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Prediction of seismic-induced structural damage using artificial neural networks

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ABSTRACT

Contemporary methods for estimating the extent of seismic-induced damage to structures include the use of nonlinear finite element method (FEM) and seismic vulnerability curves. FEM is applicable when a small number of predetermined structures is to be assessed, but becomes inefficient for larger stocks. Seismic vulnerability curves enable damage estimation for classes of similar structures characterised by a small number of parameters, and typically use only one parameter to describe ground motion. Hence, they are unable to extend damage prognosis to wider classes of structures, e.g. buildings with a different number of storeys and/or bays, or capture the full complexity of the relationship between damage and seismic excitation parameters. Motivated by these shortcomings, this study presents a general method for predicting seismic-induced damage using Artificial Neural Networks (ANNs). The approach was to describe both the structure and ground motion using a large number of structural and ground motion properties. The class of structures analysed were 2D reinforced concrete (RC) frames that varied in topology, stiffness, strength and damping, and were subjected to a suite of ground motions. Dynamic structural responses were simulated using nonlinear FEM analysis and damage indices describing the extent of damage calculated. Using the results of the numerical simulations, a mapping between the structural and ground motion properties and the damage indices was than established using an ANN. The performance of the ANN was assessed using several examples and the ANN was found to be capable of successfully predicting damage.

1. Introduction

The ability to assess the vulnerability of civil infrastructure to earthquake-induced damage is undoubtedly one of the most important challenges faced by structural engineers. Two methods are predominantly used for predicting seismic damage: numerical analysis using nonlinear finite element method (FEM) and seismic vulnerability curves. Nonlinear FEM analysis is particularly applicable when a detailed damage estimate is only required for an individual important or typical, representative structure, or a small number of structures [1–4]. However, if an assessment is required for numerous structures the process becomes time consuming and inefficient [5,6]. Seismic vulnerability curves provide a more efficient method for predicting damage to a class of similar structures. They are generally constructed based on either statistical analysis of field data and historic records [7–13] or analytically simulated data [14–23]. However, these curves typically take into account only a limited number of structural properties and use one parameter to describe ground motion. Hence they have difficulty in extending damage prognosis to wider classes of structures, e.g. buildings with a different number of storeys and/or bays, or capture the full complexity of the relationship between damage and seismic excitation parameters [6,24]. This shortcoming becomes particularly important as studies [25,26] have shown that correlations between damage and the parameters describing ground motion are very complex and a set of such parameters rather than one index would be necessary to capture the relationships.

These shortcomings stimulated research into more general methods and models capable of extending damage prediction to larger classes of structures and incorporating a wider set of parameters describing ground motions. However, research into such methods appears to be still scarce. Several authors attempted to extend the usability of vulnerability curves. Kwon and Elnashai [6] observed large variability of vulnerability curves for a single RC frame and calculated three different vulnerability curves for sets of ground motions with different peak ground acceleration to peak ground velocity ratios. Using extensive numerical simulations of single degree of freedom nonlinear oscillators characterized by period, strength, ductility and post-yield stiffness, Jeong and Elnashai [5] built a data base which could later be used to retrieve information and construct vulnerability curves faster. Serdar Kircil and Polat [24] used a statistical method to combine vulnerability curves for the same RC building

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constructed with two alternative reinforcement grades and later used regression analysis to extend their curves to buildings with a different number of storeys. From these examples it can be seen that work on generalization of damage prediction to different structures and ground motions within the framework of traditional vulnerability analysis has started but still poses a significant challenge. The use of discriminant analysis is reported by Yücemen et al. [27], who predicted building damage into a two-state or three-state damage classification. The analysis was based on post-earthquake data from the Turkish 1999 Duzce earthquake. Three structural parameters were found to discriminate the data set the most: the number of storeys, a ratio of the ground storey height to the first storey height and a ratio of the column area to the floor area. Yakut et al. [28] extended this approach and considered also local soil characteristics.

A tool that is often used to describe complex relationships influenced by numerous parameters are Artificial Neural Networks (ANNs). Although ANNs have been applied widely throughout the civil engineering [29] and structural health monitoring fields [30–32], their use for seismic damage prediction has been limited. Molas and Yamazaki [33] used an ANN to predict seismic damage in wooden framed houses represented by simple analytical single degree of freedom models. In the study, ground motion indices were related to structural ductility using the ANN. De Stefano et al. [34] described an approach to predict seismic damage mechanisms in historic churches using an ANN and Bayesian classification. The church was broken into different structural components, e.g. facade, apse, sidewalls, spire etc. These components and their arrangement were used as ANN input. The ANN was used to give the probability of each damage mechanism occurring. A similar approach was used by Aoki et al. [35] to predict the seismic collapse mechanisms in chemical plants. Erkus [36] used ANNs to predict seismic damage in analytical models of reinforced concrete (RC) frame structures. The author was able to predict damage in the frame with varying stiffness and reinforcement ratio whilst under different scaled ground motion intensities. However, no attempt was made to further extend the study to frames with different topologies, i.e. different number of storeys/bays and dimensions. Sánchez-Silva and García [37] proposed using a combination of systems theory, fuzzy logic and ANNs to assess the seismic damage in a structure. Fuzzy logic converted linguistic terms describing the earthquake severity, soil conditions and structural properties into numbers, which were the inputs into an ANN. The system was trained for several types of structures.

In this study, a method for predicting seismic-induced damage using ANNs is proposed that can be applied to a wider class of structures subjected to varying ground motions. The approach was to describe both the structure and ground motion using a number of structural and ground motion properties, thus allowing a wide range of situations to be described. The class of structures analysed were 2D RC frames that varied in topology, stiffness, strength and damping, and were subjected to a suite of ground motions characterized by their Peak Ground Acceleration (PGA), Velocity (PGV) and Displacement (PGD), Spectrum Intensity (SI), dominant frequency and duration. Dynamic structural responses were simulated using nonlinear FEM analysis and damage indices describing the extent of damage calculated. Using the results of the numerical simulations, a mapping between the structural and ground motion properties and the damage indices was then established using an ANN. The efficiency of the ANN for damage prediction was assessed using several examples illustrating the ability to extend damage prognosis.

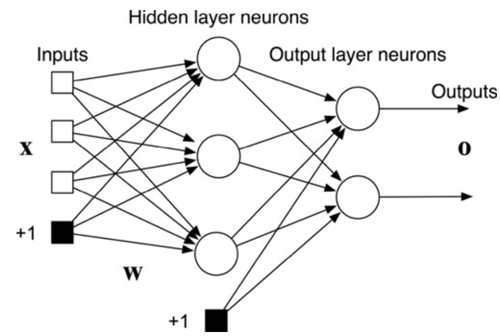

Fig. 1. Structure of a single hidden layer BP ANN.

2. Artificial neural networks

ANNs are structures deliberately designed to mimic and utilise the organisational principles observed in the brain [38]. ANNs are capable of efficiently performing tasks such as pattern recognition, classification and function approximation. Adeli [29] gives a comprehensive review of ANN applications in civil engineering.

ANNs utilising the supervised error Back-Propagation (BP) algorithm [39] are commonly referred to as BP neural networks. BP networks appear to be the most popular type of neural network employed. The structure of a BP network with a single hidden layer (HL) is shown in Fig. 1, where $\mathbf{x}$ and $\mathbf{o}$ are the input and output vectors of the network, respectively. The bias inputs into the HL and output layer (OL) have been represented by solid squares and both have the value of $+1$. The weights, denoted by vector $\mathbf{w}$, are learnt during network training and store information about the processing of input data.

The basic function of a neuron, in either the HL(s) or OL, is to calculate the weighted sum of all inputs u and compute the output y. The weighted sum of all inputs can be calculated as follows:

$$u = \mathbf{v}^{\mathrm{T}}\mathbf{z} \tag{1}$$

where superscript T denotes transposition. The input and weights vectors have been denoted by $\mathbf{v}$ and $\mathbf{z}$ to avoid confusion with $\mathbf{w}$ and $\mathbf{x}$, which are for the whole network. The output of the neuron is computed using

$$y = f(u) \tag{2}$$

where f is the neuron's activation function. Activation functions may have different forms; in this study, the tangent hyperbolic function was used.

When an ANN is to be used as a function approximator, the error between the target values and the network outputs needs to be minimised. In the vector notation, this error can be written as

$$\mathbf{e}(\mathbf{w}) = \mathbf{d} - \mathbf{o}(\mathbf{w}) \tag{3}$$

where $\mathbf{d}$ is the vector of desired network outputs or target values. The total approximation error $E(\mathbf{w})$ is a function of the weights and can be written as

$$E(\mathbf{w}) = \frac{1}{2}\mathbf{e}(\mathbf{w})^{\mathrm{T}}\mathbf{e}(\mathbf{w}). \tag{4}$$

In the training phase, an input selected from a set of known input–output pairs is supplied, and the network calculates the output from the given input. The error between the desired and actual output is then propagated backwards from the output layer to the preceding layers—hence the name "back-propagation algorithm". In this study, the Levenberg–Marquardt algorithm [40, 41] is used to minimise the error.

Introducing the Jacobian matrix $\mathbf{J}$ defined by

$$\mathbf{J}(\mathbf{w}) = \frac{\partial \mathbf{e}}{\partial \mathbf{w}} \tag{5}$$