Earthquake Ground-motion Duration Estimation by using of General Regression Neural Network

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Abstract

Accurate prediction of earthquake duration could control seismic design of structures. In this paper, a new simple method was developed to estimate such important parameter by employing artificial neural networks (ANN) capability. A generalized regression neural network (GRNN) as a special class of RBF networks was implemented in this study to reduce the computation steps required for the searching process on sparse data sets. This network with quick-design capability does not need to impose a prescribed form for mapping of the observed data. The independent variables used in the predictive model of this study were earthquake magnitude, distance measure and site conditions. The designed models were trained using the 950 accelerograms recorded at Iranian plateau. The performance of proposed approach was compared with predicted results of feed forward back propagation networks. Analyses show that the designed GRNN performs well in estimating earthquake record duration and could be applied for prediction of common measures of earthquake ground-motion duration.

Keywords: Ground motion duration; significant duration; generalized regression neural network (GRNN), RBF network, Iran

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1. Introduction

Amplitude parameters such as peak ground acceleration or spectral acceleration are mostly-used parameters in the most of seismic design codes. Nevertheless, the duration of strong motions could enlarge the degree of earthquake damage on structures. According to various studies, seismic response of a structure depends on structural framing system and earthquake characteristics including amplitude and duration [1-4]. Ground-motion duration significantly affects ductility measure, the amount of cumulative damage incurred by the structures, dissipated energy [5-6], input energy amount and the level of damage done to a structure. It is noted that the role of duration depends on several factors such as the structural model and damage metric used in the analysis [7]. From geotechnical point of view, duration of input motion is expected to be important in evaluating of seismic response of soil, liquefaction potential and lateral spread displacement resulting from soil liquefaction [8-10]. Ground-motion duration has also an imperative role for assessment of potential losses in future earthquakes as in the HAZUS standardized framework where duration is explicitly taken into account [11-12].

Several researches which have been conducted in the past attempted to obtain the earthquake ground motion duration based on regional (local) predictive equations. These predictive equations which are typically fit into a strong ground motion data by conventional regression methods could be developed for typical definitions of the ground-motion duration. Significant-duration prediction equations based on random-effects regression procedure were proposed by Kempton and Stewart [3] with respect to different parameters: magnitude, distance from site to source, soil site condition and one more factor that reflect near-field effects. The global database of Next Generation of Attenuation (NGA) has been employed by Bommer et al. [2] to present new updated empirical equations. Recently, Yaghmaei-Sabegh et al. [13] have developed a new prediction model by a nonlinear regression analysis based on earthquake ground-motion records obtained in Iran. From basic seismological theory, earthquake record duration depends on the complex fracture-mechanism on the fault plane and seismic wave radiation characteristics. Thus, utilizing of an appropriate physically-based representation for such multifaceted parameter would be very difficult and requires deep understanding about different
parameters that control the ground-motion duration. For this reason, different mathematical functions often in the nonlinear forms have been adopted in literatures. To overcome this concern, the purpose of this paper has been put in developing of a simple tool for estimating the duration of earthquake records. To this end, a simple and efficient framework is designed based on high capability of GRNN neural networks.

By increasing the computational power of engineering software, different computer-based searching algorithms including K-means, genetic programming (GP), artificial neural networks (ANNs) and autoregressive integrated moving average (ARIMA) are vastly used in both seismology and earthquake engineering [14-17]. In this paper, we will show that the nonlinear nature and high fitting ability of a special class of network named generalized regression neural networks (GRNN) make it very suitable particularity while different factors influence the results of prediction. As an advantage for a GRNN, design-decisions about the layers numbers and also unit number of hidden layers could be removed.

The purpose of this paper is an attempt to establish a suitable platform to compare capability of multi-layer feed-forward (MLFF) and GRNN networks for accurate prediction of ground motion record duration as a complex problem in seismology. The need for GRNN implementation for the purpose of this study is demonstrated by presenting the prediction results of back propagation multi-layer feed-forward networks. This paper consists of six different sections. The study of this paper could facilitate a good condition for readers to compare the prediction ability of multi-layer feed-forward neural network and GRNN models for a complex case study in seismology where training data is limited. After the introduction, a description of the artificial neural networks applications in seismology and earthquake engineering is provided in section 2. Theoretical background of implemented network is laid out in this section as well. The section 3 of paper reviews different definitions for ground-motion duration. Results of analysis in training and testing steps are discussed in section 4. This section also includes the details of the ground motion records create the analysis dataset. The prediction ability of MLFF network as the most popular ANN is evaluated and compared in section 5. Different performance evaluation indices named as root mean square error, correlation coefficients and
efficiency factor between estimated and observed dataset were used in the analysis. A summary of conclusions drawn in this study is reported in the final section of paper.

2. Artificial neural networks and applications

Capability of artificial neural network (ANN) for modeling of complex features has successfully been used in the past where conventional linear functions are not able to demonstrate high dimensional inputs. The applications of artificial neural networks as a powerful tool have broadly been evaluated in seismology, earthquake engineering and geotechnical engineering and geosciences.

The first artificial neuron as a binary threshold unit was initiated in 1943 by McCulloch, a neurobiologist, and Pitts, a statistician [18]. An ANN deduces the essential feature of biological neurons and their interconnections, takes different approach to solve a specific problem than that of conventional algorithmic computer which follows a set of instructions in order to problem-solving. Neurons (or cells) supply parallel processing nature of artificial neural networks to solve a complex problem [19]. Each neuron is responsible to carry out the received impulses from input cells to the other cells. Neural networks are able to learn during training process to achieve the generalization ability which is useful for future predictions. In this regards, neural networks could be considered as practical tool for pattern recognition and function approximation applications. Multi-layer feed-forward (MLFF) neural network, referred also as multi-layer perceptron, Kohenen’s self-organizing maps (SOM) and RBF networks are different types of neural networks, normally applied for such problem solving.

In MLFF network which is a most popular ANN architecture, feed-forward style typically are used to form connections among hidden layer neurons with those of input and output layers. The error back-propagation (BP) algorithm as highly popular algorithm for feed-forward networks uses local gradient to reach a minimum value of prediction error. The MLFF has been employed widely in the past researches as a predictor of unknown functional relations for different applications both in seismology and earthquake engineering. Pioneering researches by Dysart and Pulli [20] and Dai and MacBeth [21] were focused on the application of BP-MLFF in regional seismic event classification and identification of seismic arrival types. Application of back-propagation neural network in system identification
(stiffness and damping coefficients) and structural response prediction due to earthquake excitation have been pointed out in the literature [22, 23]. Capability of MLFF neural networks was implemented by Kuzniar et al. [24] to construct response spectra based on mining tremors data. Gentili and Bragato [25] have proposed a BP-MLFF neural network system to forecast the earthquakes location occurred in Italy. The efficiency of neural networks’ for the prediction of earthquake sizes has been evaluated by Asencio-Corte’s et al. [26] according to five databases in Japan. In 2005, peak ground acceleration values are predicted by Kern and Ting [27] in Taiwan by considering MLFF neural networks as a soft computing tool. Ahmad et al. have applied an artificial neural network to develop attenuation relationships for peak parameters as ground acceleration (PGA) [28]. They considered real earthquake data to demonstrate the accuracy of designed network to model local attenuation characteristics. A new application of MLFF neural network for estimating of earthquake record duration in Japan has been presented by Arjun and Kumar [29]. Recently, Liu et al. [30] have applied neural network as a classifier along with wavelet transform for structural damage diagnosis. A feed forward neural network (consist of 3 layers) has been used by Alarifi et al [31] for earthquakes magnitude prediction in northern Red Sea area. As another application, high ability of neural networks has been used to earthquake prediction based on correlated information to earthquake occurrence in the past [32-34].

Panakkat and Adeli [35] proposed a neural network model to provide useful information about events location and time of occurrence for major earthquakes in the California. Despite the wide application of this type of neural networks, there are a number of disadvantages for using of BP-MLFF models. The architecture designing of MLFF neural networks including optimal number of neurons in each of hidden layers is difficult. For lower number of nodes, the network does not reach the right results. In contrast, increasing the number of units increases the number of weights [36] and hence the process time in training step and sometimes it is weakening the generalization ability of the network. Typically, it can take a large number of iteration to converge to the preferred values and consequently require too much time particularly when we need a large-size network.

The feasibility of using of generalized regression neural networks (GRNN) is examined in this article for predicting of earthquake ground-motion duration. More information about RBF and GRNN
networks would be presented in sections 2.1 and 2.2. Details of mathematical theory of neural networks were extensively documented in [37].

2.1 RBF-based models

A radial basis function network (RBF) learns using a supervised training technique and consists of a single hidden layer associated with basis functions modeling a Gaussian response surface. Indeed, RBF network performs a nonlinear mapping when the data embark interior configuration of network. The advanced capability of RBF networks in civil engineering and seismological problems has been shown in estimating design parameters [38], identification and control of structures [39,40], prediction of building interference effects [41], earthquake magnitude prediction [42], seismic data inversion problem [43] in stress- strain approximation of plain concrete [44] and recently for estimating of earthquake occurrence model [45].

2.2 GRNN-based model

A statistical technique "kernel regression" performs a fundamental role in the proceeding core of GRNN which will be used for prediction herein. As a main advantage to traditional regression methods, the GRNN, like kernel methods in general, does not need to impose a prescribed form for mapping of the observed data. In fact, GRNN model is able to construct an appropriate representation based on probability density function of the input data, which facilitates smooth transition amongst different observations [46]. Training time of GRNN which is a memory-based network is short, because the bandwidths of the parameters used in the analysis are simply deliberated [47] and therefore the precise setting is not needed [48]. A typical architecture of GRNN is revealed in Fig. 1 which consists of four layers. The input and output layers in GRNN are similar to the most of neural networks. However, there is not any computational role for the neurons of input layer in this type of network where data are simply passed to the pattern layer units. Pattern and summation layers are two computational parts of GRNN that complete the structure of GRNN. Neurons are assigned for all of training data set in the pattern layer to compute the Euclidean distance based on the center point position of neuron. Finally, the RBF kernel function has been applied in this processing layer. The summation layer contains two neurons; S-summation and D-summation neurons which compute the
sum of weighted and un-weighted outputs, respectively. The summation and output layers produce a normalization of output set.

The predicted target value ( \( \hat{y} \) ) can be deliberated as follow:

\[
\hat{y} = \frac{\sum_{j=1}^{n} y_j \exp[-D(x_i, x_{ij})]}{\sum_{j=1}^{n} \exp[-D(x_i, x_{ij})]}
\]

(1)

where \( y_j \) is the weight connection between the ith unit in the pattern layer and the summation layer, \( n \) is the number of training cases ( \( x_{ij} \) ), parameter \( x_i \) is input value for testing cases and function \( D \) is described as follows:

\[
D(x_i, x_{ij}) = \sum_{i=1}^{p} \frac{(x_i - x_{ij})^2}{2\sigma^2}
\]

(2)

in which \( p \) indicates the units number of each input vector; \( \sigma \) is called “smoothing” or “bandwidth” parameter which affects prediction performance of a GRNN, is frequently calibrated for each model [49]. More information about GRNN model has been illustrated in [48, 50]. The main features of GRNN in function approximation could be summarized as follows

i) the simplicity in design where there is no need to define a learning rule

ii) high performance is often anticipated even based on small amount of data

iii) low cost of CPU processing

iv) removes making decisions step on architectural design of network

It is well to know that like an RBF network, a GRNN model is not able to extrapolate. For this reason, a GRNN designer should be aware about this important subject to control the range of the selected training data used in the analysis.

A review on the past research works illustrates different application of GRNN in seismology and earthquake engineering. The GRNN has been applied to evaluate soil composition based on CPT data by Kurop and Griffin [51]. Hanna et al. [52] used high capacity of GRNN to estimate soil liquefaction potential based on earthquake database of Turkey and Taiwan. In 2011 as an important procedure
in site-specific seismic hazard assessment, a GRRN-based procedure was suggested for site classification [47]. The results of Yaghmaei-Sabegh and Tsang [47] were validated with borehole data that is normally used in the soil classification procedure. Their results revealed high efficiency of GRNN models used for this purpose [47, 53].

3. Overview of different ground-motion duration definitions

As mentioned before, ground motion duration may be involving many variables from source, path and site effects and consequently there is not a general definition for this complex-multifaceted phenomenon among seismologists. Different typical definitions which have been presented for earthquake record duration in the past could be put into three main groups: bracketed-, uniform-, and significant duration.

The bracketed duration measure \( (D_B) \) is the time duration of ground shaking, defined as the time length from the first and last excursions than a picky pre-defined threshold of acceleration [1]. This simple definition is a sensitive measure to the acceleration threshold and can be unstable in some cases [1]. It should be noted that bracketed duration has been used by different researchers, taking into account different level of acceleration as a threshold [2, 54, and 55].

Uniform duration \( (D_U) \) is measured as the sum of numbers of discrete time intervals at the points that acceleration is greater than a pre-defined threshold. It is noted that, the sensitivity of this definition is less compared with bracketed duration. Figures 2 to 4 demonstrate the acceleration time history, bracketed and uniform duration for a destructive earthquake occurred at Tabas, northeast of Iran (recorded at Deyhook station).

Finally, significant duration \( (D_S) \) as an energy-based measure describes a continuous time window which is defined based on two pre-defined Arias intensity thresholds. The significant duration illustrates the time interval of ground motions time history that main part of input energy impose to the buildings and is more stable than the bracketed and uniform duration measures. For these reasons, two generic measure of this definition are used in the prediction procedure of this research as the time
intervals of Arias Intensity between 5-95% and 5-75% (\(D_{5-95\%}\) and \(D_{5-75\%}\)). Fig 5 represents these two common measures of significant duration for the selected record at Deyhook station.

4. Estimating of earthquake ground-motion duration

4.1 Model development

The primary step to design a GRNN model is to provide a suitable large database used in learning and testing process. The ground motion records applied in this work corresponded to 950 ground motion records obtained at important earthquakes occurred in Iran, provided by Building and Research Center (BHRC). A review of the historical earthquakes in Iran demonstrates this fact that Iran has been located in one of the world’s seismic-belt which has experienced many large events in the past long years [56].

Updated database of this paper covers the ground-motion duration data, recently used by Yaghmaei-Sabegh et al. [13] for developing of a new predictive model in Iran. The overall range for moment magnitude in the dataset is 3.75 to 7.7 with closest site-source distance ranged from 1.5 to 370 km. Figures 6 and 7 demonstrate the magnitude of earthquakes used in this study against distance measure along with the location distribution of important earthquakes across the study area, Iran. The total set of 950 values used for the modeling is separated into two data bins. 80% of dataset has been adopted as training set and 20% of data covers testing set of analysis.

In the proposed models, earthquake ground-motion duration parameter is described as a function of three independent variables; earthquake size, distance from source to site and soil type i.e. \(D_s = f(M, R, S)\). Two different models have been presented separately for two generic measure of significant duration (\(D_{5-95\%}\) and \(D_{5-75\%}\)). Closest site-source distance also is used as distance measure herein. Site effect in the proposed duration model is considered based on soil classification scheme adopted in the Iranian seismic design code (Standard 2800). Four soil classes have been defined in this code based on average shear wave velocity which is compatible with site classes in 2003 NEHRP [57]. Dummy variables 0 and 1 are simply used in the prediction process for rock and soil sites, respectively.
4.2. Results

The only factor that needs to be selected to design a GRNN model is the smoothing parameter, affects the predicted value of designed neural network. As a general rule, smoother prediction would be expected when the smoothing parameter is larger. In addition, generalization capability of designed network decreases for small value of smoothing parameter which is not a enviable quality for future predictions. Therefore suitable value of this parameter which is often experimentally determined will play a significant role for design implementation of this type of networks. In this study, different value of smoothing parameter ranging from 0 to 1 was examined and finally based on prediction performance the value of $\sigma = 0.7$ was intended through a calibration process. It is worthy of note that choosing an appropriate value for smoothing parameter will be more important if the number of observation may be small enough for prediction of a complex phenomenon.

The efficiency and robustness of designed networks has been checked based on three statistical indices named as root mean square error, correlation coefficients and efficiency factor. These indices are defined as follow:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (X_i - Y_i)^2}{N}}$$  \hspace{1cm} (3)

$$R = \frac{\sum_{i=1}^{N} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{N} (X_i - \bar{X})^2 \sum_{i=1}^{N} (Y_i - \bar{Y})^2}}$$  \hspace{1cm} (4)

$$EF = \frac{\sum_{i=1}^{N} (X_i - \bar{X})^2 - \sum_{i=1}^{N} (Y_i - \bar{Y})^2}{\sum_{i=1}^{N} (X_i - \bar{X})^2}$$  \hspace{1cm} (5)

In these equations, $X_i$ and $Y_i$ are defined as the observed and predicted values; $\bar{X}$ and $\bar{Y}$ are the mean value of observed and predicted data, respectively [58]. $N$ is the number of data in dataset of analysis.

The three well-known indices which have been used in this study reflect the degree of fit for the
proposed models and could evaluate the ANN output error between the actual and the predicted output. Figures 8 through 11 illustrate ability of designed network with presenting of scatter plots of predicted values against observed values for predictive models of \( D_{s-5-95\%} \) and \( D_{s-5-75\%} \). Observed/estimated = 1 line is also superimposed to the figures. Comparisons of GRNN performance for training and testing dataset are reported in Table 1 as well. It is revealed that the value of the RMSE and EF of \( D_{s-5-95\%} \) and \( D_{s-5-75\%} \) model is close to each other and designed GRNN model could be able to predicate these two parameters almost with similar accuracy. The total residual as another indicator is employed to evaluate the performance of soft computing predictions by GRNN. Fig. 12 and 13 show the residuals scattering for significant durations in logarithmic units \((\text{Ln}(\text{observed}) - \text{Ln}(\text{predicted}))\) based on the predictive models for \( D_{s-5-95\%} \) and \( D_{s-5-75\%} \) against magnitude and distance measures. The spread of residuals in these figures represents the variability of individual data values, which could demonstrate the quality of a predictor. Residuals of the proposed models for \( D_{s-5-95\%} \) and \( D_{s-5-75\%} \) varied in the range of -1.5 to 1 which show less scattering than the predicted results of Bommer et al., models [2]. The residuals for both definition of significant duration do not show any trend with magnitude or distance, which confirm that the fitting procedure is robust and appropriate. Similar conclusion has been made in Bommer et al., work [2] when their suggested functional form was used in the analysis (see Fig 1 and 2 in Ref. 2).

The scatter plot of residuals between the observed and prediction values against soil site conditions has been illustrated in Fig 14. From inspection of this figure same prediction quality could be recognized for rock and soil sites.

A more comprehensive comparison between the different ground-motion duration prediction equations is shown in Fig 15 and 16. In order to get an accurate evaluation and by the way of exploring the validity of predicted values, models prepared in this paper have re-examined by predictions in a specified distance (taken as 30 km) at rock sites for different values of magnitude ranged from 4.5 to 8. Results of predicted values based on recently published empirical relationships by Bommer et al. [2] and Yaghmaei-Sabegh et al. [13] have been superimposed onto these figures. According to Fig 15 and 16 the suggested model is well-matched with those of Bommer et al. and Yaghmaei-Sabegh et al. [2,
which re-confirms the validity of ANN models designed in this paper. However some discrepancy could be observed among three models which might be related to the database size and their different features. Plotting on the logarithmic scale has been adopted for these figures which is consistence with other publications in this path. Fig. 17-a shows the variation of significant duration $D_{s-5.95\%}$ on distance for moment magnitude $M_w = 7$ at rock sites based on the proposed model and Bommer et al. [2] predictions. Good agreement particularly for distance larger than 10km could be observed in this figure. Variation of significant duration $D_{s-5.95\%}$ on moment magnitude for rock and soft sites at a fixed distance measure (R=30 km) has been presented in Fig17-b. This figure may possibly highlight soil effects on earthquake duration for strong earthquakes.

5. Comparative analysis of GRNN and BP-MLFF models

The prediction capability of multi-layer feed-forward (MLFF) network as the most popular ANN is evaluated in this section to show there was a need of developing a GRNN model. The structure of implemented feed-forward neural network has been shown in Fig 18. As already discussed in section 2 of paper, these types of neural networks have been extensively applied in the past, however finding the number of neurons forming hidden layers remains as one of the unsolved tasks in the application of such networks. Neurons number in hidden layers which controls the generalization capability of network plays important role in design of a MLFF. A single hidden layer although with different neurons numbers was used in the analysis to highlights this matter herein. The Kolmogorov’s theorem [59, 60] could be considered as a simple rule (or initial guess) to recommend the neurons number of hidden layer ($NHN$):

$$NHN = 2NIN + 1$$

where $NIN$ is the input neurons numbers. Thus the neurons number in hidden layer based on Kolmogorov’s theorem was taken as $2 \times 3 + 1 = 7$, since there are 3 input neurons. Consequently, the training analysis is started based on 7 units in the hidden layer to learn the target mapping and continued by increasing neurons numbers to 9, 12, 15 and 18. A trial-and-error approach leads to a optimal network architecture. The back propagation (BP) learning scheme [61] that is including two phase of propagation and weight updating was adopted in this study as a common training technique in
ANNs. The Levenberg-Marquardt training process as a variation of the Newton method was followed to train the designed BP-MLFF networks with different architectures. Weights were randomly selected for each training analysis. The tan-sigmoid function has been adopted herein as an activation function of neurons in hidden layer. Training and testing data sets have been chosen similar to GRNN model. Predicted results of designed BP-MLFF models with different processing units have been presented in Fig 19 and 20. Results contain prediction of two common measure of significant duration; $D_{s-5-95\%}$ and $D_{s-5-75\%}$ separately. According to these figures, when there are few neurons (as the ANN configuration of 3-7-1), network could not predict large values of significant duration well. Hence, nonlinear features of function are not modeled by the designed network and the learning process may fail miserably. On the other side, with increasing the neurons number of hidden layer, the prediction capacity is improved but the network loses its ability to generalize.

Similar to GRNN models, the performance of ground-motion duration predictions resulting from training and testing data set are evaluating by the three indices; RMSE, R and EF. Results have been summarized in Table 2, 3 for $D_{s-5-95\%}$ and $D_{s-5-75\%}$, respectively. The maximum values of EF and R along with lowest value of RMSE which have been achieved based on the results of testing data set shows higher generalization ability of networks with 7 and 9 neurons among others. Comparison of Table 2 and 3 with that of Table 1 demonstrates higher performance of GRNN models obviously. This important result could be concluded based on whole of three evaluation indices used in this paper. As an example, efficiency factor (EF) of GRNN model for prediction of $D_{s-5-95\%}$ is 0.78 and 0.74 in training and testing set where the lower corresponding values of 0.53 and 0.51 were calculated for BP-MLFF networks in the best case. Root mean square error increases significantly when the BP-MLFF networks are applied in prediction procedure. It is worth noting that the purpose of this section of paper is not to suggest a suitable structure for a BP-MLFF network. However, the results of BP-MLFF networks confirm that the prediction ability of such networks is very sensitive to the structure of designed network and is lower than then GRNN performance. In this regards, designing and training of various networks to reach satisfactory results are required. As a result, because of the complex nature of earthquake ground-motion duration, prediction for such kinds of data with conventional BP-MLFF
is difficult and requires special care where GRNN as a powerful technique could resolve this problem simply.

6. Summary and conclusions

Improvement of prediction models which are able to relate given ground motion characteristics to the seismological parameters has been known as a very imperative step in seismic hazard analysis. In this article, a new artificial network-based scheme was proposed for estimation of earthquake record duration. A generalized regression neural network (GRNN) were implemented in the analysis and examined for prediction of a multifaceted parameter “earthquake ground motion-duration”. Designed models have been presented for two typical definitions of significant ground-motion duration that were defined based on 5-95% and 5-75% Arias Intensity ($D_{5-95\%}$ and $D_{5-75\%}$). Different models were trained using the 950 ground motions recorded at active tectonic regions of Iran. Results of analysis showed a good fitting with the training and testing records.

Unlike of BP-MLFF network that needs too much convergence time, the time process of designed GRNN in this works is less than 5 second. It should be noted that the speed of convergence in nonlinear least square regression algorithm is depended on the quality of an initial guess for the solution which is not easy in all cases. The proposed method in this paper is able to remove this main shortcoming of conventional method used to develop ground motion prediction (GMPEs) equations. The only parameter that needs to be selected for general regression neural network is the smoothing parameter which plays a significant role to reach an accurate prediction. Different values of this parameter for different models were examined in this study to compare the adaptively of design neural network for general practical application. According the analysis results, the smoothing parameter $\sigma = 0.7$ was the preferred for prediction of earthquake duration in the recommended models.

Based on the results of this paper, the easy-to-use proposed GRNN model is found to be more effective for prediction purpose of a complex parameter in seismology, ground-motion duration. This model could provide more accurate results than the models established based on BP-MLFF networks. The GRNN network gives the best generalization performance when $RMSE$ takes 4.1, 2.68 values for two comment measures of significant duration; $D_{5-95\%}$ and $D_{5-75\%}$, respectively whereas the BP-
MLFF network gives higher values of 6.35 and 4.1. Efficiency factor of GRNN model for prediction of $D_{s-5-95\%}$ is 0.78 and 0.74 in training and testing set, respectively where the lower corresponding values of 0.53 and 0.51 were calculated for BP-MLFF networks in the best case. Finding the number of neurons forming hidden layers of MLFF networks, remains as one of the unsolved tasks in the application of such networks. Therefore, designing and training of various networks to reach satisfactory results are required in the most cases particularly when the nature of data is complex. The comparative results of this article showed that the proposed GRNN model could solve such problem simply and reduce time of analysis as well. Noted that proposed GRNN could resolve unsuccessful prediction of BP-MLFF at long duration, however the predicted duration with GRNN is underestimated for longer observation.

It is worth noting that the main focus of current paper was on capability of artificial neural networks and as a future work, comparison of accuracy of the proposed method with other classical techniques as autoregressive integrated moving average (ARIMA) could be useful.

Acknowledgement

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References


Figures Captions

Fig. 1 A typical architecture for generalized regression neural network

Fig. 2 Acceleration time history of 1978 Tabas ground motion recorded at Deyhook station

Fig. 3 Bracketed duration \((D_{\beta})\) estimated for 1978 Tabas earthquake recorded at Deyhook station

\((\text{Acc}^2\) is the square of the ground acceleration\)

Fig. 4 Uniform duration \((D_{\gamma})\) estimated for 1978 Tabas earthquake recorded at Deyhook station

\((\text{Acc}^2\) is the square of the ground acceleration\)

Fig. 5 significant duration estimated for 1978 Tabas earthquake recorded at Deyhook station \((D_{s-5-95\%})\) and \((D_{s-5-75\%})\) [13]

Fig. 6 Magnitude vs. closest site-source distance of dataset used in this study
Fig. 7 Location distribution of major earthquakes used in this study for the prediction of earthquake-ground motion duration [13]

Fig. 8 Predicted values of significant duration $D_{s=5-95\%}$ versus observed values in training set

Fig. 9 Predicted values of significant duration $D_{s=5-95\%}$ versus observed values in testing set

Fig. 10 Predicted values of significant duration $D_{s=5-75\%}$ versus observed values in training set

Fig. 11 Predicted values of significant duration $D_{s=5-75\%}$ versus observed values in testing set

Fig. 12 The distribution of residuals between the observed and predicted significant duration ($D_{a5-95\%}$) for the proposed model with respect to (a) closest site-source distance and (b) magnitude

Fig. 13 The distribution of residuals between the observed and predicted significant duration ($D_{a5-75\%}$) for the proposed model with respect to (a) closest site-source distance and (b) magnitude

Fig. 14 The distribution of residuals between the observed and predicted significant duration for the proposed model with respect to site conditions

Fig. 15 Comparison of proposed model for significant duration $D_{s=5-95\%}$ at a fixed distance measure (R=30 km) on rock sites

Fig. 16 Comparison of proposed model for significant duration $D_{s=5-75\%}$ at a fixed distance measure (R=30 km) on rock sites

Fig. 17-a Variation of significant duration $D_{s=5-95\%}$ on distance for moment magnitude $M_w = 7$ at rock sites

Fig. 17-b Variation of significant duration $D_{s=5-95\%}$ on moment magnitude for rock and soft sites at a fixed distance measure (R=30 km)

Fig. 18 Architecture of MLFF network used in this study

Fig. 19 Observed values of $D_{s=5-95\%}$ vs. predicted values by BP-MLFF networks with different number of neurons in hidden layer

Fig. 20 Observed values of $D_{s=5-75\%}$ vs. predicted values by BP-MLFF networks with different number of neurons in hidden layer
Table Captions

Table 1 Performance of designed GRNN for predicting of $D_{5\%}$ and $D_{5\%-7\%}$

Table 2 Performance of designed BP-MLFF for predicting of $D_{5\%}$

Table 3 Performance of designed BP-MLFF for predicting of $D_{5\%-7\%}$

<table>
<thead>
<tr>
<th>Duration</th>
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<th>Testing set</th>
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<td></td>
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<td>EF</td>
<td>RMSE(sec)</td>
<td>R</td>
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<td>4</td>
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<tr>
<th>BP-MLFF Topology</th>
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Fig. 1 A typical architecture for generalized regression neural network

Fig. 2 Acceleration time history of 1978 Tabas ground motion recorded at Deyhook station
Fig. 3 Bracketed duration \( (D_b) \) estimated for 1978 Tabas earthquake recorded at Deyhook station \( (Acc^2\text{ is the square of the ground acceleration}) \)

Fig. 4 Uniform duration \( (D_u) \) estimated for 1978 Tabas earthquake recorded at Deyhook station \( (Acc^2\text{ is the square of the ground acceleration}) \)
Fig. 5 significant duration estimated for 1978 Tabas earthquake recorded at Deyhook station ($D_{s-5.95\%}$ and $D_{s-5.75\%}$) [13]

Fig. 6 Magnitude vs. closest site-source distance of dataset used in this study
Fig. 7 Location distribution of major earthquakes used in this study for the prediction of earthquake-ground motion duration [13]
Fig. 8 Predicted values of significant duration $D_{4.5-95\%}$ versus observed values in training set

Fig. 9 Predicted values of significant duration $D_{4.5-95\%}$ versus observed values in testing set
Fig. 10 predicted values of significant duration $D_{t-5-75\%}$ versus observed values in training set.

Fig. 11 predicted values of significant duration $D_{t-5-75\%}$ versus observed values in testing set.

a)
Fig. 12 The distribution of residuals between the observed and predicted significant duration ($D_{m-95\%}$) for the proposed model with respect to (a) closest site-source distance and (b) magnitude.
Fig. 13 The distribution of residuals between the observed and predicted significant duration ($D_{\alpha=75\%}$) for the proposed model with respect to (a) closest site-source distance and (b) magnitude.
Fig. 14 The distribution of residuals between the observed and predicted significant duration for the proposed model with respect to site conditions.

Fig. 15 Comparison of proposed model for significant duration $D_{5-95\%}$ at a fixed distance measure $(R=30 \text{ km})$ on rock sites.
Fig. 16 Comparison of proposed model for significant duration $D_{s,5-75\%}$ at a fixed distance measure (R=30 km) on rock sites

Fig. 17-a Variation of significant duration $D_{s,5-95\%}$ on distance for moment magnitude $M_w = 7$ at rock sites
Fig. 17-b Variation of significant duration $D_{s-5-95\%}$ on moment magnitude for rock and soft sites at a fixed distance measure (R=30 km)

![Diagram of MLFF network](image)

Fig. 18 Architecture of MLFF network used in this study
Training data set: R=0.72
BP-MLFF: 3-7-1

Observed
Predicted
Ideal fit

Testing data set: R=0.72
BP-MLFF: 3-7-1

Observed
Predicted
Ideal fit

Training data set: R=0.68
BP-MLFF: 3-9-1

Observed
Predicted
Ideal fit

Testing data set: R=0.66
BP-MLFF: 3-9-1

Observed
Predicted
Ideal fit
Fig. 19 Observed values of $D_{r-5\%}$ vs. predicted values by BP-MLFF networks with different number of neurons in hidden layer.

Fig. 19 continued
Training data set: $R=0.70$
BP-MLP: 3-7-1

Testing data set: $R=0.64$
BP-MLP: 3-7-1

Training data set: $R=0.66$
BP-MLP: 3-9-1

Testing data set: $R=0.65$
BP-MLP: 3-9-1
Fig. 20 Observed values of $D_{p-75\%}$ vs. predicted values by BP-MLFF networks with different number of neurons in hidden layer.
Brief Technical Biography

Samand Yaghmaei-Sabegh obtained his Ph.D. from Iran University of Science and Technology and was awarded the Elite Prize by the university in 2006 and 2007 years. He is currently Associate professor at The University of Tabriz and has been Visiting Scholar at The University of Melbourne, Australia since 2007. He is Member of the Iranian Earthquake Engineering Association. He has published more than 40 technical articles and has won award in the 14th International Conference on Earthquake engineering in 2008 as a young researcher.