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# RELEVANT SEISMIC INTENSITY MEASURES FOR DAMAGE PREDICTION WITH ARTIFICIAL NEURAL NETWORKS

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## ABSTRACT

The selection of appropriate engineering seismological (IM) parameters to describe the intensity of an earthquake in vulnerability analysis has been a concern for engineers and geologists since the early days of earthquake engineering. For the prediction of the structural damage, either nonlinear dynamic analyses or empirical or semi-empirical vulnerability curves can be used to predict the expected seismic damage to structures.
Fragility curves have traditionally been defined by describing the ground acceleration in a single IM. The selection of an appropriate IM was classically done by simple correlation analyses or by using simpler linear or nonlinear models. In the last decade, there have been increasing attempts in the scientific field to use machine learning methods to predict the expected seismic damage to structures. Here, many IMs as well as structural properties have been used as input simultaneously. However, using a sensitivity analysis, it is also possible to draw conclusions about the relevance of IMs in the investigated data set and to make a new statement about suitable IMs for fragility analysis based on the nonlinear statistical models.

## INTRODUCTION

For the selection of relevant seismic intensity measures, several conditions have to be considered. The main criteria is the efficiency of the IM to describe the engineering demand parameter (EDP) (Luco und Cornell 2007). Also, the sufficiency of the IM describing the dependency between probabilistic seismic hazard analysis (PSHA) and fragility analysis has to be considered. Additionally, further points that are relevant for the selection can be the complexity and scalability of the IM, existing Ground Motion Prediction Equations and independency from structural properties (Marafi et al. 2016). While classically linear models have been used for the calculation of the efficiency of an IM, nonlinear connections between IM and EDP cannot always be recognized. For this purpose, the sensitivity of an artificial neural network train to predict the EDP from a given set of IMs is investigated in this work.
There are many approaches for the use of artificial intelligence in structural engineering (Adeli 2001), but most of them are limited to the field of research. The study of building damage using artificial neural networks (ANN) has also been investigated in some approaches. Molas and Yamazaki (Molas und Yamazaki 1995) investigated the relationship between individual ground shaking parameters and a combination of two or three parameters with the ductility factor for typical Japanese wood structures using artificial neural networks. Lautour and Omenzetter (Lautour und Omenzetter 2009) used for the input data set, in addition to ground vibration parameters, 13 structural parameters which contained relevant properties of the considered reinforced concrete structures. Hereby they successfully determined the Park-Ang damage indicator. However, for an unknown earthquake, they obtained a large scatter of results.

Morfidis and Kostinakis published in 2017 (Morfidis und Kostinakis 2017) a study regarding combinations of earthquake parameters for the optimal prediction of the damage state of R/C buildings using artificial neural networks. In this study, the maximum interstory drift ratio was used as the damage index, and two versions of the stepwise method (forward and backward) and the Garson's approach were used for the sensitivity analysis of the model. However, the classification of the seismic parameters based on their correlation with the damage state was not clear, as it depends on the configuration and training algorithm of the ANNs, as well as on the method used for the classification. The best results were obtained for Housner intensity.

In 2019, Mashmouli (Mashmouli et al. 2019) used the model-dependent sensitivity analysis method of partial derivative on ANNs with wavelet activation functions on a single-mass oscillator. However, no IM could be uniquely identified.

Therefore, in the following, one model-dependent and one model-independent sensitivity analysis methods will be used to identify the most relevant IM.

## ARTIFICIAL NEURAL NETWORKS

Artificial neural networks can recognize patterns comparable to natural neural networks by sufficient training and then apply these patterns to unknown problems. An artificial neuronal network consists of several layers $i$ with neurons $j$ which have weighted connections $w_{i,j}$. The input information is passed in modified from one layer to another.

An artificial neural network typically consists of Input-, Hidden- and Output Layer. To achieve the best configuration for the network, the number of hidden layers as well as the number of neurons per hidden layer can be modified.

The function of a neuron consists in calculating the weighted sum of all inputs from the previous layer $net_j$ (1). Each of the information given from one neuron $o_i$ to the next is given a weighted connection $w_{i,j}$.

$$net_j = \sum_{i \in I} (o_i \cdot w_{i,j}) \tag{1}$$

Combined with this information and the bias $\Theta_j$ the activation function $f_{act}$ calculates the output of the neuron $a_j(t)$ (2). (Kruse et al. 2015).

$$a_j(t) = f_{act}(net_j(t), a_j(t-1), \Theta_j) \tag{2}$$

The most common activation functions are the Heaviside, Linear and Sigmoid functions. The output function (3) finally calculates the information from the activation, which is passed on to the following neurons.

$$f_{out}(a_j) = o_j \tag{3}$$

In the training process, the error of the net is calculated and an attempt is made to adjust the error function by adjusting the weights. $E_D$ to minimize (4). In backpropagation, the error is minimized backwards (i.e. from output to input) by adjusting the weights (Kruse et al. 2015). By minimizing the error, step by step, an attempt is made to approach a local minimum.

$$E_D = \sum_{l,c} \frac{1}{2} (o^{l,c} - t^{l,c})^2 \tag{4}$$

A wide range of training algorithms is available to optimize parameters and minimize errors. One of the fastest training algorithms is the Levenberg-Marquardt-Algorithm (LM) (Beale et al. 2017). This is a variation of the Gaussian-Newton method, which has the advantage of not requiring the second derivation of the error. This combines the advantages of the fast convergence of the Gaussian-Newton method with the secure convergence of the gradient descent (Schröder und Buss 2017).

## SENSITIVITY ANALYSIS METHODS

Different methods exist for the sensitivity analysis of artificial neural networks. These can be divided into model-dependent and model-independent methods. The model-dependent methods use the weights of the ANN and calculate the rank of the input parameters. The model-independent approaches only take the data into account and classify the importance of the characteristics based on evaluation functions. For the evaluation of the input variables of the ANN, the Permutation Importance (model-independent) and Partial Derivative (model-dependent) method were selected, which are explained in more detail below.

## PERMUTATION IMPORTANCE

This algorithm analyses the sensitivity of features using the trained model (Breiman 2001; Altmann et al. 2010). Features importance are calculated by measuring how metrics change when one of the features is not available. This can be achieved by removing each of the features from the training dataset and retraining the model. It turns out that the input layer of the network itself needs to be changed each time. Because of that, Permutation Importance takes a different approach. Instead the feature values are replaced one by one with random noise while leaving the target and all other columns in place. In order to keep the value distribution, this can be achieved by shuffling the existing feature values.

In detail, the permutation importance is calculated as follows. First, a model is fitted and a baseline metric is calculated on some data. Next, a feature from the same data is permuted and the metric is evaluated again. The permutation importance is defined to be the difference between the permutation metric and the baseline metric. These steps are computed for all the columns in the dataset to obtain the importance of all the features. A high value means that the feature is important for the model. In this case, the shuffling of the values brakes the relationship with the target and results in low-quality predictions (high error). Instead, a low value means the permutation metric is near to the original one, i.e., a low predictive power.

## PARTIAL DERIVATIVE

Partial derivative is a model-dependent sensitivity analysis method that evaluates local sensitivity, i.e., the effect of changes at each of the input nodes on the output values (Mashmouli et al. 2019). The partially derived sensitivity analysis method requires the extraction of learned weight matrices containing coefficients for each of the neurons in all input, hidden, and output layers during the training process.

$$\boldsymbol{SI} = \sum_{n=1}^{c} \left( \boldsymbol{S}_{\boldsymbol{n}\times\boldsymbol{l}}^{\boldsymbol{2}} \right) / c \quad \text{with} \quad \boldsymbol{S}_{\boldsymbol{n}\times\boldsymbol{l}} = \boldsymbol{f}_{\boldsymbol{3}}' \times [\boldsymbol{w}_{\boldsymbol{3}}]_{l,k} \times \boldsymbol{f}_{\boldsymbol{2}}' \times [\boldsymbol{w}_{\boldsymbol{2}}]_{k,j} \times \boldsymbol{f}_{\boldsymbol{2}}' \times [\boldsymbol{w}_{\boldsymbol{1}}]_{j,i} \tag{5}$$

This method involves computing the Jacobian matrix, which is computed for observations in a given dataset, and stores the weights assigned to each neuron in the input layer. The squared weights for each feature are summed and assigned to each feature for scoring (*5*).

## DATASET

To investigate the relationship between engineering seismological parameters and damage on the structure, nonlinear dynamic analyses of four structures are performed using the finite element program OpenSees (Pacific Earthquake Engineering Research Center).

Four buildings with different heights are used to cover a spectrum of common structures. Each of the two, four, six, and eight-story building models is of reinforced concrete frame construction. For simplicity, the buildings are represented as 2D models. All reinforced concrete beams are provided with a permanent and a variable load. The structures are designed according to the specifications of DIN EN 1998 and DIN EN 1992. The properties of the created building models can be seen in Figure 1.

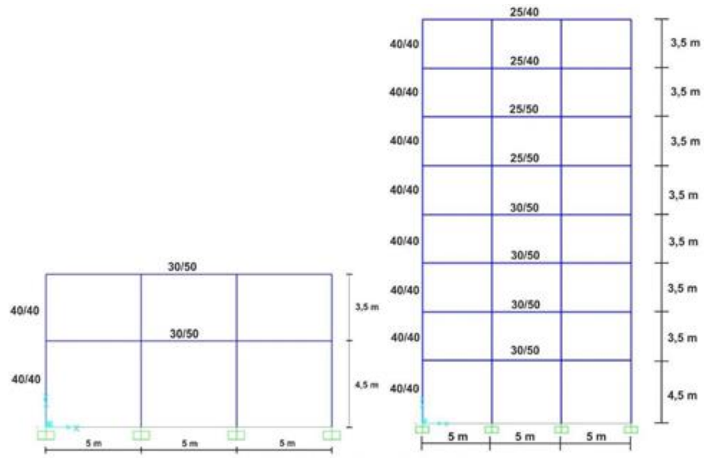


Figure 1: Considered structures

Damage indicators are used to quantify damage in the structure. A large number of such indicators can be found in the literature. The most common local damage indicator was developed by Y. J. Park and A. H-S. Ang proposed in 1984. The efficiency of the parameter in describing the building damage was confirmed in prior research works (Alavanitopoulos et al. 2009, Buratti 2012). Park and Ang used the test results of reinforced concrete components from the USA and Japan to precisely calibrate their indicator. The damage indicator defines the damage of an element as a linear combination of deformation and energy, each normalized by the capacity (6). The energy is calculated with the coefficient of β to consider the influence of cyclic loading or the reduction in stiffness. In the following, the rotation is used as the deformation parameter θ (Elenas and Meskouris 2001). The Overall Structural Damage Index was calculated to obtain the global damage of the structure from the local damage to the components. This adds up the damage indicators of the individual components and weights them as a function of the hysteresis energy.

$$DI_{ParkAng} = \frac{\theta_{max}}{\theta_u} + \beta * \int \left(\frac{\theta_n}{\theta_u}\right)^{\alpha} \frac{dE}{E_c(\theta_n)} \tag{6}$$

The selection of earthquake histories for the nonlinear analysis of a structure is done by means of target spectrum according to Eurocode. A set of 280 earthquake time histories from New NGA-West 2 Ground Motion Database (Pacific Earthquake Engineering Research Center) is selected. For a distance between 15 and 100 km, a magnitude of between 5.5 and 7.5 and assumed target spectrum according to Figure 2.

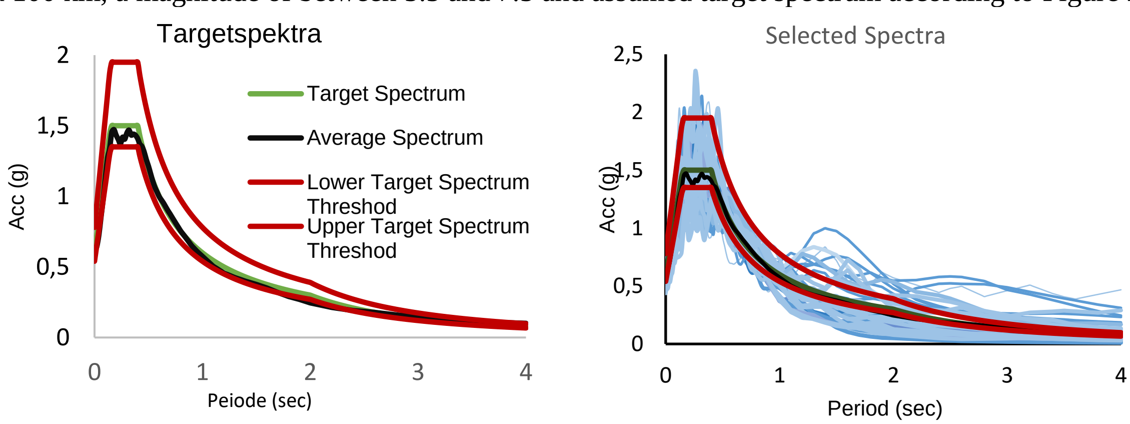


Figure 2: Spectrum of the selected earthquake time series

For the description of the earthquake acceleration record, seismic intensity measures are used. Many IMs exist for the engineering description of an earthquake. Classical values for these are the maximum ground acceleration, which is often used for very stiff buildings, or the spectral ground acceleration in the first eigenmode, which is used for structures dominated by the first mode. For deeper investigation, 12 different IMs were selected, which are listed in Table 1. The selection was made to include all different types of IMs: acceleration-, displacement-, and velocity-based IMs as well as spectral- and energy-based IMs.

Table 1: Investigated seismic intensity parameters

| IM | Name | Reference |
|---|---|---|
| $PGA = max(\|a(t)\|)$ | Peak ground acceleration | |
| $v_{rs} = \sqrt{\int_0^{t_{max}} v^2(t)dt}$ | Root square velocity | |
| $CAV = \int_0^{t_{max}} [a(t)]dt$ | Cumulative absolute velocity | |
| $Sa_{avg}(c_1T_1, \ldots, c_nT_1) = \left(\prod_{i=1}^{N} Sa(c_iT_1)\right)^{1/N}$ | Geometrical Mean of Sa $c_1 = 0{,}1\ und\ c_n = 2$ | (Eads et al. 2015) |
| $D_s$ | Significant duration | |
| $I_a = \frac{\pi}{2g}\int_0^{t_{max}} [a(t)]^2 dt$ | Arias Intensity | |
| $S_a(T_1)$ | Spectral acceleration in the first eigen period | |
| $d_{sq} = \int_0^{t_{max}} d^2(t)dt$ | Squared displacement | |
| $E_{inp} = \frac{1}{2}mv_t^2 + \int cv\,\mathrm{du} + \int f_s\,\mathrm{du}$ | Spectral Energy in the first eigen period | (Lönhoff et al. 2017) |
| $FIV = \max\{V_{s,max1} + V_{s,max2} + V_{s,max3,}\|V_{s,min1} + V_{s,min2} + V_{s,min3,}\|\}$ $V_s(t) = \left\{\int_t^{t+\alpha T_n} \ddot{u}_{gf}(\tau)d\tau, \forall t < t_{end} - \alpha T_n\right\},$ | Filtered Incremental Velocity | (Dávalos und Miranda 2019) |
| $S^* = S_a(T_1)\left[\frac{S_a(2T_1)}{S_a(T_1)}\right]^{0.5}$ | $S^*$ | (Cordova et al. 2001) |
| $S_{N1} = Sa(T_1)^{\alpha} \cdot Sa(CT_1)^{1-\alpha}$ with $\mathbf{c = 1,50\ and\ \alpha = 0,5}$ | $S_{N1}$ | (Lin et al. 2011) |
| $SI_{a,v,d} = \begin{cases} \frac{1}{0.157} SI_H(\beta, 0.028, 0.185); T \in [0.118, 0.5]s \\ \frac{1}{1.715} SI_H(\beta, 0.285, 2); T \in [0.500, 5]s \\ \frac{1}{8.333} SI_H(\beta, 4.167, 12.500); T \in [5.00, 14.085]s \end{cases}$ | $SI_{a,v,d}$ | (Nau und Hall 1984) |

## RESULTS

First, as part of pre-processing, the created dataset was Box-Cox transformed (G. E. P. Box und D. R. Cox 1964) and then scaled between 0 and 1 to obtain a better normally distributed dataset, which is a prerequisite for most machine learning models. The dataset was randomly divided into 20% test, 20% validation, and 80% training data. An ANN was created with two hidden layers of 12 neurons each. For optimization, the Levenberg-Marquardt Algorithm (Hagan und Menhaj 1994) was used in combination with a Sigmoid activation function. The ANN was then trained for each structure separately and analysed using the permutation method previously described in chapter 3. Sensitivity Analysis.
Figure 3 shows the regression plot of the trained ANN. These contrasts, for a test data set, the predicted Park-Ang with those previously calculated in the FE model. The coefficient of determination is in average 95,4%.

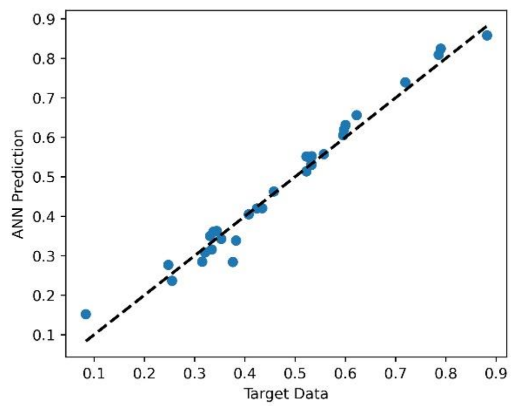


Figure 3:Regression plot ANN test data

The results of the sensitivity analysis of the trained ANN using the Permutation Intensity is listed in Table 2 for each structure separately. While the results of both methods structural independent are represented in Table 3. Differences between the ranking of the IMs for each structure can be recognized. Also, it is clear which IMs are always highly ranked, namely Root Squared Velocity, $\boldsymbol{S}^{*}$, Spectral Energy, and the geometric mean of the Spectral Acceleration. At the same time, the IMs where the ANN reacted low sensitive to changes were mostly PGA, CAV and significant duration. The sensitivity to $\boldsymbol{S}^{*}$ Spectral Energy reduces for softer structures, while the sensitivity to $\boldsymbol{FIV}$ seems to change independently. Since the training of an ANN always contains randomness in weights and bias, the results can change on each run. While this influenced the IMs with medium rank, the highest and lowest-ranked IMs stays constant.
Instead of training the ANN on each structure separately, all structures can be combined in one dataset if structural parameters are added to the input data. This can be achieved for example by adding the eigenfrequency of the structure. Again, the ANN is trained and a sensitivity analysis is applied. The results are shown in Table 3. It can be seen, that again, the ANN reacts most sensitive to changes of Root Squared Velocity.
Since the ranking of IMs represents the sensitivity of the ANN to predict the target data, also the second-ranked IM is of interest. This could be used for vector IMs.

| Rank | 2 Stories | 4 Stories | 6 Stories | 8 Stories |
|---|---|---|---|---|
| 1 | $S^*$ | $v_{rs}$ | $v_{rs}$ | $v_{rs}$ |
| 2 | $v_{rs}$ | $S^*$ | $SI_{a,v,d}$ | $SI_{a,v,d}$ |
| 3 | $E_{inp}$ | $E_{inp}$ | $Sa_{avg}$ | $d_{sq}$ |
| 4 | $FIV$ | $FIV$ | $S^*$ | $S^*$ |
| 5 | $d_{sq}$ | $I_a$ | $E_{inp}$ | $Sa_{avg}$ |
| 6 | $Sa_{avg}$ | $CAV$ | $S_{N1}$ | $E_{inp}$ |
| 7 | $CAV$ | $S_{N1}$ | $D_s$ | $FIV$ |
| 8 | $S_{N1}$ | $D_s$ | $I_a$ | $S_{N1}$ |
| 9 | $I_a$ | $Sa_{avg}$ | $d_{sq}$ | $D_s$ |
| 10 | $PGA$ | $d_{sq}$ | $FIV$ | $CAV$ |
| 11 | $SI_{a,v,d}$ | $SI_{a,v,d}$ | $PGA$ | $I_a$ |
| 12 | $D_s$ | $PGA$ | $CAV$ | $PGA$ |

Table 2: Ranking of the IMs for each Structure

| Rank | Permutation Importance | Partial Derivative |
|---|---|---|
| 1 | $v_{rs}$ | $v_{rs}$ |
| 2 | $S^*$ | $S^*$ |
| 3 | $E_{inp}$ | $FIV$ |
| 4 | $Sa_{avg}$ | $Sa_{avg}$ |
| 5 | $FIV$ | $SI_{a,v,d}$ |
| 6 | $SI_{a,v,d}$ | $d_{sq}$ |
| 7 | $d_{sq}$ | $S_{N1}$ |
| 8 | $S_{N1}$ | $D_s$ |
| 9 | $I_a$ | $E_{inp}$ |
| 10 | $CAV$ | $I_a$ |
| 11 | $D_s$ | $CAV$ |
| 12 | $PGA$ | $PGA$ |

Table 3: Ranking for the IMs for an ANN with Structural Input

## CONCLUSION

The search for a suitable seismic intensity parameter has occupied earthquake engineers for several years. In the process, the IMs developed became more and more complex and were increasingly developed only for specific building classes. The use of ANNs instead of linear models has been increasingly investigated in recent years. The higher accuracy of these could also be shown in this work. By applying sensitivity analysis to ANNs, a statement can be made about the weighting of the IMs within the input data of the ANNs. Different methods of sensitivity analysis for ANNs were applied and the results were compared, showing that in all methods the IM Root Squared Velocity receives the best ranking. A larger dataset of IMs as well as structural parameters will be investigated for further studies.

Both sensitivity Approaches have its advantages. The partial derivative approach allows, compared to Garson's methodology (Ghanizadeh et al. 2020) the application to ANN with two hidden layers. This ANN design allows a more robust interpretation of the problem. The permutation impotence in comparison can be applied to any other model and is due to this, widely used and accepted.

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