levels. The resulting relationships are compared to those published in ATC-13 (ATC, 1985) and HAZUS99 (FEMA, 1999). The comparison shows that the relationships developed in the project are quite different from the published models; however, the loss estimates resulting from the application of the models are similar. [7]

Another study which emphasis soil related damage is called Estimated Ground Motion from 1994 Earthquake Northridge, California, Earthquake at the Site of the Interstate 10 and La Cienega Boulevard Bridge Collapse, West Los Angeles, California by David M. Boore, James F. Gibbs, William B. Joyner, John C. Tinsley, and Daniel J. Ponti. Bridges at two sites along the interstate highway I-10 corridor in the western part of Los Angeles collapsed or suffered major damage Both sites at which the bridges suffered major damage or collapse are underlain by considerably thicker Holocene deposits than those underlying nearby bridges that suffered minor to moderate damage. The paper proposes that that the near-surface materials are softer at the collapse site than at nearby sites [3]

3. Overview of ATC 38 Database

Applied Technology Council (ATC), the United States Geological Survey (USGS), and several other northern California organizations systematically documented non-instrumeneted but closely located to strong motion recording stations buildings to improve earthquake induced motion-damage relationships.

Immediately after the Northridge earthquake, ATC licensed civil and structural engineers surveyed 500 buildings within approximately 300 meters in the vicinity of strong-motion recording sites. The objective was to obtain data to correlate recorded ground shaking, the observed performance of buildings (both damaged and non-damaged), and key structural characteristics, such as design date, structural framing type, and number of stories.

Building characteristics and their performance was gathered via survey forms called ‘post-earthquake building performance assessment form’. The data collected for each building included: structural characteristics, nonstructural characteristics, geotechnical effects, performance characteristics, fatalities and injuries, and loss of use of facility. Eighteen of the stations are operated by the California Division of Mines and Geology (CDMG), 7 are operated by the University of Southern California (USC), and 6 are operated by USGS. Digitized strong motion recordings were collected. Although surveyed buildings were non-instrumented, the ground motion accelerations for these structures are assumed to be the same as those recorded at the nearby stations. ATC released a report called ‘Database on the Performance of Structures Near Strong-Motion Recordings: 1994 Northridge, California, Earthquake’ on 13 September 2001.

Damage is defined in both qualitative terms relating to reparability and in quantitative terms (estimated damage repair costs as a percentage of building replacement value).

The analysis presented in this paper are based on dataset provided by ATC 38 Report called ‘Database on the Performance of Structures Near Strong-Motion Recordings: 1994 Northridge, California Earthquake’.

The survey was conducted by teams of licensed civil and structural engineers, with the objective of obtaining data to correlate recorded ground shaking, the observed performance of buildings (both damaged and non-damaged), and key structural characteristics, such as design date, structural framing type, and number of stories. Such correlations can be used to: (1) develop improved relationships between ground motion and structural performance; (2) calibrate and improve the characterization of ground shaking in seismic loading criteria for the design of new structures and the rehabilitation or retrofit of existing structures; and (3) improve existing ground-shaking intensity scales.

The survey studies were sponsored by the U. S. Geological Survey, the Southern California Earthquake Centre, the California Office of Emergency Services, and the Institute for Business and Home Safety.

Table1 - General Damage Classifications (based on ATC-13, 1985)

Code	Description
N	None . No damage is visible, either structural or non-structural
I	Insignificant. Damage requires no more than cosmetic repair. No structural repairs are necessary. For non-structural elements this would include spackling partition cracks, picking up spilled contents, putting back fallen ceiling tiles, and righting equipment.
M	Moderate. Repairable structural damage has occurred. The existing elements can be repaired in place, without substantial demolition or replacement or elements. For non-structural elements this would include minor replacement of damaged partitions, ceilings, contents or equipment.
H	Heavy. Damage is so extensive that repair of elements is either not feasible or requires major demolition or replacement. For non-structural elements this would include major or complete replacement of damaged partitions, ceilings, contents or equipment.

4. Analysis Methodology

Seismic vulnerability curves or linear and inelastic structural analysis are mostly used methods to determine seismic induced structural damage these methods become inefficient for larger stock.

Neural networks methodology is used in the analysis. ANNs is a promising tool commonly used in many disciplines as well as in the geotechnical branch of civil engineering. Artificial (ANNs), is a system based on simulation of biological structure of neural networks of the human brain and neural system. Similar to human brain that learns from experiences, ANNs is an adaptive system that learns from previous examples to build a system of neurons. ANNs can be used to build a complex relationship between input and output or to find patterns in data. Differently than statistical data modeling tools, neural networks have the ability to model non-linear relationships. Once trained, neurons are able to make new decisions, classifications, and forecasts.

A neural network is connected by neurons or nodes are simple processing elements whose computing ability is typically restricted to a rule for combining input signals and an activation rule that takes restricted to a rule combining input signals and activation rule that the combined input to calculate an output signal. Output signals may be sent to other units along connections known as weights.

An ANNs simulator is used for this study. This simulator is a tool which is able to "learn" patterns from training data and be able to make its own classifications, predictions, or decisions when presented with new data.

Typically, the architecture of ANNs's consists of a series of processing elements (PEs), or nodes, that are usually arranged in layers: an input layer, an output layer, and one or more hidden layers, as shown in Figure 1. The input from each PE in the previous layer xi is multiplied by an adjustable connection weight wji. At each PE, the weighted input signals are summed and a threshold value θj is added. This combined input Ij is then passed through a nonlinear transfer function f (xi) to produce the output PE. [6]

In this study, we are investigating the relationship between soil properties and seismic structural damage following an earthquake. The relationship between soil parameters and structural damage cannot be defined in an equation form as this case is a complex interaction between soil, superstructure and earthquake parameters.

There are many different types of neural network architecture. Most popular ones can be named: feedforward neural network, radial basis function, back propagation neural network, general regression neural network.

4.1 General Regression Neural Network

Among many neural network analysis, analysis with general regression neural network provided be more successful results. GRNN demonstrated better results in all trials.

Differently from other architectures a smoothing factor, a value ranging from 0 to 1 is applied to the GRNN architecture invented by Donald Spetch (1991) model. This factor is determined through a calibration process undertaken by the simulator program. The smoothing factor determines how tightly the network matches its predictions to the data in the training patterns. [6]

5. Analysis and Results

Input parameters used in the analysis are described below:

- Soil conditions. ATC report named 3 different soil types : Alluvium or rock
- Number of Basement Levels (Nb)
- Number of stories (Ns)
- Epicentre distance (Ed)
- Peak ground horizontal acceleration (PGAh)
- Peak ground vertical acceleration (PGAv)
- Modified Mercalli intensity scale (MMI)

General damage states explained in Table 1 are used as output data. Standardization of datasets is a common requirement for many machine learning estimators and its implemented in the network training is often more efficient, which leads to a better predictor. For this reason input and output data is normalized before implementing into ANN simulator.

Table 2 – Input and Output Parameters and Value Ranges

Input Parameter	SC	PGAh	Ed	PGAv	MMI	Nob	Nos	GenDam
Min	0	0	0	0	0	0	0	0
Max	1	1	1	1	1	1	1	1
Mean	0,54	0,23	0,51	0,25	0,81	0,054	0,06	0,32
Standard Deviation	0,14	0,15	0,24	0,19	0,071	0,13	0,094	0,21

A smoothing factor, a value ranging from 0 to 1 is applied to the model. Best smoothing factor is determined through a calibration process undertaken by the simulator program. The smoothing factor determines how tightly the network matches its predictions to the data in the training patterns. 0,0294118.

Table 3 – GRNN Network Parameters

Architecture	General Regression Neural

	Networks
% Test Extraction	20
Smoothing factor	0,0294118
Number of Inputs	7
Number of Outputs	1
Scale Function	logistic
Calibration	Genetic, adaptive
Distance Metric	City Block

Table 4 – Results for GRNN Network

R squared	0,4900
r squared	0,4909
Mean square error	0,023
Mean absolute error	0,097
Min. absolute error	0
Max. absolute error	0,665
Correlation coefficient r	0,7006

Table 5 – Contribution factors for GRNN

Parameter	**Contribution Factor**	**Orders of the Cont. Function**
SC	1,35294	1
PGAh	3,00000	2
Ed	2,95294	3
PGAv	1,01177	4
MMI	0,00000	5
Nob	0,08235	6
Nos	1,47059	7

The coefficient of multiple determination is used to compare the accuracy of the model to the accuracy of a trivial benchmark model wherein the prediction is just the mean of all of the samples. A perfect fit would result in an r squared value of 1, a very good fit near 1, and a very poor fit less than 0. Analysis resulted coefficient of determination r2 (coefficient of correlation) is 0,4909.

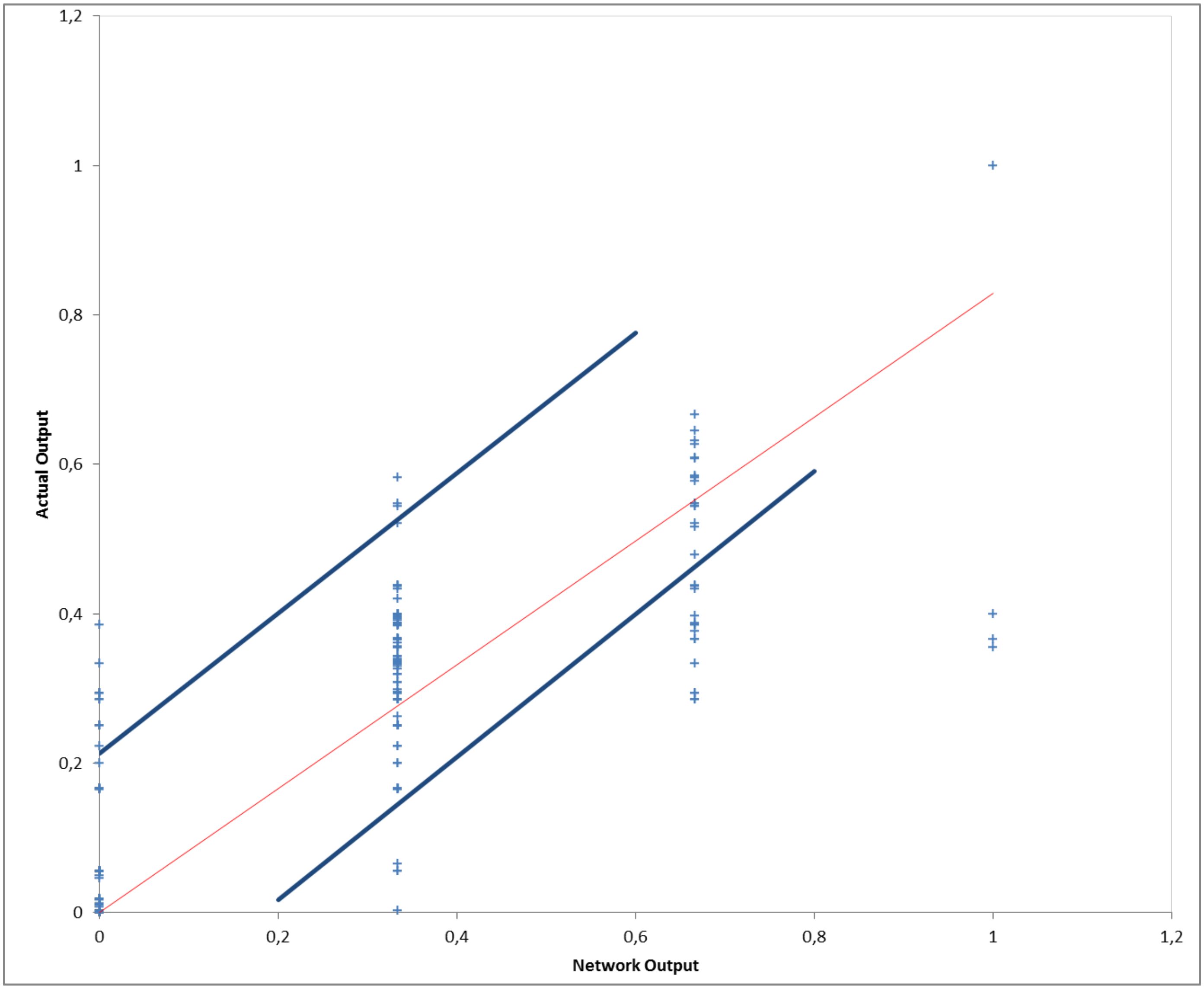

Figure 1 Actual- Network output scatter for GRNN Model

5.Conclusion

This research has introduced artificial intelligence for soil structure interaction for Northridge earthquake. The complexity of building a relationship between input and output data was well handled with neural network methodology. Multiple trials showed that GRNN is the best model to predict soil related structural damages. From this study, it can also be concluded that soil conditions founding the buildings is the most important component among other soil related inputs which affects structural damage during Northrige 1994 earthquake.

6. Copyrights

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