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Research paper

Prediction of peak ground acceleration of Iran's tectonic regions using a hybrid soft computing technique

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ABSTRACT

A new model is derived to predict the peak ground acceleration (PGA) utilizing a hybrid method coupling artificial neural network (ANN) and simulated annealing (SA), called SA-ANN. The proposed model relates PGA to earthquake source to site distance, earthquake magnitude, average shear-wave velocity, faulting mechanisms, and focal depth. A database of strong ground-motion recordings of 36 earthquakes, which happened in Iran's tectonic regions, is used to establish the model. For more validity verification, the SA-ANN model is employed to predict the PGA of a part of the database beyond the training data domain. The proposed SA-ANN model is compared with the simple ANN in addition to 10 well-known models proposed in the literature. The proposed model performance is superior to the single ANN and other existing attenuation models. The SA-ANN model is highly correlated to the actual records ($R = 0.835$ and $\rho = 0.0908$) and it is subsequently converted into a tractable design equation.

1. Introduction and background

Peak ground acceleration (PGA) is a well-known engineering parameter of an earthquake, which can be applied to seismic structural analysis and risk assessment. This key element can be predicted using different methods such as physical modeling and on-site investigation (Alavi and Gandomi, 2011). However, implementing such a method is extensive, cumbersome and costly and, most of the time, is impossible (Gullu and Ercelebi, 2007; Gandomi et al., 2011).

An approach to assess the PGA is to use attenuation relationships which play a key role in seismic analysis. They usually formulate the PGA with various independent variables such as distance from the source to site, earthquake magnitude, local site conditions, and earthquake source characteristics (Kramer, 1996; Gullu and Ercelebi, 2007; Gandomi et al., 2011). Developing a correlation between the PGA and the predictors is difficult due to high complexity and nonlinearity.

Soft computing has been widely used to resolve a variety of classification or prediction problems in science, medicine and engineering (e.g. Yaghouby et al., 2010a, 2012). Artificial neural network (ANN) as a commonly used predictor in soft computing mimics the network structure of actual human brain and has been applied to several classification or prediction problems (Yaghouby et al., 2009). This empirical modeling tool has a great capability of adaptively learning from experience and extracting various correlations. This soft computing technique, ANN, has been widely utilized for geotechnical engineering modeling in the last two decades (e.g. Goh, 1994; Azmathullah et al., 2005; Das and Basudhar, 2008; Samui and Sitharam, 2010; Gandomi and Alavi, 2011; Guven et al., 2012; Fister et al., 2014) and have recently been used to predict ground motion characteristics (e.g. Gullu and Ercelebi, 2007; Ahmed et al., 2008; Cevik and Cabalar, 2009; Alavi and Gandomi, 2011; Alavi et al., 2011; Gandomi et al., 2011). A major constraint in application of ANN is the network's tendency to become trapped in local minima (Hamm et al., 2007). To obtain an optimal solution and avoiding this problem, an ANN may be trained using global optimization algorithms (e.g. Das et al., 2011). Ledesma et al. (2007) have recently combined ANN and a well-known derivatively-free global optimization algorithm named simulated annealing (SA) to improve the ANN efficiency. They used a new cooling schedule based on temperature cycling for implementing SA. It was shown that the networks trained using temperature cycling outperformed those trained by the conventional exponential or linear cooling schedules (Ledesma et al., 2007; Alavi and Gandomi, 2011).

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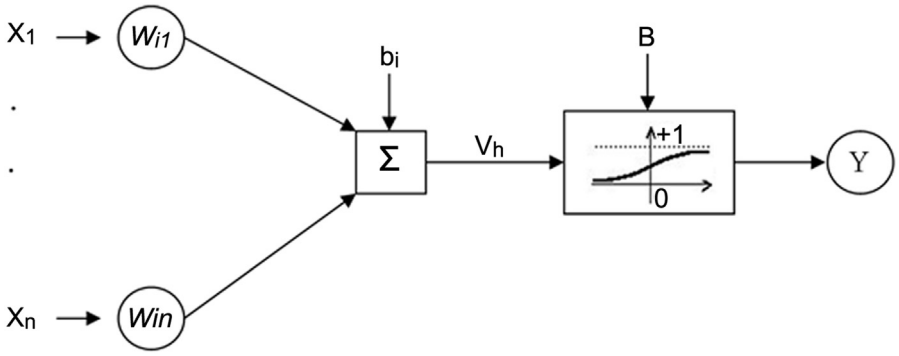

Figure 1. A basic representation of an MLP neural network.

In this study, the SA-ANN technique is used to derive an explicit formula for the PGA. In the hybrid algorithm, SA strategy is used to assign initial starting values to the weights and biases of the network before performing ANN. The SA-ANN system can derive a prediction model for PGA by directly extracting the knowledge contained in the experimental data. An ANN model is usually considered as a black-box system; therefore it cannot be used later. To deal with this issue, the optimal SA-ANN-based model is converted into an explicit equation. The results obtained by the developed model are further compared with those provided by the 10 other models proposed in the literature. The proposed model is developed based on a comprehensive database of strong ground-motion recordings of 36 earthquakes.

2. Methodology

2.1. Artificial neural network

McCulloch and co-workers founded the ANN method in the early 1940s (Perlovsky, 2001). ANNs is a predictive tool to build a mathematical model for an unknown system. Multi-layer perceptron (MLP) ANN (Cybenko, 1989) is the most well-known class of ANNs and usually has feed-forward architectures. The MLPs are usually trained with back-propagation algorithm. The MLP network consists of one input and one output layer, and at least one hidden layer. Each of these layers has a number of nodes and contains processing unit(s) and each unit is fully interconnected with weighted connections (w_{ij}) to subsequent layer units (Alavi et al., 2010). The output (Y) is obtained by passing the sum of the product through an activation function. Fig. 1 shows a basic representation of an MLP ANN. In this figure X_i shows the inputs and b/B shows the biases between different layers.

For complex and nonlinear problems, the hyperbolic tangent function or sigmoid function (or log-sigmoid) can be adopted as the activation function.

2.2. Simulated annealing

SA is a global search algorithm used for solving optimization problems, which makes use of the Metropolis algorithm (Metropolis et al., 1953) for computer simulation of annealing. This algorithm was initially used for optimization problems by Kirkpatrick et al. (1983). SA is very useful for solving nonlinear problems with multiple local optima (Aarts, 1989). When a metal is heated to a high temperature and thereafter it is gradually cooled to relieve thermal stresses is called annealing. The cooling process is simulated by SA to optimize a function in a certain design space. The objective function relates the energy state and moving to any different set of design variables corresponds to changing the crystalline structural state (Gandomi et al., 2013). The abilities and shortcomings of SA are well summarized by Ingber (1993).

2.3. Hybrid artificial neural network-simulated annealing

A hybrid computational approach could be optimized by combining more than one soft computing technique in an efficient way so that the final model would outperform original one in a specific problem (e.g. Yaghouby et al., 2010b; Gandomi and Alavi, 2013). An ANN can be trained from a set of data known as a training set. During the training process, the network's weights are optimized until reaching the stop criteria. The training procedure has two main steps including initialization and optimization (Alavi and Gandomi, 2011). In the initialization process initial values to the weights of the network are assigned. The initial weights can be

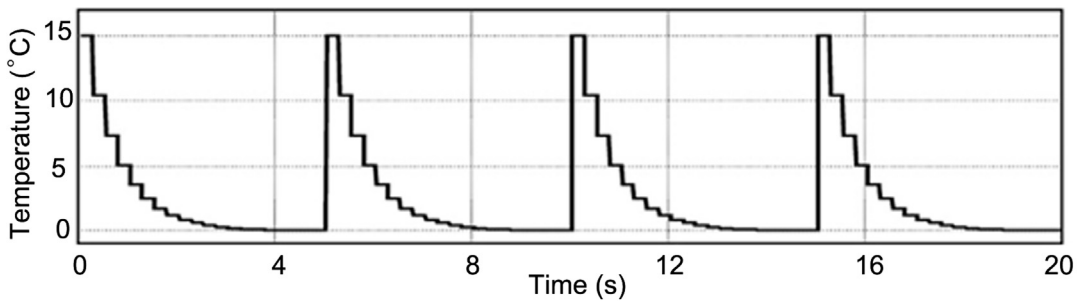

Figure 2. Temperature cycling (after Ledesma et al., 2007).

Table 1
Basic descriptive statistics and normalization values of the variables used in the model development.

Parameter	M_w	R_{Epi}	d_f	V_{s30}	F	PGA
Minimum	5	4	3	165	1	1.45
Average	5.88	56.74	15.33	701.74	1.51	3.8
Max	7.4	188	32	1961	2	6.88
Standard deviation	0.67	33.37	7.74	331.88	0.5	1.14
Normalization value	8	200	35	2200	3	8

assigned randomly or obtained using a powerful global optimization method such as SA. The optimization process is usually a gradient-based algorithm which is suitable for local search. This shows the optimization process requires a starting point obtained from a global search to be successful. Therefore a robust training process needs both the initialization and optimization processes (Ledesma et al., 2007). In contrast with other optimization methods, SA is a global optimization method and does not fall easily into local minima (Ledesma et al., 2007). For the initialization step, SA randomly perturbs the weights of the network during the iterations. When the weights are perturbed, the network performance is evaluated based on the defined objective function. The cooling schedule during iterations can be linear or exponential. Additionally, the cooling schedule may increase the number of iterations at a specific temperature when objective function is improved (Huang et al., 1986). Each time a new solution is generated, the algorithm decides whether the new solution is either accepted or rejected. Metropolis et al. (1953) incorporated the probability of accepting a new solution (P_a) as given below:

$$P_a(\Delta E, y) = \begin{cases} \exp\left(-\dfrac{k\Delta E}{y}\right) & \Delta E > 0 \\ 1 & \Delta E \le 0 \end{cases} \quad (1)$$

where ΔE is error, y is current temperature and k is the acceptance constant. As the temperature decreases, the algorithm is more selective (Ledesma et al., 2007). When implementing SA for the ANN's initialization, the most important factor is adjusting the acceptance constant which is dependent on the temperature range, training set and weight allowed values (Alavi and Gandomi, 2011). Generally cooling schedules start gradually from high temperatures to until a specified low temperature is reached (Luke, 2007). However, the hybrid SA-ANN method needs the temperature to increase and decrease periodically. There are two cycling cooling schedules, linear and temperature cycling. As presented in Ledesma et al. (2007) and Gandomi and Alavi (2011), the temperature cycling cooling schedule can outperform the linear one. Therefore, temperature cycling is used in this study, which is presented in Fig. 2.

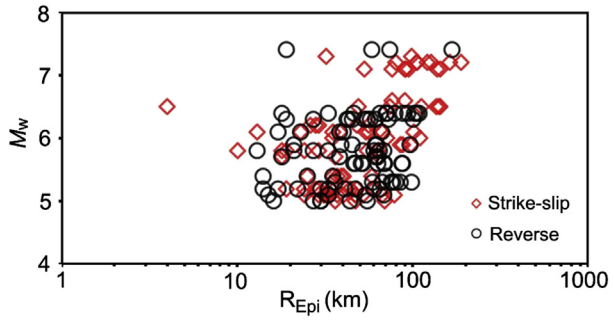

Figure 3. Distribution of the earthquake records of Iran's tectonic regions.

Table 2
Parameters setting of the SA-ANN algorithm.

	Parameter	Value
SA setting	Acceptance constant (k)	1500
	Initial temperature (°C)	15
	Final temperature (°C)	0.015
	Number of levels	5, 10, 15
	Iterations per temperature	25, 50, 100
ANN setting	Activation function	Purelin, log-sigmoid, tan-hyperbolic
	Optimization method	Conjugate-Gradient, Levenberg–Marquardt
	Number of hidden nodes	10-Apr
	Epochs	500, 1000

3. Modeling of peak ground acceleration

The damage potential of an earthquake depends on the PGA and local site conditions (Alavi and Gandomi, 2011). PGA is frequently presented as functions of different seismic variables. The first two parameters are distance from source to site and earthquake magnitude. Advanced attenuation models (Abrahamson and Silva, 2008; Boore and Atkinson, 2008; Campbell and Bozorgnia, 2008) are mainly considered the source to site distance, earthquake magnitude, geotechnical site condition, and faulting mechanism and stress drop, rupture propagation, directivity, and nonlinear soil behavior are not considered as they notably reflect the uncertainties (Cevik and Cabalar, 2009; Gandomi et al., 2011). Soft computing approaches have already been employed in the literature to predict attenuation relationships. The study uses the SA-ANN approach to derive alternative for PGA in Iran's tectonic regions. The most important factors representing the PGA behavior are selected based on a literature review and trial study (Gullu and Ercelebi, 2007; Abrahamson and Silva, 2008; Boore and Atkinson, 2008; Campbell and Bozorgnia, 2008; Cevik and Cabalar, 2009; Alavi and Gandomi, 2011; Gandomi et al., 2011). Consequently, the formulation of PGA (cm/s^2) is considered to be as follows:

$$\ln(PGA) = f\left(M_w, R_{Epi}, d_f, V_{s30}, F\right) \quad (2)$$

where,

M_w: Earthquake magnitude;
R_{Epi} (km): Epi-distance to the rupture;
d_f (km): Focal depth;
V_{s30} (m/s): Average shear-wave velocity over the top 30 m of site;
F: Fault indicator 1: Strike-slip (horizontal slip) and 2: Reverse (dip slip with hanging-wall side up).

3.1. Strong-motion database and data preprocessing

A database compiled by Rahpeyma et al. (2013) is employed for the model development. The database covers a broad range of earthquake magnitude and distance. This database includes 179 ground motion datasets recorded from 36 different earthquakes happened during 30 years (between 1978 and 2008). The predictors included in the current study are M_w, R_{Epi} (km), V_{s30} (m/s), d_f (km), and F. The statistical parameters involved with the dependent and independent variables are presented in Table 1. The distribution of the records used here is also visualized in Fig. 3.

For the analysis, the database is randomly divided into training and testing subsets. The unseen testing sets are used to model testing after training. To reach a consistent data division, different combinations of the training and testing sets are considered. The selection is such that the maximum, minimum, mean and standard

Table 3
Weight and bias values.

h	Weights						Biases	
	W_{1h}	W_{2h}	W_{3h}	W_{4h}	W_{5h}	V_h	$bias_h$	$Bias$
1	5.069	−42.351	7.472	−30.299	17.624	−1.182	3.6	−0.346
2	40.235	60.728	−12.307	−73.911	−26.781	1.053	−37.359	
3	36.956	10.032	−2.599	−45.45	−15.714	−1.483	−14.567	
4	247.34	−63.536	21.617	−27.215	−11.914	0.645	−159.332	
5	−165.485	−190.407	−87.805	−121.142	10.431	0.889	215.38	
6	140.906	−115.362	37.044	21.431	15.973	1.188	−120.482	
7	153.973	−52.419	55.093	−147.993	5.037	1.06	−84.328	

deviations of the PGA are consistent in the both the training and the testing datasets (Gandomi et al., 2011). Out of the 179 datasets, 144 datasets (80%) are taken for the training process and the remaining 35 datasets (20%) are used for the testing of the models.

Frank and Todeschini (1994) proposed a minimum ratio of the number of datasets over the number of input variables for model acceptability, which is equal to 3 and also recommended the ratio be greater than. In the present study, this ratio of training and testing are respectively 144/5 = 28.8 and 35/5 = 7. Therefore, both training and testing datasets are much higher than the suggested ratio.

Before using the data in the modeling process, they are normalized between 0 and 1. Therefore all the parameters should be divided by a value, which is slightly more than the maximum value of each parameter. The normalization value of each parameter is presented in the last row of Table 1.

3.2. Performance measures

The optimal SA-ANN model is chosen on the basis of a two-objective strategy proposed in (Gandomi et al., 2010) as:

(1) Providing the best fitness value on the training datasets;
(2) Providing the best fitness value on the testing datasets.

The following objective function (OBJ) is constructed to satisfy these two objectives simultaneously. Then selections of the optimal models are deduced by the minimization of following objective function (Gandomi et al., 2010):

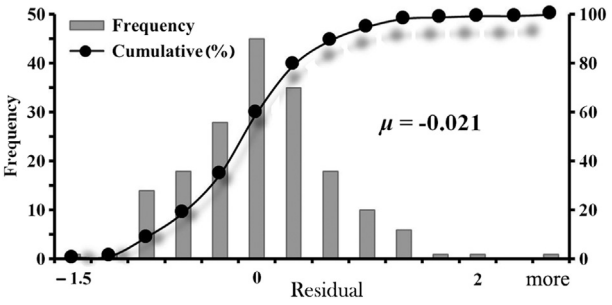

Figure 6. Residual distribution of the proposed SA-ANN model.

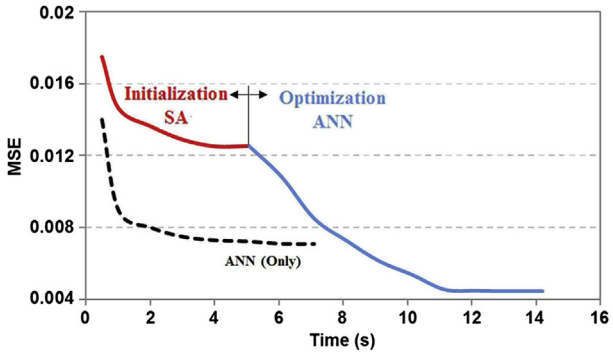

Figure 4. Variations of the MSE values with time during the SA-ANN training process.

Table 4
Defined range for the models in the literature.

Reference	M_w	R_{Epi}
Campbell and Bozorgnia (2008)	4–7.5	0–200
Boore and Atkinson (2008)	5–8	0–200
Abrahamson and Silva (2008)	5–8.5	0–200
Chiou and Youngs (2008)	4–8	0–200
Saffari et al. (2012)	5–7.3	15–135
Rahpeyma et al. (2013)	4–7.4	5–188
Ghodrati Amiri et al. (2007)	4.5–7.5	5–150
Akkar and Bommer (2009)	5–7.6	0–100
Kalkan and Gulkan (2004)	4–7.5	1–250
Bindi et al. (2010)	4–6.9	0–100
Current study	4–7.4	5–188

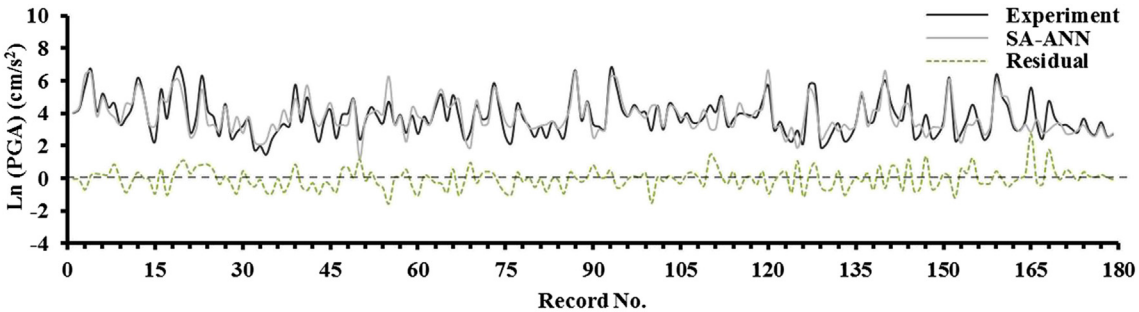

Figure 5. Measured versus predicted Ln(PGA) values using the SA-ANN model.

Table 5
Comparison of the prediction results for all models.

Reference	MAE (%)	RMSE (%)	R	r^2	ρ
Campbell and Bozorgnia (2008)	0.1997	0.2482	0.5596	0.9433	0.1592
Boore and Atkinson (2008)	0.2015	0.2562	0.5926	0.9397	0.1609
Abrahamson and Silva (2008)	0.2029	0.2501	0.5654	0.9425	0.1597
Chiou and Youngs (2008)	0.2148	0.2602	0.5735	0.9378	0.1654
Saffari et al. (2012)	0.2049	0.2526	0.4958	0.9399	0.1689
Rahpeyma et al. (2013)	0.1968	0.2439	0.5867	0.9453	0.1537
Ghodrati Amiri et al. (2007)	0.2068	0.2565	0.514	0.9393	0.1694
Akkar and Bommer (2009)	0.2243	0.2716	0.5845	0.934	0.1714
Kalkan and Gulkan (2004)	0.1992	0.2459	0.5864	0.9444	0.155
Bindi et al. (2010)	0.2261	0.2768	0.544	0.9311	0.1793
ANN	0.16	0.2089	0.7364	0.9599	0.1203
SA-ANN	0.128	0.1667	0.8352	0.9745	0.0908

$$OBJ = \left(\frac{No._{\text{Train}} - No._{\text{Test}}}{No._{\text{All}}}\right)\frac{MAE_{\text{Train}}}{R^2_{\text{Train}}} + \frac{2No._{\text{Test}}}{No._{\text{All}}}\frac{MAE_{\text{Test}}}{R^2_{\text{Test}}} \quad (3)$$

where $No._{\text{All}}$, and $No._{\text{Test}}$ are respectively, the number of datasets and testing datasets. *MAE* and *R* are respectively mean absolute error and correlation coefficient. *MAE* and *R* functions can be found in the Appendix.

3.3. Parameter settings of SA-ANN algorithm

To determine an efficient parameter setting, several runs are conducted with different parameters. Then the best parameters are

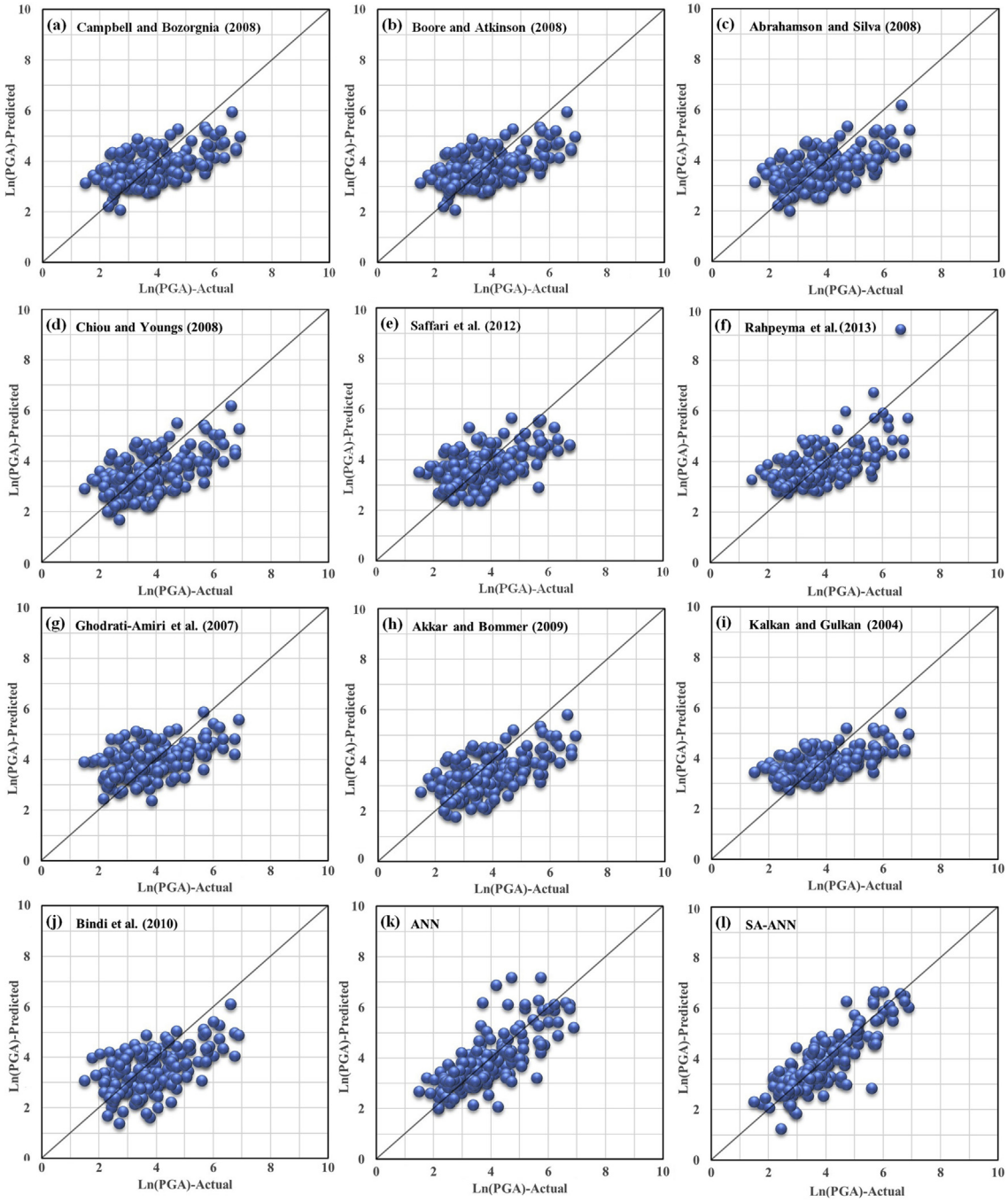

Figure 7. Measured versus predicted Ln(PGA) values using different models.

selected after a trial and error approach and based on previously suggested values (Ledesma et al., 2007; Alavi and Gandomi, 2011). The parameters setting of SA-ANN algorithm are presented in Table 2. The performance of an ANN model mainly depends on the network architecture. Based on a universal approximation theorem (Cybenko, 1989), a single hidden layer ANN is sufficient for uniformly approximating any nonlinear and continuous function. Choosing the number of hidden nodes plays a very important role in the model construction. Hecht-Nelson (1987) suggested a maximum value for the number of hidden neurons based on Kolmogorov's theorem as $nh \leq 2ni+1$, where nh is the number of hidden neurons and ni is the number of inputs. As there are 5 inputs for the current problem, the upper bound is $2 \times 5 + 1 = 11$ to avoid overfitting. Therefore, hidden neurons are changed from 4 to 10 and finally 7 nodes are chosen for the final model. Different training algorithms are used here and finally conjugate gradient algorithm is chosen. Several SA-ANNs with different settings are also trained using this algorithm to reach the best configurations. The SA-ANN algorithm is implemented by using the Neural Lab S/W for ANNs (Ledesma, 2009).

3.4. SA-ANN-based PGA model

The best model architecture for the prediction of the PGA is found with the OBJ = 1.0234. To have an explicit model, first the weights and biases are frozen after the SA-ANN were well trained. The SA-ANN-based mathematical model of PGA is as follows:

$$\mathrm{Ln\ (PGA)} = 8 \times Logsig\left(\mathrm{Bias} + \sum_{h=1}^{nh} V_h Logsig\left(\mathrm{bias}_h + \sum_{i=1}^{ni} w_{ih} x_i\right)\right) \quad (4)$$

where nh is equal to 7 and ni is equal to 5. In this formula $x_1 = M_w/8$, $x_2 = R_{\mathrm{Epi}}/200$, $x_3 = d_f/35$, $x_4 = V_{s30}/2200$, and $x_5 = \mathrm{F}/3$. All weights and biases are presented in Table 3.

Mean square error (MSE) of training as a function of time for the normalized output data is presented in Fig. 4. As it is shown, MSE is minimized during the initialization phase using the SA algorithm which indicates SA has globally reached good initial weights for the ANN. Thereafter, the training process switches to the optimization phase using ANN. Results of the best ANN model (OBJ = 1.4535) without the initialization phase is also presented in Fig. 4. The results clearly show that ANN converged to a local minimum which has more error than the point obtained by SA-ANN. A comparison of the real and predicted Ln(PGA) values by SA-ANN is illustrated in Fig. 5. The distribution of the residual is also presented in Fig. 6 which is almost Gaussian noise (zero-mean normal distribution) and has a sharp autocorrelation peak at zero.

4. Comparison and discussion

There are many prediction models proposed for PGA in the literature (Douglas, 2003). The results of the SA-ANN model are compared with those provided by the well-known models of Abrahamson and Silva (2008), Boore and Atkinson (2008), Campbell and Bozorgnia (2008) and Chiou and Youngs (2008) for PGA as well as some special PGA models for Iran such as Ghodrati Amiri et al. (2007), Saffari et al. (2012) and Rahpeyma et al. (2013). Three other models are also chosen for comparison which may have some benefits to use for Iran's tectonic regions as models proposed for Middle-East, Turkey and Italy regions, respectively by Kalkan and Gulkan (2004), Akkar and Bommer (2009), and Bindi et al. (2010). The workability ranges of these well-known models are presented in Table 4. For a fair comparison, these models are only used within their defined range. We have also compared our model with the simple ANN model as a benchmark of the proposed method.

Results of the proposed SA-ANN, ANN and other models proposed in the literature are presented in Table 5. The mathematical formulation of all error functions (MAE and RMSE) and correlation functions (R and r^2) used in this table can be found in Appendix A. In addition, another criterion called performance index is proposed by (Gandomi and Roke, 2013) as $\rho = \mathrm{RMSE}/(1+R)$ where RRMSE is the relative RMSE is also presented in this Table for a general comparison. The prediction results of all models are also visualized in Fig. 7.

From the statistical results presented in Table 5, the SA-ANN model has the lowest errors and the best correlations. The ρ of the proposed model is also less than the other PGA models. Therefore, it can be concluded that the hybrid model clearly

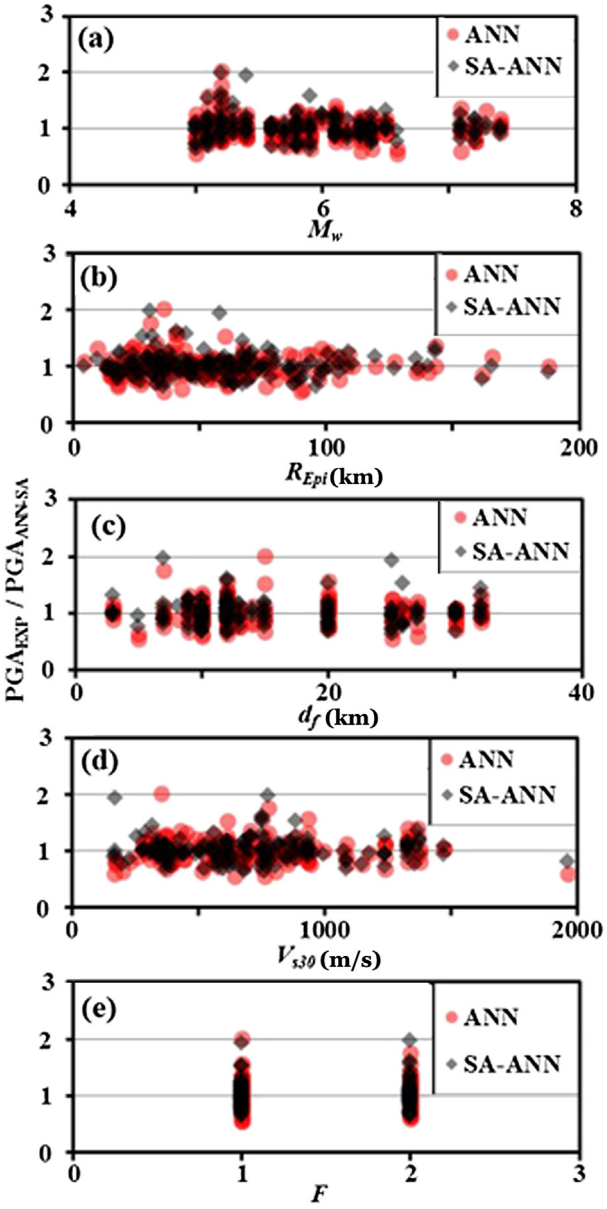

Figure 8. The ratio between the predicted and actual PGA values using ANN and SA-ANN with respect to compressive strength.

outperform the simple ANN model and also the other models proposed in the literature. According to a rational hypothesis (Smith, 1986), if a model gives correlation coefficient (R) > 0.8, it shows a strong correlation between the predicted and measured values. Therefore, among all the models presented here only the proposed SA-ANN model has good performance.

The ratios of the PGA using actual to predicted values using ANN and SA-ANN algorithms with respect to the M_w, R_{Epi} (km), V_{s30} (m/s), d_f (km), and F are shown in Fig. 8, respectively. It can be seen from these figures that the PGA predictions using the proposed model have good accuracy with no significant trend with respect to the input parameters.

5. Conclusions

In this research, a hybrid soft computing method, combining SA and ANN, is proposed to build a prediction model for PGA. The proposed PGA model was developed based on an Iran tectonic database containing 179 records. The main conclusions of this paper is that the proposed SA-ANN relationship provides reliable estimation of the PGA and has high degree of accuracy ($\rho = 0.0908$) and better than basic ANN and well-known methods proposed in the literature. The parametric study also confirms that there is not any trend with respect to the variables. The closed form of SA-ANN-based design equation provides analysis tool for future research. The explicit formula can be easily used in a spreadsheet or hand calculations to give predictions of the PGA values especially in Iran's tectonic regions.

Appendix A. Error and Correlation functions

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|h_i - t_i|}{n} \tag{A.1}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(h_i - t_i)^2}{n}} \tag{A.2}$$

$$R = \frac{\sum_{i=1}^{n}\left(h_i - \overline{h}_i\right)\left(t_i - \overline{t}_i\right)}{\sqrt{\sum_{i=1}^{n}\left(h_i - \overline{h}_i\right)^2 \sum_{i=1}^{n}\left(t_i - \overline{t}_i\right)^2}} \tag{A.3}$$

$$r^2 = \frac{\sum_{i=1}^{n}(h_i)^2 - \sum_{i=1}^{n}(h_i - t_i)^2}{\sum_{i=1}^{n}(h_i)^2} \tag{A.4}$$

$$\rho = \frac{\mathrm{RMSE}}{\overline{h}_i}\frac{1}{R+1} \tag{A.5}$$

where h_i and t_i are respectively the measured and predicted PGA values for the ith output, $\overline{h}_i$ and $\overline{t}_i$ are the average of the measured and predicted outputs, and n is the total number of earthquakes.

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