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Prediction of Peak Ground Acceleration by Artificial Neural Network and Adaptive Neuro-fuzzy Inference System

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Abstract

An attenuation relationship model belonging to a region with a high earthquake hazard is important. It is used for engineering studies to know how the peak ground acceleration (PGA) value depends on the distance where there are no stations. This study used earthquakes with magnitudes greater than 4 that IzmirNET recorded between 2009 and 2017 to determine the PGA through an artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS), which are widely applied in engineering seismology studies. For this purpose, 2925 records from 62 earthquakes were analysed in the ANN and ANFIS applications. Magnitude, focal depth, hypocentral distance (Rhyp), and site conditions comprise the inputs, and PGA values are the outputs. Using the Karaburun earthquake, we compared the ANN and ANFIS models using different ground motion prediction equations (GMPE) and the appropriate criteria. We determined the proximate values to PGA values measured at IzmirNET stations of the Karaburun earthquake, which was $M = 6.2$ in 2017, were used to test the ANN and ANFIS. The results were examined and indicated that the ANN and ANFIS are good candidates for obtaining PGA values for future earthquakes in the studied area. In addition, the PGA values of subsequent earthquakes can be calculated more quickly without any preliminary evaluation using an ANN and ANFIS.

Keywords: Peak ground acceleration (PGA); Artificial neural network (ANN); Adaptive neuro-fuzzy inference system (ANFIS); Ground motion prediction equations (GMPE); Izmir-Western Turkey

1. Introduction

It is essential to know the properties of earthquake ground motion for engineering design and construction. PGA analysis is one of the commonly used approaches to estimate ground motion parameters for seismic hazard assessment. The PGA is used to define the behaviour of the ground motion at the time of the earthquake. Generally, regression analysis estimates PGA values using earthquakes that have already occurred in the region. Using Ground

Motion Prediction Equations (GMPEs) in PGA estimations has some advantages and disadvantages depending on certain assumptions based on parameters. GMPEs give an estimated PGA instead of the actual PGA value in places with no station network. However, these estimations based on different parameters determined by regression analysis may give inaccurate results in terms of using some ambiguous parameters while giving the distance-dependent PGA value. In regression analysis, PGA is usually calculated as a function of independent variables such as hypocentral or epicentral distance, magnitude, local site conditions, path, and fault type [Douglas 2003]. As an evaluation process, these independent variables cause to describe the source parameters of ground motion, both physical properties and some uncertainties arising from the calculation. The coefficients of the regression equation are directly affected by the heterogeneity of the independent variables. For these reasons, GMPEs have some limits in predicting the PGA values. Therefore, different techniques and methods have been applied to overcome the deficiencies in PGA estimation. To close the gap in this area, many researchers have begun applying artificial neural networks to earthquake engineering for seismic risk assessment.

Artificial neural networks (ANNs) are one of the nonlinear data tools used for modelling complex relationships between inputs and outputs. As an ANN is not defined as a form of a particular equation, it can find solutions or investigate relationships among nonlinear and complex interactions of variables given as input and output datasets. The actual dependence is established in an ANN directly from the data and can be used as a model for the selection of simple functional forms [Pozos-Estrada et al. 2014; Thomas et al. 2016]. ANN studies are also widely used to manage the Earthquake Early Warning System and the seismic risk studies, particularly emergency management and hazard preparedness [Panakkat and Adeli, 2008; Adeli and Panakkat, 2009; Rafiei and Adeli, 2017]. Kaftan et al. [2017] applied an ANN and ANFIS to process earthquake catalogue data of Western Turkey.

Derras and Bekkouche [2011] applied an ANN to predict PGA values using the KiK-net seismic database in Japan. They also applied GMPEs to the same data set to compare the results obtained from two methods. Kerh and Ting [2005] estimated PGA at the railway line in Taiwan by using different combinations of epicentral distance, earthquake magnitude, and focal depth of the input layer and compared their results to microtremor measurements. Güllü and Erçelebi [2007] used strong motion data on Turkey to define attenuation relationships with an ANN. García et al. [2007] developed the ANN model in the Mexican subduction zone using magnitude, epicentral distance, and focal depth as input parameters. Pozos-Estrada et al. [2014] also studied to determine PGA and pseudo-spectral accelerations with Mexican subduction earthquakes. Günaydın and Günaydın [2008] applied three different ANN models to determine the PGA values by taking advantage of the earthquake records in the Marmara Region. Derras et al. [2012] used the ANN model on earthquake data from Japan's KiK-net using moment magnitude, epicentral distance, time-averaged shear wave velocity, fundamental frequency, and focal depth as input parameters. In addition to ANN studies in predicting PGA, ANFISs also have been applied for the same purpose. ANFISs combine the learning abilities of an ANN and the reasoning abilities of fuzzy logic to provide enhanced prediction abilities in Thomas et al. [2016]. An ANN and a randomized adaptive neuro-fuzzy inference system (RANFIS) were used for predicting the parameters of ground motion as PGA, PGV (peak ground velocity), and PGD (peak ground displacement). Ahumada et al. [2016] used recent earthquake records from the USA and Taiwan with magnitudes of 5 or greater to derive attenuation relationships for PGA with fuzzy logic. Raghucharan et al. [2019] applied an ANN to predict ground motion model for the Himalayas and Indo-Gangetic plains. Das and Chakraborty [2021] developed an ANN models for predicting one of the important ground vibration parameter, PGA, besides the peak particle velocity (PPV).

This study aims to develop the PGA estimation models for Western Turkey by using ANN and ANFIS methods. Magnitude, distance, site conditions, and the focal depth of the earthquakes recorded by IzmirNET [Gok et al., 2014] were used as inputs to predict PGA. To evaluate the performance of the ANN and ANFIS in predicting PGA, the dataset of the Karaburun earthquake was used as test data. Also, the obtained results of the two methods were compared with the results of the classic GMPE approach. The results of all datasets showed that the ANN and ANFIS gave reasonable solutions in predicting PGA for Western Turkey. The obtained results indicate that the ANN can catch the trend of the recorded PGAs. This approach seems to be a promising alternative to describe earthquake events despite the limited observations and qualitative information of geotechnical site conditions of the recording stations, which leads to the reasoning of a partially defined behaviour.

2. IzmirNET strong-motion network

The data used in this study was recorded by IzmirNET in Izmir and its environs. Figure 1 shows the study area included using earthquakes and stations. The IzmirNET strong-motion network consists of 19 stations equipped with three-component digital accelerometers. The study dataset consists of 2925 records. The hypocentral distances for the selected records vary between 10 km to 400 km, and only events with a moment magnitude $M_w \geq 4$ are considered. The distribution of the data concerning the focal depth, hypocentral distance, and moment magnitude (M_w) is given in Figure 2. Values of moment magnitudes are mostly changed between $M_w = 4$ and $M_w = 5.3$. The depth of the events ranged from very shallow to about 30 km. The greatest event occurred on July 20, 2017 ($M_w = 6.5$; depth = 19.44 km) and the other events were selected to include a broad spectrum of cases in the testing database.

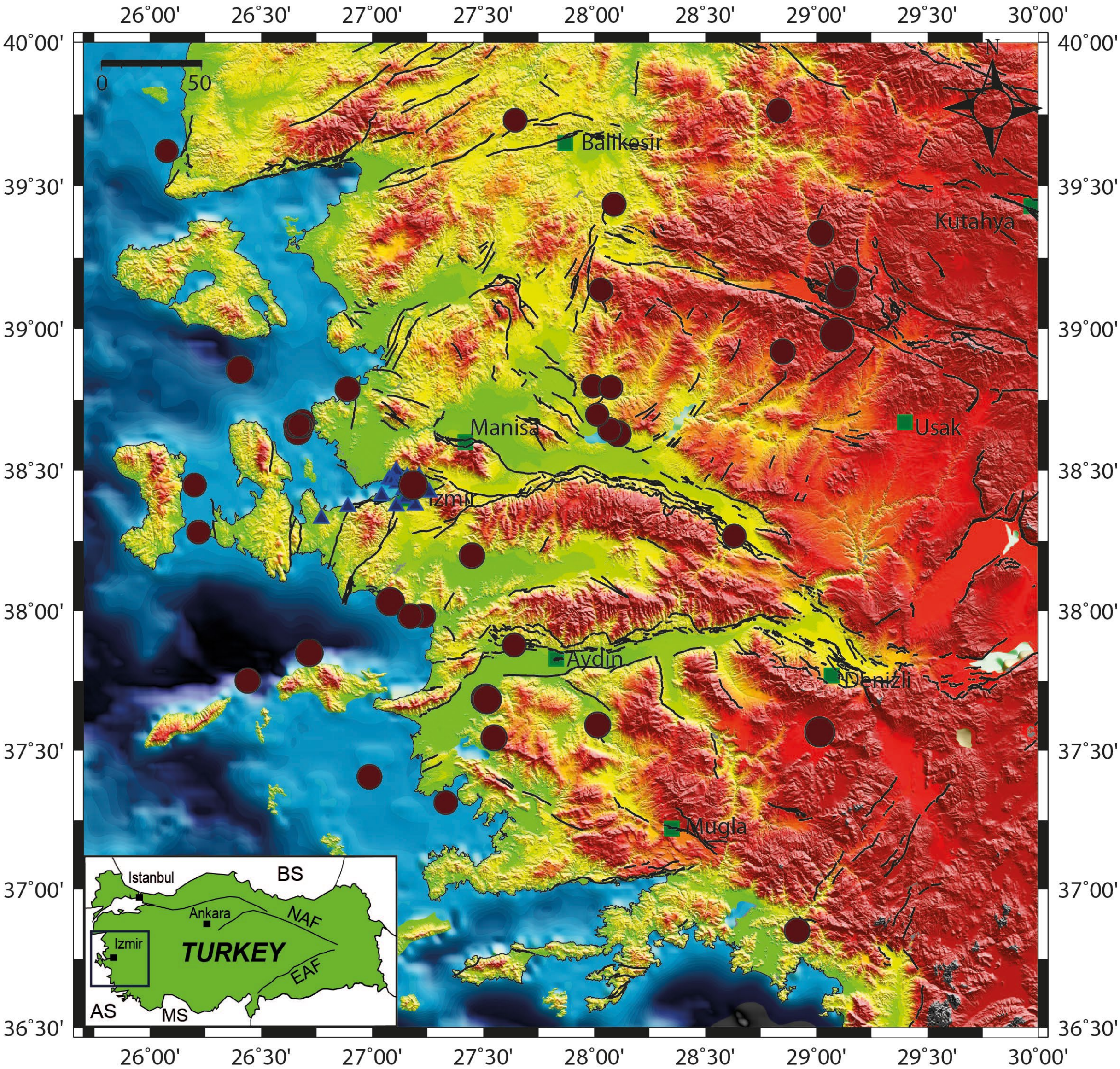

Figure 1. Topography and principal tectonic units of Western Anatolia. The stations of IzmirNET are shown with solid blue triangles. Epicenter of the events analyzed in this study were indicated by solid circles. Provincial centers in the surrounding area are also indicated on the map. (Inset Map: box denotes the study area and AS: Aegean Sea; BS: Black Sea; MS: Mediterranean Sea; NAF: North Anatolian Fault; EAF: East Anatolian Fault). This image is created using GMT software [Wessel et al., 2013].

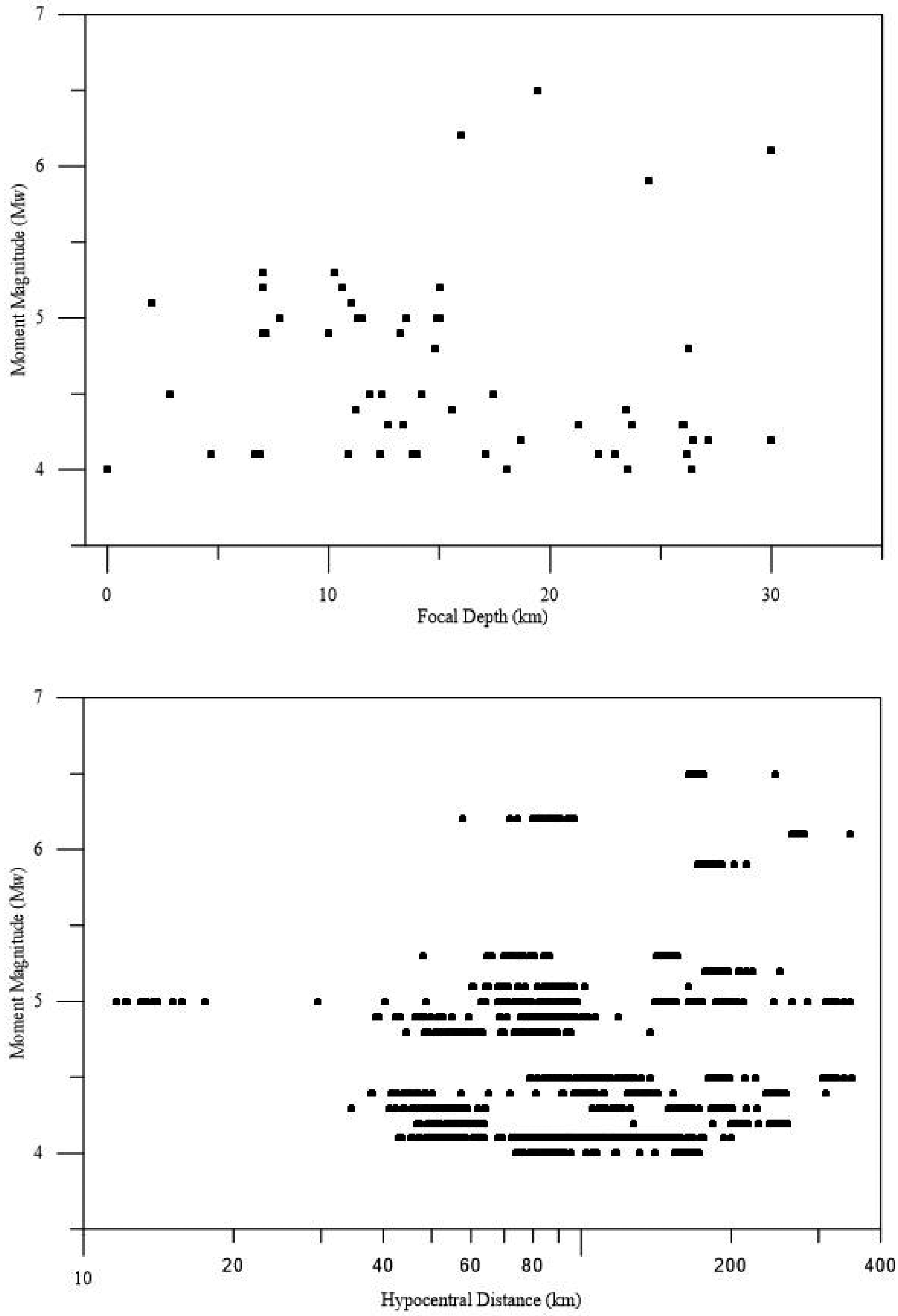

Figure 2. Distributions of the IzmirNET data used in the present study as a function of (a) moment magnitude (Mw) and focal depth and (b) moment magnitude and hypocentral distance.

3. Materials and methods

3.1 Artificial neural network (ANN)

An ANN, popularly known as a neural network, is a computational model that has been created with inspiration from biological neural networks. The fundamental unit of computation in an ANN is called a neuron, a node, or a processing element.

A multilayer perceptron neural network (MLPNN) is one of the most applied neural networks and has many application areas ranging from medicine to engineering. The network comprises an input layer, one or more hidden layers, and an output layer. Synaptic weights provide the connections between all the network components. A backpropagation algorithm regulates the mentioned weights to get a nonlinear mapping. The output of the j^{th} neuron in the hidden layer is given by:

$$y_j = f\left(v = \sum_i^N w_{ji} * x_i + b_j\right) \tag{1}$$

where x_i represents the input vector, w_{ji} shows the synaptic weight between the input i and the neuron j, y_j represents the output of the j^{th} neuron, b_j is called as bias, and $f(v)$ shows the activation function. The sigmoid and the hyperbolic tangent functions are the most preferred activation functions in ANN applications. The sigmoid function is given as:

$$f(v) = \frac{1}{1 + e^{-\alpha v}} \tag{2}$$

where α is the slope parameter of the function each neuron in the network generally includes a nonlinear differential activation function.

A supervised neural network – MLPNN is one of the well-known ANN types – is trained with the input and matching output set. The backpropagation algorithm for training the network is based on the steepest descent gradient method applied to minimize a defined energy function related to the instantaneous error between the actual and desired output. The energy function to be minimized can be given as:

$$E_k = \frac{1}{2}(d_k - y_k)^T(d_k - y_k) \tag{3}$$

where d_k shows the desired network output vector for the k^{th} input pattern and y_k represents the actual output vector for the k^{th} input pattern of the MLPNN given by Figure 3. The learning rule for a network weight adaptation in any one of the network layers using the steepest-descent gradient approach is given by:

$$\Delta w_{ji}^{(s)} = -\mu^{(s)} \frac{\partial E_k}{\partial w_{ji}^{(s)}} \tag{4}$$

where μ represents the learning rate parameter, which is greater than zero, $s = 1,2,3$ gives the corresponding layer numbers, $\Delta w_{ji}^{(s)}$ determines the difference between the current and previous weight for the corresponding layer s. For the obtained weight formulations [Haykin, 1994; Ham and Kostanic, 2000], the network is trained until it reaches a predetermined accuracy level to produce correct responses for the training patterns. A separate data set is applied to the network after the training phase to test the network's performance.

3.2 Adaptive neuro-fuzzy interference system (ANFIS)

Jang [1993] developed ANFIS in the early 1990s. This method has been applied in various fields, from chaotic time series to signal processing studies. The developed ANFIS model generally uses the hybrid learning algorithm. It takes advantage of both structures as it integrates ANN and a fuzzy logic inference system. ANFIS can be accepted as a basis for generating a set of fuzzy if-then rules with proper membership functions to generate the stipulated input-output pairs. In this study, a hybrid learning algorithm was applied for fuzzy inference system parameter identification. A given dataset is emulated for training fuzzy inference membership function parameters by combining the least-squares and the backpropagation gradient descent methods.

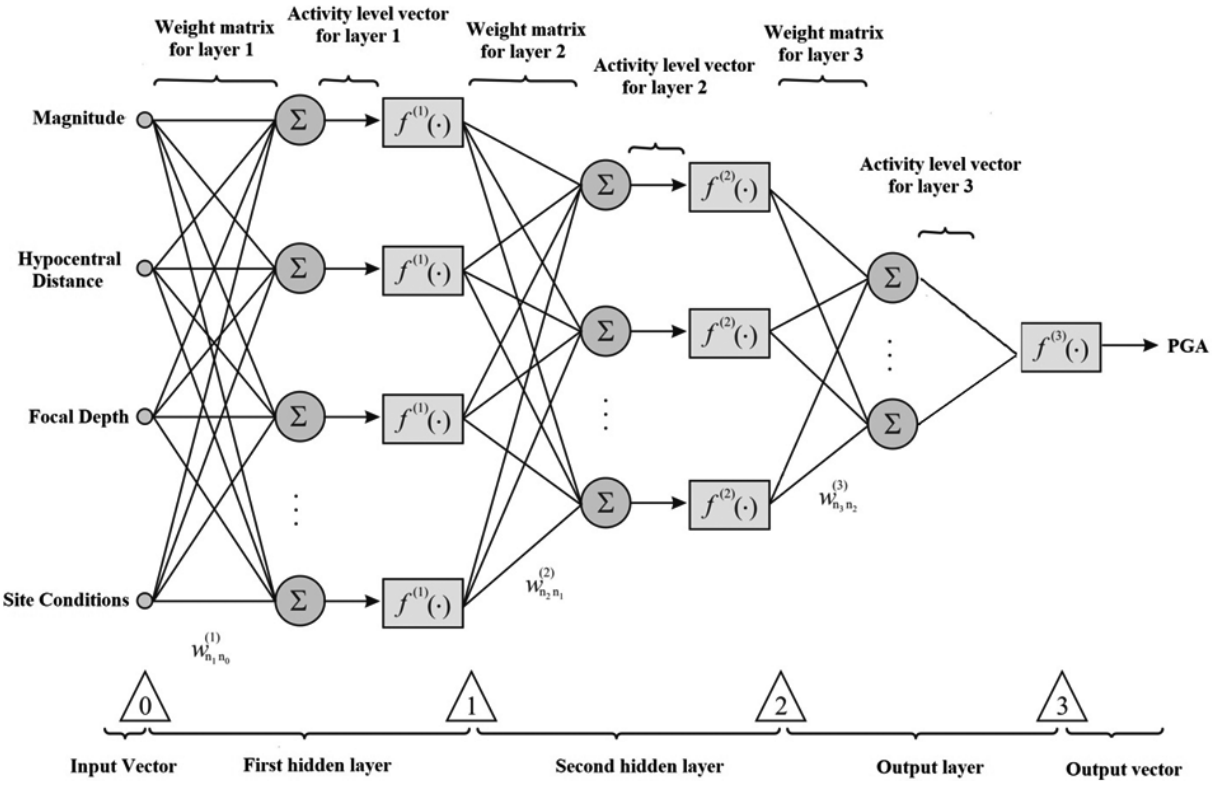

Figure 3. Multi-Layer Perceptron Neural Network structure.

3.3 Applications of ANN and ANFIS

This study developed ANN and ANFIS models to predict the PGA for Izmir and its surroundings. For this purpose, earthquake magnitude, focal depth, hypocentral distance, and site conditions are used as input parameters to develop the PGA prediction model. The first variable is the moment magnitude of the earthquakes, and the range of M_W is from $M_W = 4$ to $M_W = 6.5$. The second variable, hypocentral distance, ranges from 10 km to 400 km for this study. The focal depth of the recorded earthquakes changes between 5 km to 30 km as the third variable for this study. All events were recorded at alluvial deposits, sandstones-mudstones, limestones, and volcanic-andesite [Gok et al. 2014]. Therefore, four site condition classes were used as a defined rock (site-A), stiff soil (site-B), soil (site-C) and soft soil (site-D) as the fourth variable.

The 2925 records of IzmirNET stations were divided into two parts: 80% for training (corresponding to 2340 records) and 20% for testing. The optimum network structure for ANN training sessions was obtained after trying a different number of hidden layers. Various combinations were also applied to find the optimum number of neurons in these layers. After these experiments, the optimum network structure was determined to be an ANN with two hidden layers consisting of 50 and 20 neurons, respectively. The most reasonable result was obtained for the learning rate parameter 0.01. To evaluate the accuracy of the obtained results, the correlation coefficients and network error were analyzed. The correlation coefficient (R) is defined as:

$$R = \frac{\sum_{i=1}^{N}\left(X_i - mean(X)\right) - \left(Y_i - mean(Y)\right)}{\sqrt{\sum_{i=1}^{N}\left(X_i - mean(X)\right)^2 \sum_{i=1}^{N}\left(Y_i - mean(Y)\right)^2}} \tag{5}$$

where X_i represents the observed PGA value at the i^{th} record, Y_i is the predicted PGA value at the i^{th} record, and N is the total number of records. As shown in Figure 4 for ANN applications, the correlation coefficients between observed and predicted PGA values for training and test sets are obtained as 0.7859 and 0.7761, respectively.

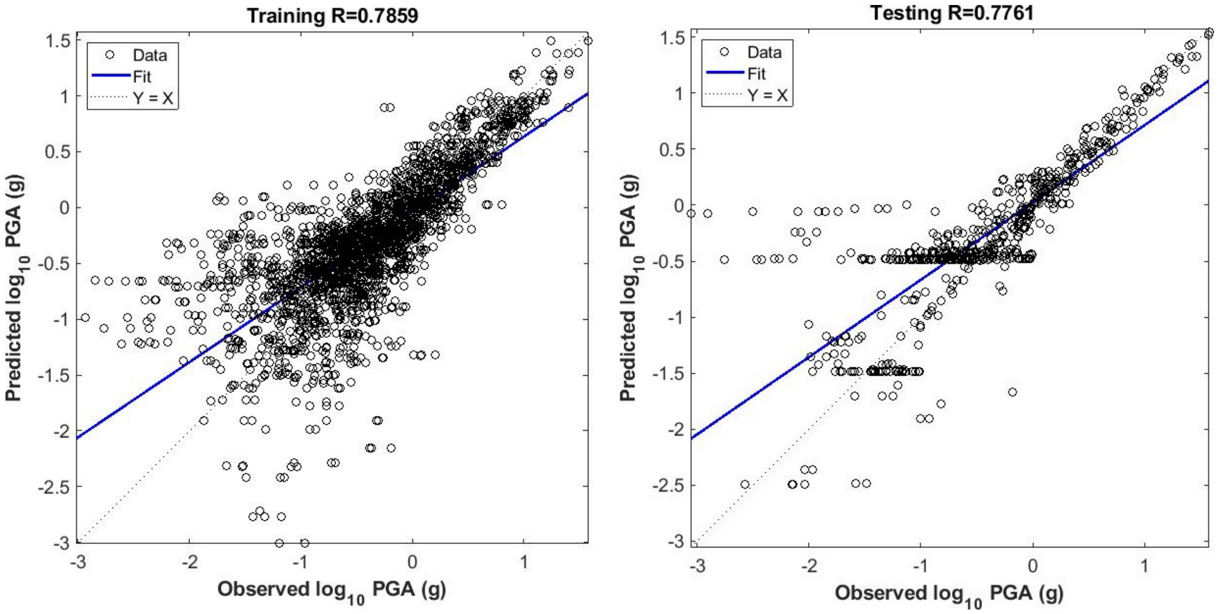

Figure 4. Observed versus predicted PGA (g) relationships by the ANN model during training, and testing data sets. The diagonal dotted line (Y = X) indicates the ideal fit condition.

Similar to ANN applications, the same training and test data set was used to estimate PGA values in the ANFIS model. As in the previous stage, we used four input parameters to apply to the ANFIS model. These are magnitude, hypocentral distance, focal depth, and site conditions. The same dataset used in previous steps was figured out by using various membership functions. Along the training process, different numbers of rules were tried, and the best results were estimated with two. The triangular membership function yielded more satisfactory results than the other membership functions. Similarly, the accuracy of the obtained results is analysed with the correlation coefficients (equation 5). The reasonable results for training and test set are obtained as 0.7552 and 0.7426, respectively (Figure 5).

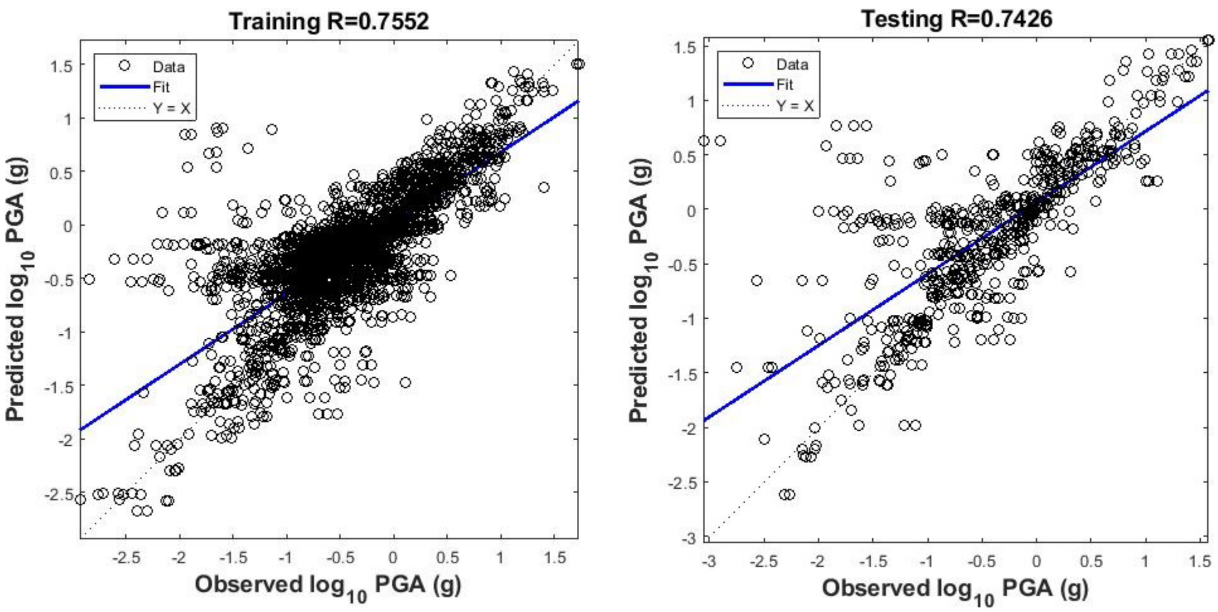

Figure 5. Observed versus predicted PGA (g) relationships by the ANFIS model during training, and testing data sets. The diagonal dotted line (Y = X) indicates the ideal fit condition.

The root mean square error (RMSE) is calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Y_i - X_i)^2}{N}} \tag{6}$$

where X, Y, and N show observed PGA value at the i^{th} record, the predicted PGA value at the i^{th} record, and the total number of records, respectively. RMSE values between observed and predicted PGA values for training and test sets are obtained as 0.4235 and 0.5726 according to ANN results. In the ANFIS applications, RMSE values for training and test set are obtained as 0.4765 and 0.6091 (equation 6).

It can be said that the ANN gives comparatively higher correlation coefficient values with a reasonable error percentage. When the acquired results are examined, both an ANN and ANFIS can be successfully applied to estimate PGA (Table 1).

Models	RMSE		R	
	Training	Testing	Training	Testing
ANN	0.4235	0.5726	0.7859	0.7761
ANFIS	0.4765	0.6091	0.7552	0.7426

Table 1. RMSE and correlation coefficient (R) ratios of the training and testing results of the ANN and ANFIS models.

4. Results and discussions

We compared our results of ANFIS and ANN methods to six different GMPEs. The reasons for choosing them are the similarity of magnitude ranges, distance, or study area. To analyze the ANN and ANFIS applications, the Karaburun earthquake was used as test data to estimate PGA values for all site types. The GMPEs proposed are from Ambraseys et al. [1996], Sadigh et al. [1997], Lussou et al. [2001], Berge-Thierry et al. [2003], Kalkan and Gülkan [2004], and Akyol and Karagöz [2009]. GMPEs from Ambraseys et al. [1996] were derived from Europe, Middle East database that lower limit of magnitude is equal to 4.0, last 200 km for distance, and use four site conditions at first but retain three. The second model was proposed by Sadigh et al. [1997]. It is the same as Ambraseys et al. [1996] regarding distance dependence and magnitude, but its region is the Western USA (United States of America) and used rock and deep soil as site condition parameters. GMPEs from Lusso et al. [2001] were derived from the Japanese Kyoshin network and used magnitude and hypocentral distance ranges between 3.5 and 6.3 and 10 km and 200 km, respectively. This model uses four site classes that are defined by the shear-wave velocity in the uppermost 30 m. Berge-Thierry et al. [2003] operated with European and US data to obtain a ground motion model using $4.0 < M_s$, hypocentral distance 4 < Rhyp < 330 km, and site condition parameter rock and alluvium. Kalkan and Gülkan [2004] studied Turkish data with a magnitude greater than 4, a Joyner-Boore distance [Joyner and Boore, 1993] range of 1 < Rjb < 250 km, and three site classes to define the region. The ground motion model of Akyol and Karagöz [2009] is the most appropriate study of the parameters that we should express in our study area. For the regression analysis, they selected earthquakes from Western Anatolia with four site classes, a magnitude greater than 4, and hypocentral distances ranging between 15 km and 200 km.

Figure 6 compares six fitted relationships to PGA data from the strongest earthquake of the study area recorded on site A and site D, five fitted curves on sites B and C. The earthquake that occurred on 12.06.2017 at 12h28 is called the Karaburun earthquake. The depth and moment magnitude of the Karaburun earthquake are $h = 15.9$ km and $M_w = 6.2$, respectively, and it has a normal faulting mechanism. Source parameters of the Karaburun earth-

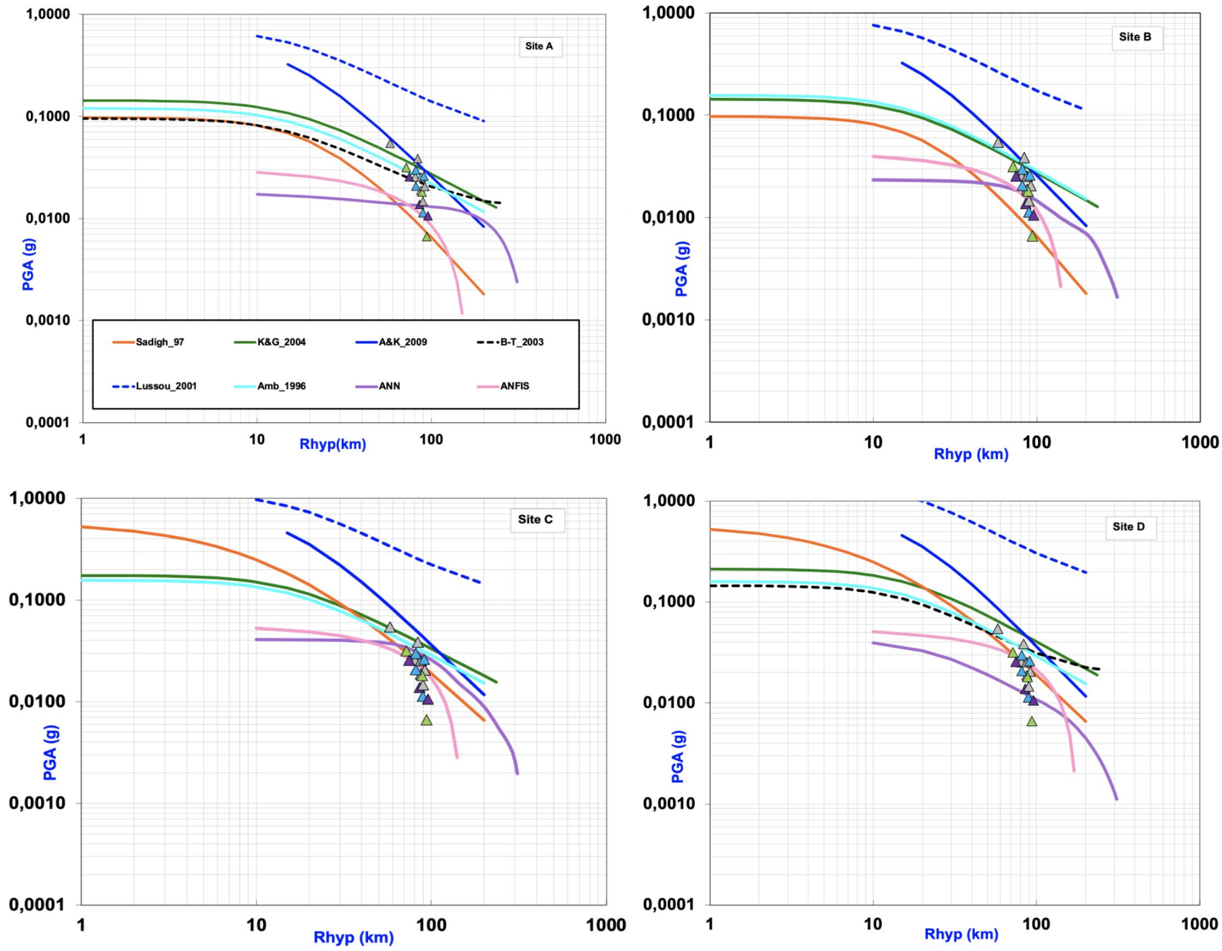

Figure 6. Investigation of 12.06.2017 12h28, Mw=6.2 Karaburun Earthquake to compare the GMPEs, ANN and ANFIS (purple and pink curves, respectively) results for different sites. GMPE abbreviations are Sadigh_97: Sadigh et al. 1997, K&G_2004: Kalkan and Gülkan 2004, A&K_2009: Akyol and Karagöz 2009, B-T_2003: Berge-Thierry et al. 2003, Lussou_2001: Lussou et al. 2001, Amb_1996: Ambraseyyes et al. 1996.Different colored triangles represent different stations which are deployed various site conditions; purple triangles indicate volcanic-andesite, green ones indicate limestones, blue triangles indicate sandstones-mudstones, and gray triangles indicate alluvial deposits (Gok et al. 2014).

quake are taken from the Disaster and Emergency Management Presidency [AFAD, 2017]. The hypocentral distance range of the stations to the earthquake is between 58 km and 96 km.

Theoretical attenuation relationship models and PGA values measured for the Karaburun earthquake were compared. Attenuation relationship models that are used, such as magnitude and distance, are also considered. Selected models can be used for the Karaburun earthquake as a criterion. In terms of size and distance conditions, these models provide the validity conditions of the models. Model graphics in Figure 6, Berge-Thierry et al. [2003] are not included in types B and C, although they are prepared according to five different ground classes. The lines in the graphs are the curves of theoretical attenuation models produced by different authors in different years, as mentioned before. Triangles are the peak acceleration values of the Karaburun earthquake measured by IzmirNET strong-motion stations. The stations are classified in different colors according to the results obtained from the previous studies and the characteristics of the site where they are located [Gok et al., 2014]. The vertical axis represents the PGA values, while the horizontal axis indicates the hypocentral distance.

Site A: It can be seen that the estimation obtained with Lussou et al. [2001] overestimates the response for the event. The other relationship equations closely estimate the PGA of the event. The actual PGA values at stations are shown with triangles. The ANN shows accurate results at this distance and for this site. ANFIS presents coherent results the same as ANN. According to others, the ANN and ANFIS give low PGA values at 10 and 100 km of hypocentral distance. Unlike the ANFIS, which started to decrease after about 100 km, the ANN suddenly dropped after 200 km.

Site B: For this site, the condition results of the ANN and ANFIS are higher than expected for rock the site. When the equation of Lussou et al. [2001] gives exaggerated results, the relationships of the ANN and ANFIS approach other GMPEs. They are also compatible with the real PGA of the earthquake.

Site C: The PGA values measured for this site are below the theoretical models. However, studies with the ANFIS and ANN are more reflective of actual PGA values.

Site D: In this type of site, however, the measured values for the Karaburun earthquake are less than the theoretical values. The ANFIS results are closer to actual values, whereas the ANN has a lower model in D type.

As observed in the four graphs, the actual PGA values measured are well below the theoretical models. The six attenuation models tested give more exaggerated results than the actual PGA values measured by the seismic network. However, the values obtained using the ANN and ANFIS reflect more realistic results. Based on these results, PGA values for the Karaburun earthquake measured by the IzmirNET accelerometer network established in the Izmir settlement area and the ANN and ANFIS results are more sensitive and accurate than theoretical models.

If the PGA values used in earthquake hazard studies are to be used according to the distances of the earthquakes that occur in and around Izmir, the above relations from the ANN and ANFIS can be used. These results need to be tested in different earthquakes in the case of larger magnitudes and earthquakes nearer to earthquake stations. The model derived from Western Anatolia also gives closer solutions.

5. Conclusions

GMPEs provide empirical relationships between ground motion intensities and magnitude, epicentral or hypocentral distance, site characteristics, etc. Generally, unknown coefficients of the earthquake parameters are calculated by regression analysis at process of GMPEs. With the increase in seismic stations and the sensitivity of the earthquake parameters, the regression models have become more complex to explain the variables. For this reason, the suitability of the selected parameters and the interpretability of the obtained results are of significant value.

In this study, PGA values belonging to the region were recorded using the ANN and ANFIS and records of earthquakes with a magnitude of 4 and above estimated by IzmirNET stations. When the obtained results are examined, it is seen that the determined PGA values are within acceptable error limits. For the two models used in this study, the RMSE and R ratios of both training and test results were examined. The ANN model was found to be more successful than the second model since the correlation coefficient was higher. When we examine the RMSE values, it is concluded that the training and test values of the ANN model are lower than the ANFIS model, and the RMSE is lower. However, the RMSE and R values of both models are very close to each other because of both training and testing studies. This indicates the successful applicability of both models in PGA studies.

With this method, it may be possible to determine the PGA values by using the earthquake records that have already taken place in the region when considering the problems that may arise in the stations or the loss of data. New earthquakes to be added to the dataset and the sensitivity of the PGA values determined by the records of these earthquakes are possible.

The attenuation models of the ANN and ANFIS are completely data-driven and, without any a priori assumption, are generally very close to those detailed with classic methods. The division of sites into learning and test datasets would play a fundamental role in developing such models. These studies testing GMPEs improve the predictive performance of the models.

We observed that the ANN and ANFIS have the potential to predict the attenuation of the earthquakes with distance and the magnitudes of the earthquakes of the Izmir area based on these comparisons. The applicable GMPEs for the study area were examined using data from the Karaburun earthquake that occurred in the area. As a result of the evaluation, when the actual PGA values recorded by the IzmirNET stations and the GMPEs obtained by empirical correlations are compared, we determined that the GMPEs have overestimated the PGA values. However, the results obtained with the ANN and ANFIS are more realistic. Since it is important to get results quickly when an earthquake occurs, these ANN and ANFIS models accelerate the process and get closer to the result.

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