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NEURAL NETWORKS FOR THE PREDICTION OF SEISMIC DAMAGE IN REINFORCED CONCRETE STRUCTURES

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The possible seismic damage to structures can be evaluated using either vulnerability curves or non-linear dynamic analyses. However, the nonlinear dynamic analyses are time-consuming and the vulnerability curves can only be applied to a certain type of structures. There have been approaches to find correlation between several ground motion parameters and damage indices for buildings in the past (Lönhoff, 2017; Kwon, 2006; de Lautour, 2009).

For this purpose, this paper deals with the idea of using artificial neural networks to significantly simplify the calculations. In fact, neural networks are able to find complex correlations in large data sets. Since the aim of the investigation is to determine the damage caused by an earthquake, suitable acceleration time curves must first be selected as training data. The correct selection of input data is crucial for the successful training of an artificial neural network. For the analysis of the damage, only strong earthquakes with a distance of more than 15 km were used, because near-field earthquakes show special damage behaviour due to the peak loads.

In order to investigate the relationship between engineering seismological parameters and structural damage, non-linear dynamic analyses of different structures are performed with the finite element program OpenSees. Four buildings of different heights are used to cover a wide range of common structures. The models are all made of reinforced concrete components and consist of a two-storey, a four-storey, a six-storey and an eight-storey building. To simplify matters, the buildings are analysed as 2D models. To investigate the damage, the Overall Structural Damage Index for the widely used damage indicator Park-Ang with Equation 1 and Kunnath were calculated for the given structures for each earthquake (Park Ang, 1984). Additionally, the maximum displacement of the floors among each other (MIDR) and the maximum roof displacement (MRDR) have been calculated as global damage indicators. There have been several damage indicators investigated to verify the independence of the surrogate model from the utilized damage index.

$$DI_{ParkAng} = \frac{\theta_{max}}{\theta_u} + \beta * \int \left(\frac{\theta_n}{\theta_u}\right)^{\alpha} \frac{dE}{E_c(\theta_n)} \quad (1)$$

Once both, the input and target values of the artificial neural network have been defined, the modeling of the network can begin. For verification purpose, 100 nets were trained, the maximum, mean and minimum regression values for the test datasets are listed in Table 1. The regression of the training dataset is above 95 % for all investigated damage indicators. Regarding the different number of storeys, for two storey the regression was significantly worse due to a lack of data of buildings with high damage.

In Figure 1 there is an example for the regressioplots of the test dataset for a model with eight storeys and the damage index by Park and Ang (1984). The regression of the test data set was 98.6% . The X-axis shows the damage indicators determined using the FE program, the Y-value was determined using the artificial neural network.

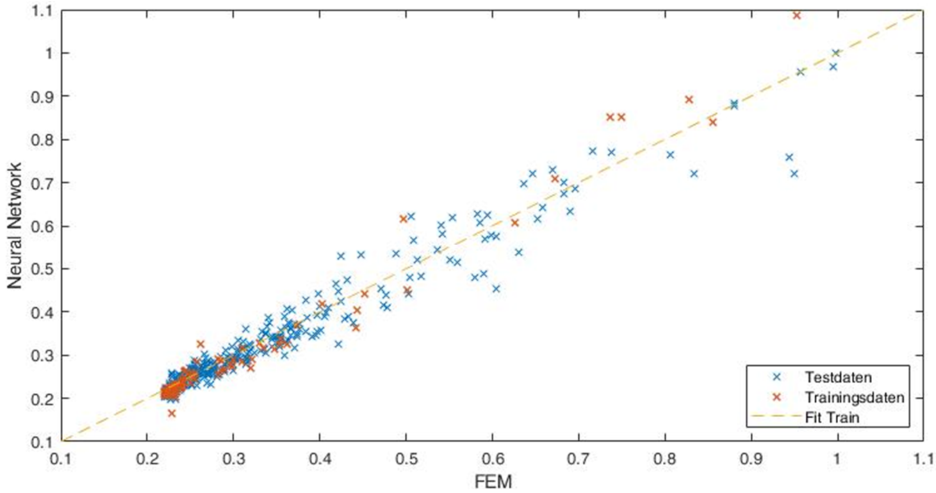

Figure 1. Example test regression plot for a model with 8 storeys and the damage index by Park and Ang.

Table 1. Comparisons of the regression of the test dataset for buildings with different number of floors and different damage indices over 100 trained networks.

	Number of stories of the building				Damage Indicator			
	2	**4**	**6**	**8**	**Park Ang**	**Kunnath**	**MIDR**	**MRDR**
Maximum	0.954	0.968	0.976	0.986	0.986	0.987	0.978	0.975
Mean	0.772	0.923	0.944	0.948	0.948	0.956	0.948	0.950
Minimum	0.410	0.837	0.892	0.895	0.895	0.855	0.892	0.908

Various types and different configurations of neuronal networks were tested, whereas, using a forward cascading network turned out to be the most effective solution.

Based on the results, artificial neural networks were found to be a suitable alternative to the current methods for predicting the possible seismic damage to reinforced concrete structures.

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