Predicting the Seismic Performance of Cylindrical Steel Tanks Using Artificial Neural Networks (ANN)

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Abstract: The main purpose of this study is to predict the seismic performance of liquid storage tanks using an Artificial Neural Network (ANN) model. In order to develop this model, 240 seismic data were collected from relevant literature. Fifty samples were randomly selected as a test set, while the remaining 190 samples were used to train the network. The data used in the ANN model were arranged in a format of six input parameters: peak ground acceleration (PGA), tank diameter (D), tank height (H), ratio of H/D, height of liquid during earthquake (HLIQ), and percent full (% Full). The output parameter, damage state (DS), was provided for measuring the seismic performance of the liquid storage tanks. The model outputs confirmed that an artificial neural network has acceptable potential for predicting the seismic performance of liquid storage tanks. The applicability of the developed technique was then validated by comparing the outputs to the actual damage states of the affected tanks according to HAZUS.

Keywords: Artificial Neural Network; cylindrical tank; seismic performance

1 Introductions

The performance of liquid storage tanks during past seismic events has shown that these structures are seismically vulnerable. Liquid storage tanks in oil refineries and petrochemical plants usually contain hazardous material. For this reason, damage to these structures may cause serious indirect impacts, such as explosions and environmental pollutions. Therefore predicting the seismic performance of existing liquid storage tanks is an important task in seismic risk analysis of industrial plants. The dynamic behavior of liquid storage tanks is very complex. The seismic performance of liquid storage tanks may be affected by several parameters such as H/D, % Full, etc. For this reason, it is very difficult to estimate the seismic performance of liquid storage tanks and to obtain a mathematical representation of uncertain and nonlinear dynamic processes [1]. Hence, the Artificial Neural Network (ANN) may be a useful tool for estimating the seismic performance of such a complex structure.

In conventional modeling methods, different statistical tools, such as regression analysis, are utilized for developing a model to predict the seismic performance of liquid storage tanks. Available fragility functions of liquid storage tanks are samples of conventional modeling methods. For the last two decades, various modeling methods based on Artificial Neural Network (ANN) have become popular and have been used by many researchers for a variety of engineering applications such as concrete engineering [2, 3], traffic engineering [4] and earthquake engineering [5, 6]. The ANN is able to solve very complex problems with the help of interconnected computing elements [3]. It is also a powerful data analysis tool that is able to capture and represent complex input/output relationships. The true power and advantage of neural networks lies in their ability to represent linear and non-linear relationships and in their ability to derive these relations directly from the data being modeled [7]. Traditional linear models are simply inadequate when it comes to modeling data that contains non-linear characteristics.

The objective of this study is to present a methodology designed by ANN for predicting the seismic performance of liquid storage tanks. The model is expected to determine the damage state of the tanks.

2 The Seismic Performance of Liquid Storage Tanks

Over the past few decades, many liquid storage tanks were damaged due to earthquakes. During an earthquake, the upper part of the contained liquid moves in a long-period motion. This part of the liquid may apply upward hydrodynamic pressure to the tank roof or may cause overflowing of the liquid. The other part moves rigidly with the tank [8]. Moreover, during an earthquake large amounts of hydrodynamic pressure can be applied to the tank shell. The hydrodynamic pressure may cause damage to the tank shell. Many of the on-grade tanks, even anchored ones, may experience shell uplift due to the strong ground motion. The shell uplift may cause ruptures of the shell-to-base-plate junction, rupturing of pipes and/or appurtenances. Elephant-foot buckling (Elastic-Plastic failure) may occur by large axial compressive stresses in the tank wall. Also, distortion of the tank roof or rupturing of the roof-to-wall junction may occur due to the strong ground motion.

There are various methods for classification of the damage states of cylindrical steel tanks. ATC 13 [9] and HAZUS [10] classifications are two common classifications of tank damage states. ATC 13 [9] considers seven different damage states for tanks which are: no damage, slight damage, light damage, moderate damage, heavy damage, major damage, and destroyed. HAZUS [10] considers five damage states which vary from no damage to collapsed tanks, based on the serviceability, loss of content, and the occurrence of shell buckling.

HAZUS damage states are described in Table 1. It should be mentioned that five of ATC13 damage states – none, light, moderate, heavy and destroyed – are equivalent to HAZUS DS1 to DS5 damage states respectively [11]. Herein HAZUS damage states are considered for classifications of damage in tanks.

Table 1
Description of damage states based on HAZUS

Damage State	Description
DS1	No damage.
DS2	Minor damage without loss of content or functionality. Damage to roof, localized wrinkles in steel.
DS3	Considerable damage with minor loss of content. Elephant-foot buckling without loss of content.
DS4	Severe damage. Tank going out of service. Elephant-foot buckling with loss of content.
DS5	Collapse. Losing all of content.

3 Architecture of the Artificial Neural Networks

The neural network-based modeling process involves five main aspects: (a) data acquisition, analysis and problem representation; (b) architecture determination; (c) learning process determination; (d) training of the networks; and (e) testing of the trained network for generalization evaluation [12]. There are different common architectures for artificial neural networks. The multi layer perceptron (MLP), radial basis function network (RBFN), the probabilistic neural network (PNN), the cascade correlation neural network (Cascor), the learning vector quantization (LVQ), and the self-organizing feature map (SOM) are some popular neural network architectures [13, 14]. They differ in aspects including the type of learning, the node connection mechanism, the training algorithm, etc. The most common neural network model is the multilayer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. A typical structure of an artificial neuron is shown in Fig. 1.

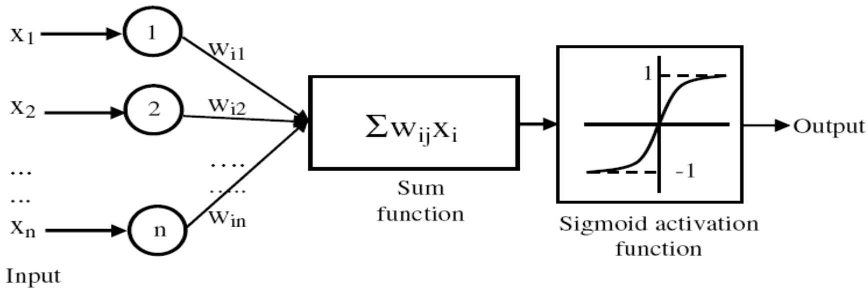


Figure1
A typical structure of an artificial neuron

An error incurred during the learning process can be expressed as a mean square error (MSE) or a root-mean-squared (RMS) as given in the following equation:

$$MSE = \frac{1}{p}\sum_j (o_j - t_j)^2 \tag{1}$$

$$RMS = \sqrt{(\frac{1}{p}) * \sum_j \left| t_j - o_j \right|^2} \tag{2}$$

In addition, the absolute fraction of variance (R^2) and sum of the squares error (SSE) can be calculated by utilizing Eqs. 3 and 4, respectively:

$$R^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right) \tag{3}$$

$$SSE = \sum_j (o_j - t_j)^2 \tag{4}$$

where *t* is the target value, *o* is the output value and *p* is the pattern.

In this study, the back propagation (BP) algorithm is used to train and construct the present ANN model and the hyperbolic tangent function transfer function is adopted. The tangent function is nonlinear and, therefore, the original data before training the network are normalized. The overall flowchart of the procedure of this study is given in Fig. 2.

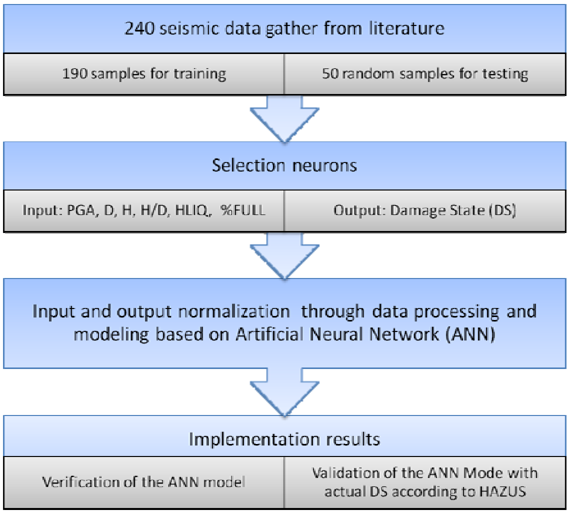


Figure 2

Flowchart of the methodology of this study

4 Proposed Neural Network Model

The ANN model developed in this study is used to predict the seismic performance of liquid storage tanks. In order to produce an effective ANN model, it is vital that the network be properly trained. Therefore, 240 tanks which experienced strong ground motion in past earthquakes were selected. The data of damaged tanks were adopted from [15] (see Table 2). The range of the six input variables, including peak ground acceleration (PGA), tank diameter (D), tank height (H), ration of H/D, height of liquid during earthquake (HLIQ), percent full (% full) and one output, damage state (DS), are given in Table 3.

Table 2

List of the selected triggered tanks

Seismic event	Year	PGA range (g)	Number of affected tanks	Reference
Long Beach	1933	0.17	37	15
Kern County	1952	0.19	23	15
Imperial Valley	1979	0.24-0.49	19	15
Coalinga	1983	0.71	11	15
Loma Prita	1989	0.13	86	15
Landers	1992	0.15-0.56	26	15
Northridge	1994	0.55-1.0	38	15

Table 3
Range of input-output parameters in databases

Input parameters	Minimum	Maximum
PGA (g)	0.13	1
D (m)	3.2	83.2
H (m)	4.9	19
H/D (%)	18	416
HLIQ (m)	0	15.2
% Full	0	100
Output parameter		
DS	1	5

In order to determine the best structure, five different architectures as [6-6-2-1 to 6-6-6-1] are considered and, based on MSE and R^2 criteria, the best one is selected. Table 4 presents the obtained results for each structure. As can be observed, the decrease in MSE causes the increase of R^2 and is approaching to 1. Therefore, the best structure is [6 6 6 1] (see Table 4). The architecture of the proposed ANN is also illustrated in Fig. 3.

Table 4
Evaluation of ANN architecture

Structure	Mean Square Error	Train Error	Test Error	R^2
[6 6 2 1]	0.170	0.681	0.313	0.5328
[6 6 3 1]	0.147	0.586	0.223	0.6200
[6 6 4 1]	0.147	0.588	0.238	0.6182
[6 6 5 1]	0.242	0.967	0.345	0.4575
[6 6 6 1]	0.101	0.416	0.154	0.7793

To test the reliability of the proposed ANN model, 50 samples are randomly selected as the test set, while the remaining 190 samples were used to train the network. Herein, the Matlab neural network toolbox was used to construct and train the supervised network. In training a supervised ANN, weights between the neurons are adjusted to minimize the error in the output. The values of parameters used in this research are as follows:

- Number of input layer units = 6
- Number of hidden layers = 2
- Number of output layer units = 1
- Learning rate = 0.75
- Learning cycle = 1000

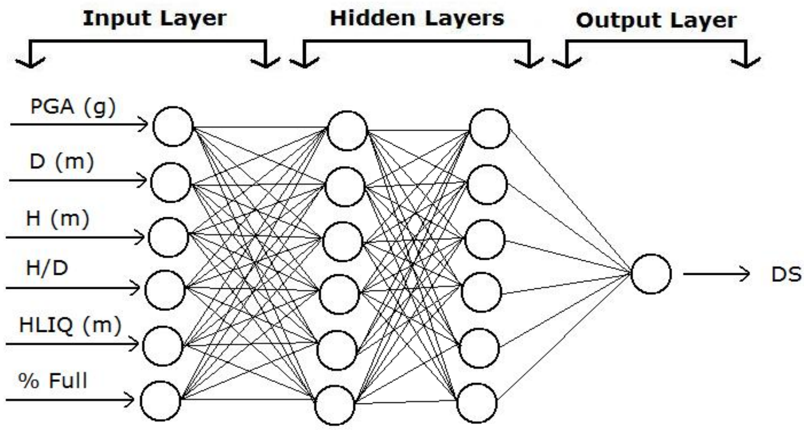


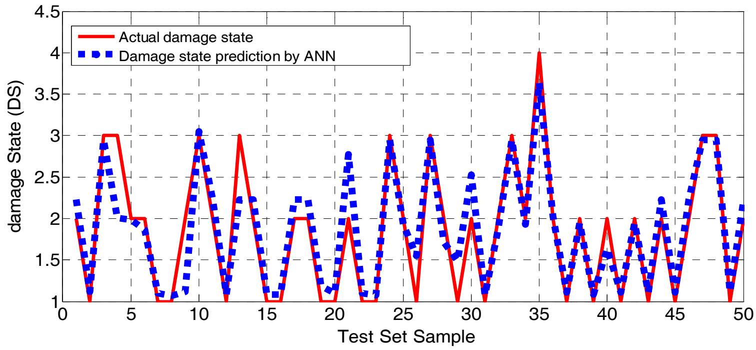
Figure 3
Proposed ANN architecture

5 Implementation Results

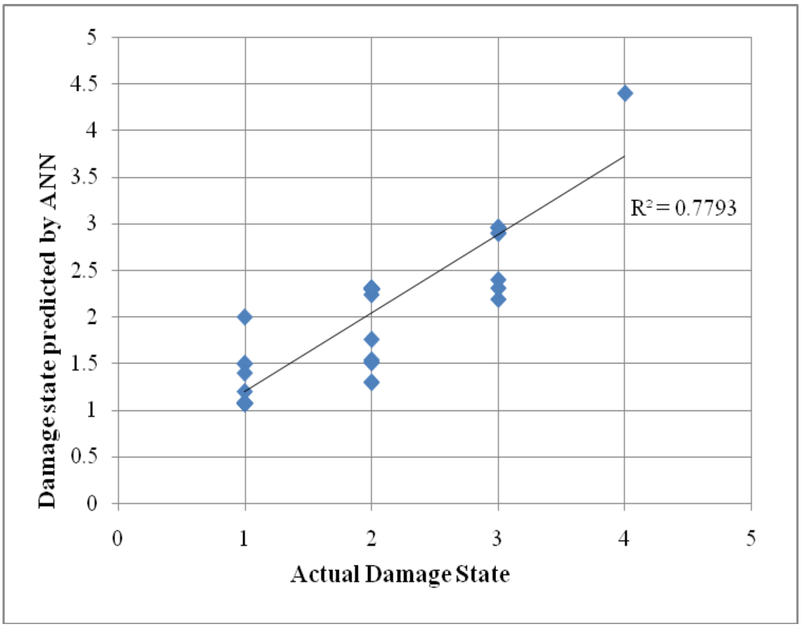
The developed ANN model in this research is utilized to predict the damage state for the seismic performance of liquid storage tanks. The error between the predicted and the target values for the damage state (DS) is plotted in Fig. 4, which includes row numbers up to 50. As indicated in Fig. 4, the neural network was capable of deriving the relationship of input variables and the output. The correlation factor is $R^2 = 0.7793$, which is acceptable for liquid storage tanks [11].

In order to indicate the accuracy of the ANN prediction, various earthquake-affected tanks of different H/D, %Full, and PGA were randomly selected. The actual damage states of the affected tanks (according to HAZUS) were compared to the ANN prediction. The comparison of actual performances and ANN predictions in different ranges of PGA are indicated in Figs. 5 to 8.

As can be observed in these figures, the ANN prediction is acceptable for various models – especially for PGAs less than 0.3 g (see Figs. 5 and 6). It is worth mentioning that the prediction of the ANN model in this study was not accurate enough for the higher PGAs (See Figs. 7, 8). The main reason for such unacceptable prediction is the lack of enough data for training the model in higher PGAs.



(a)



(b)

Figure 4

(a) Comparison of predicted data to test samples (b) Predicted data vs. actual damage state

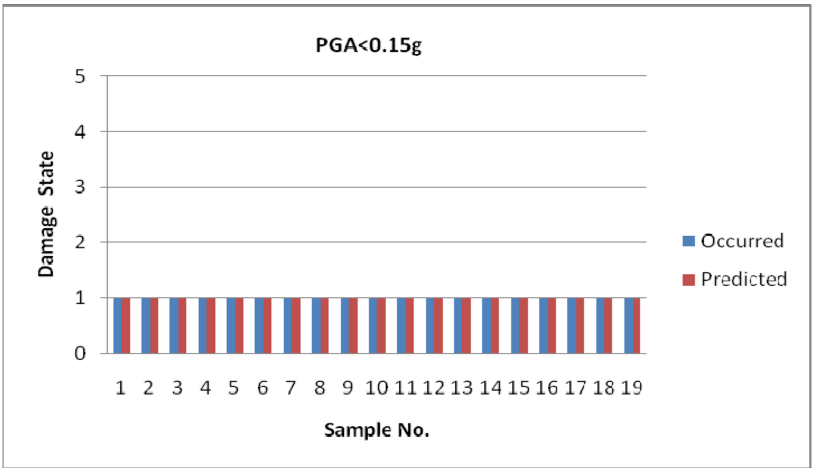


Figure 5
Comparison of ANN prediction to actual damage state for PGA<0.15 g

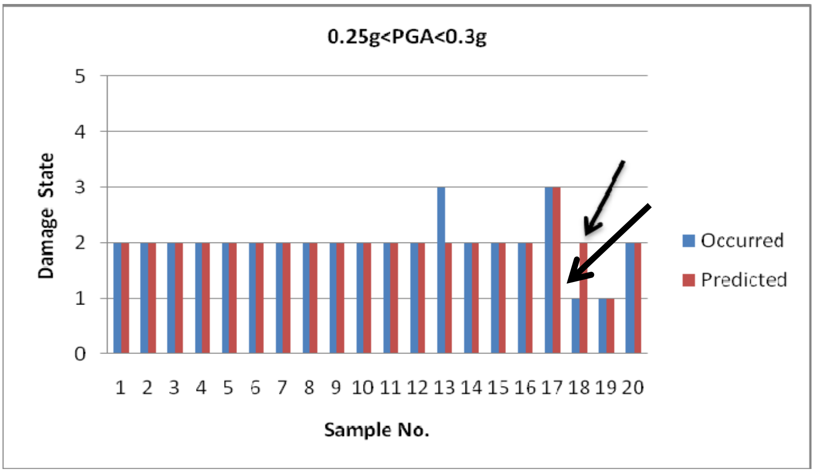


Figure 6
Comparison of ANN prediction to actual damage state for 0.25 g <PGA<0.3 g

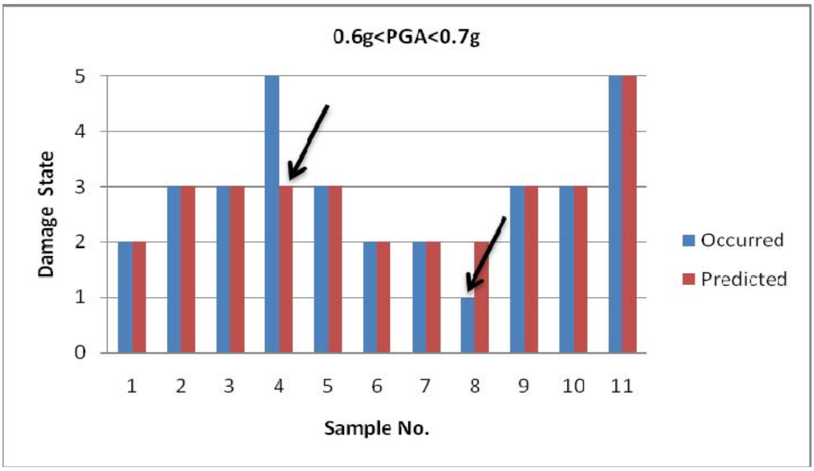


Figure 7
Comparison of ANN prediction to actual damage state for 0.6 g <PGA<0.7 g

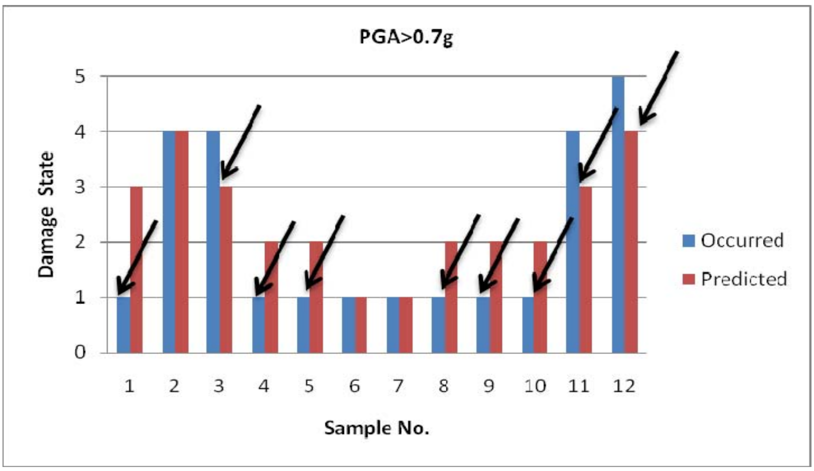


Figure 8
Comparison of ANN prediction to actual damage state for PGA>0.7 g

Conclusions

This study was aimed at investigating the possibilities of adopting artificial neural networks to predict the seismic performance of liquid storage tanks. To this end a data bank of 240 earthquake-affected tanks was selected. Five back propagation ANN of different architectures were designed and trained with 190 data. The main findings of the study are outlined below:

1) The results of this study showed that artificial neural network has acceptable potential for predicting the seismic performance of liquid storage tanks.

2) Based on the results given in table 4 for evaluation of ANN architecture, the best correlation factor (R^2 =0.7793) was obtained from the [6 6 6 1] model with the lowest Mean Square Error (0.101).

3) For PGAs less than 0.3 g, the ANN model accurately predicted the damage state and for 0.6 g <PGA<0.7 g, the ANN predictions are also acceptable, but for PGA>0.7 g, because of the lack of the data in this range for training the model, the predictions in the most cases are higher than the actual damage state, so they were not accurately predicted. It is worth mentioning that seismic events with PGAs higher than 0.7 g are very strong earthquakes and usually have long return periods. In other words these extraordinary earthquakes are rare. Hence the neural network can accurately predict the seismic performance of cylindrical steel tanks for a wide range of PGAs.

The results of this study reveal that an artificial neural network can be used for the development of seismic performance relations (such as fragility curves). In other words, the proposed methodology is a useful tool in seismic risk analysis of tank farms with potential PGAs less than 0.7 g.

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