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Peak Ground Velocity attenuation relationships using Genetic Programming

E. Kermani & S. Barzegari
The Pennsylvania State University, USA

Y. Jafarian
International Institute of Earthquake Engineering and Seismology, Tehran, Iran

M.H. Baziar
Iran University of Science and Technology, Tehran, Iran

ABSTRACT: Peak Ground Velocity (PGV) is one of the most important ground motion parameters that has been widely used as a damage potential indicator, as well as in seismic design of structures and assessment of buried pipelines and liquefaction potential analysis. Therefore, estimating a precise value for this parameter is of great importance. In this paper, Genetic Programming (GP), a well-known Artificial Intelligence method is utilized to develop an attenuation relationship for PGV based on the strong ground motion database released by Pacific Earthquake Engineering Research center (PEER). Different PGV attenuation relationships are proposed for strike-slip, normal, and reverse faulting mechanisms as functions of earthquake magnitude, source to site distance, and local site geotechnical condition. The values of coefficient of determination, root mean square error and mean absolute error are calculated for the developed PGV attenuation relationships and reveal the accuracy of proposed model. Results of the parametric study demonstrate that PGV is higher for larger earthquake magnitudes while it is lower for sites which are located farther from the source and have lower shear wave velocities.

1 INTRODUCTION

Earthquakes are among the most major natural catastrophes that can cause significant damage to buildings and infrastructure. The seismological effects of earthquakes are generally function of earthquake characteristics such as magnitude, duration, fault-to site distance, faulting mechanism, and site conditions, and can be effectively described using strong ground motion parameters, which include Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), Peak Ground Displacement (PGD), and PGV/PGA ratio (Alavi & Gandomi, 2011, Kia & Sensoy, 2014). PGA and PGV are two most important amplitude/intensity ground motion parameters and has many applications in geotechnical and earthquake engineering. For instance, PGA is widely used in dynamic or pseudo-static analysis of structures, slopes, embankments and liquefaction problems (Kermani et al., 2009b). PGV on the other hand has been used in seismic analysis (de-sign and assessments) of buried pipelines, assessment of liquefaction potential, and as an indirect indicator of potential of damage to structures (Bommer & Alarcon, 2006). Furthermore, it should be noted that PGV is less sensitive to the higher components of earthquake motion com-pare to PGA, hence, it can potentially characterize ground motion amplitude at intermediate frequencies (Kramer, 1996, Kermani et al., 2009a).

A common challenge in seismology is to establish relationships to predict the value of the strong ground motion parameters at a given site to use for aforementioned application, known as attenuation relationships. This can be achieved through physical modeling, or by analysis of

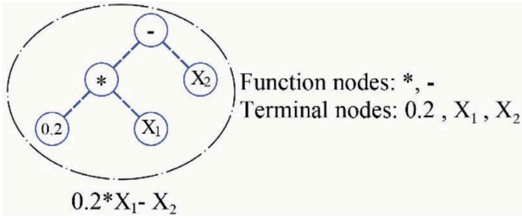

Figure 1. Schematic representative of GP tree

available earthquake data which. The latter has been traditionally conducted through regression analysis (e.g., Çağnan et al. 2017; Sedaghati & Pezeshki 2017). However, regression analysis is usually accompanied by notable errors, which are due to various simplifications and approximations involved (Alavi & Gandomi, 2011). More recently using Artificial Intelligence (AI) in analysis of earth-quake data has gained significant attention in this context, and various researchers have used different AI techniques (e.g., Artificial Neural Networks, Genetic Algorithm, Fuzzy Logic, Neuro Fuzzy, Genetic Programming, etc.) to develop attenuation/predictive equations for strong ground motion parameters (e.g. Jafarian et al., 2010; Kermani et al., 2009a; Ahumada et al., 2015; Yilmaz, 2011; Thomas et al., 2013; Thomas et al. 2016). Despite the importance and extensive applications of PGV, much less focus has been directed toward developing attenuation relationships for PGV compare to PGA. Most notably, Alavi & Gandomi (2011), Amiri et al. (2012), Kia & Sensoy (2014), Maleki et al. (2014), and Khosravikia et al. (2018) have used different AI methods to propose attenuation relationships for PGV based on different earthquake databases and ground properties.

This study aims to propose a closed-form attenuation relationship for PGV as a function of earthquake magnitude, source to site distance, faulting mechanics and shear wave velocity by using Genetic Programming (GP), a novel and robust AI technique. The database of Pacific Earth-quake Engineering Research Center (PEER) has been used for this purpose.

2 GENETIC PROGRAMMING

Genetic programming (GP) is a special form of Genetic Algorithm (GA), initially developed by Koza (1992). GA is as an optimization technique to search for the minimum of a function through evolution of a populations of individual solutions based on their fitness values over numbers of generations. The GP populations are computer programs consisting of functions (e.g., +, -, LOG, SIN, etc.) and terminals (e.g., arguments/parameters, numerical constants, etc.), presented in form of GP trees (e.g. Figure 1).

Initially GP generates a random population of computer programs and based on a set of input data and the fitness values (difference between predicted and actual values), it breeds these computer programs through numbers of generations using genetic operators (e.g., crossover and mutations). Finally, it may lead to providing predictive equations for unknown conditions based on the general trend of the input data. More detailed information about Genetic Programming procedure and method can be found in Kermani et al. (2009a) and Jafarian et al. (2010). In this study, GPLAB, a genetic programming toolbox for MATLAB written by Silva (2018) was utilized in this study.

3 DATABASE

The database released by Pacific Earthquake Engineering Research center (PEER), which contains strong ground motion of shallow crustal earthquakes recorded at active tectonic regions of the world has been used in this study (Power, 2006). This database consists of

Table 1. Maximum and minimum of M, R_{jb}, V_{s30} for strike-slip, normal and reverse fault types.

Faulting mechanism	M		R_{jb} (km)		V_{s30} (m/s)		ln (PGV)	
	min	max	min	max	min	max	min	max
Strike-slip (490 data)	4.53	7.9	0	199.27	116.35	1428	−2.003	4.763
Normal (112 data)	4.92	6.9	0	133.34	196.25	1000	−2.044	3.847
Reverse (834 data)	5.33	7.62	0	193.91	116.35	1525.85	−0.44	5.136

earthquake magnitude (moment magnitude) M, closets distance to the surface projection of the fault plane (R_{jb}), average shear wave velocity for the top 30 m of soil at the site (V_{s30}), and faulting mechanisms (i.e., strike-slip, normal and reverse) for 1436 records of 60 mainshocks. The maximum and minimum of these predictor variables are summarized in Table 1.

The input data for GP for predictor variables (i.e., magnitudes, distances and shear wave velocities) is normalized based on the maximum and minimum for each faulting mechanism using Equation (1):

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

All the data for each faulting mechanism is divided into two data subsets, called training set (with 80% of data) and validation set (with 20% of data). The training set is used to train the GP model, while the validation set is used to ensure the ability of the proposed attenuation relationships to predict unseen cases.

4 THE PROPOSED ATTENUATION RELATIONSHIPS

Genetic programming is used to propose three attenuation relationships to predict PGV as a function of moment magnitude, source to site distance and shear wave velocity for strike-slip, normal and reverse faulting mechanisms (Equations 2-4).

PGV attenuation relationship for strike-slip faulting mechanism:

$$\begin{aligned} ln(PGV)_{Normalized} = & -1.071R^3 + (-0.536V + 2.336)R^2 + \\ & + 0.551 + [-M^2 + 1.264M - 1.903 + (-M + 0.732)V]R \\ & + 0.536M - 0.25V \pm \sigma_{ln(PGV)} \end{aligned} \tag{2}$$

Where,

$$V = \frac{V_{s30} - 116.35}{1428 - 116.35},\ R = \frac{R_{jb}}{199.27},\ M = \frac{M' - 4.53}{7.9 - 4.53},\ \sigma_{ln(PGV)} = 0.20$$

$$ln(PGV)_{Predicted} = -2.003 + 6.766 ln(PGV)_{Normalized}$$

PGV attenuation relationship for normal faulting mechanism:

$$\begin{aligned} ln(PGV)_{Normalized} = & \ 0.661R^2 + (0.175M^4 - 1.224)R + \\ & 0.193(M^2V + M - V) + 0.731 \pm \sigma_{ln(PGV)} \end{aligned} \tag{3}$$

Where,

$$V = \frac{V_{s30} - 196.25}{1000 - 196.25},\ R = \frac{R_{jb}}{133.34},\ M = \frac{M\prime - 4.92}{6.9 - 4.92},\ \sigma_{ln(PGV)} = 0.215$$

$$ln(PGV)_{Predicted} = -2.044 + 5.891 ln(PGV)_{Normalized}$$

PGV attenuation relationship for reverse faulting mechanism:

$$\begin{aligned} ln(PGV)_{Normalized} = {} & -R^3 + 2.207R^2 + (0.609V - 1.796)R + 0.334M \\ & - 0.338V + 0.6 \pm \sigma_{ln(PGV)} \end{aligned} \tag{4}$$

Where,

$$V = \frac{V_{s30} - 116.35}{1525.85 - 116.35},\ R = \frac{R_{jb}}{193.91},\ M = \frac{M\prime - 5.33}{7.62 - 5.33},\ \sigma_{ln(PGV)} = 0.13$$

$$ln(PGV)_{\text{Predicted}} = -0.44 + 5.576 ln(PGV)_{\text{Normalized}}$$

Where *M, R_{jb}, V_{s30}*, are moment magnitude, Boore-Joyner distance, shear wav velocity over the top 30m of site soil, and standard deviation of the equations, respectively.

To demonstrate the accuracy and robustness of the GP proposed attenuation relationships for PGV, the values of coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE) between predicted and measured/actual PGV values are calculated as:

$$R^2 = \frac{\sum_1^N X_m^2 - \sum_1^N \left(X_m - X_p\right)^2}{\sum_1^N X_m^2} \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_1^N \left(X_m - X_p\right)^2}{N}} \tag{6}$$

$$MAE = \frac{\sum_1^N |X_m - X_p|}{N} \tag{7}$$

Table 2 presents the calculated values of R^2, RMSE and MAE for the proposed *ln* (PGV) attenuation relationships for both training and validation sets.

Figures 2-4 show the predicted PGV values by GP versus the corresponding measured/ actual *ln* (PGV) values for both training and validation datasets for strike-slip, normal and reverse fault types, respectively. As it can be seen, the results of the proposed attenuation relationships for validation sets are consistent with training sets and demonstrate the ability of proposed PGV attenuation relation-ships in predicting unseen/untrained cases. Furthermore, the proposed equations show rational accuracy in prediction of PGV.

Table 2. The values of R^2, RMSE and MAE for the proposed ln (PGV) attenuation relationships derived by GP

		GP results		
Faulting mechanisms	Groups	R^2	RMSE (sec)	MAE (sec)
Strike-slip	Training	0.934	0.55	0.420
	Validation	0.932	0.51	0.425
Normal	Training	0.87	0.480	0.36
	Validation	0.92	0.375	0.27
Reverse	Training	0.96	0.55	0.430
	Validation	0.95	0.60	0.45
All faulting mechanisms	All data	0.947	0.548	0.425

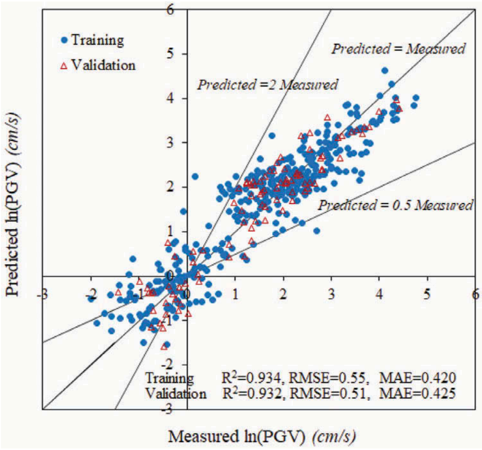

Figure 2. The predicted ln (PGV) by GP versus the measured ln (PGV) for strike-slip faulting mechanism

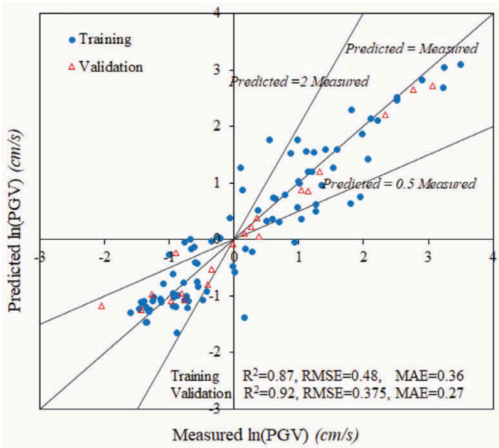

Figure 3. The predicted *ln* (PGV) by GP versus the measured *ln* (PGV)for normal faulting mechanism

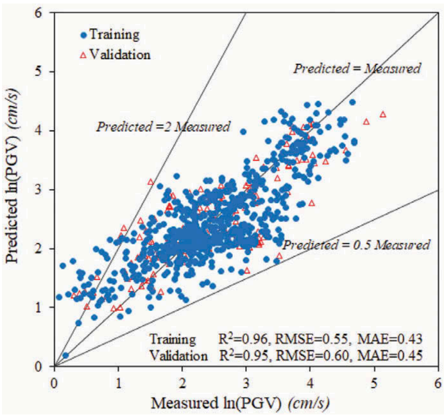

Figure 4. The predicted *ln* (PGV) by GP versus the measured *ln* (PGV) for reverse faulting mechanism

Table 3. The values of R^2, RMSE and MAE for the proposed derived by GP

Faulting mechanisms	Methods	GP results		
		R^2	RMSE (sec)	MAE (sec)
Strike-slip	GP	0.937	0.55	0.424
	Boore and Atkinson	0.923	0.56	0.441
Normal	GP	0.92	0.406	0.28
	Boore and Atkinson	0.90	0.52	0.41
Reverse	GP	0.954	0.561	0.437
	Boore and Atkinson	0.94	0.57	0.446
All faulting mechanisms	GP	0.952	0.55	0.429
	Boore and Atkinson	0.95	0.57	0.44

To demonstrate the ability of GP in developing attenuation relationships for PGV, the proposed equations are compared with results of PGV attenuation relationship by Boore & Atkinson (2007), which were proposed based on regression analysis. Boore & Atkinson (2007) employed the same database but their equations are limited to (1) $M = 5 - 8$; (2) $R_{jb} < 200\ km$ and (3) $V_{S30} = 180 - 1300\ m/s$. Therefore, the comparison is only performed on 1261 data.

Table 3 presents the calculated values of R^2, RMSE and MAE for ln (PGV) attenuation relationships proposed in the present study and Boore & Atkinson (2007).

As can be noticed in Table 3, in general both methods are in good agreement. However, GP equations result in higher R^2 values and lower RSME and MAE errors, which is indication of higher accuracy of the GP-proposed models in comparison to Boore & Atkinson (2007)'s results.

5 PARAMETRIC STUDY

A parametric study is conducted using the proposed PGV attenuation relationships in order to study the dependency of PGV on M, R_{jb} and V_{s30}. For each case, the variation of PGV with respect to one of the predictor variables are studied while the other two are kept constant. Figures 5, 6 and 7 show parametric study on effects of R_{jb}, M and V_{s30} on PGV, respectively.

As it was expected, PGV increases as earthquake magnitude increases while it decreases by increase in source to site distance and shear wave velocity.

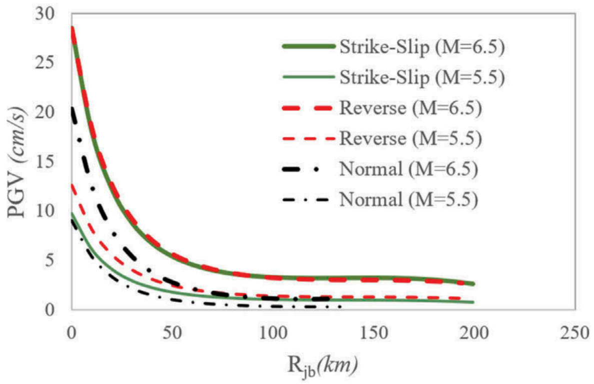

Figure 5. Variations of PGV with respect to R_{jb} for strike-slip, normal and reverse faulting mechanism; *M=5.5, 6.5 and* $V_{s30} = 500\ m/s$

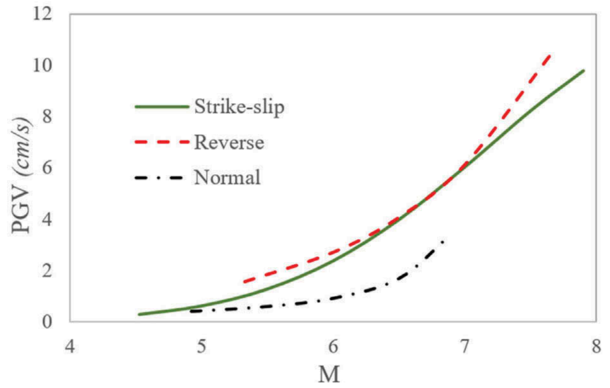

Figure 6. Variations of PGV with respect to M for strike-slip, normal and reverse faulting mechanism; R_{jb} =70 *km and* V_{s30} = 500 *m/s*

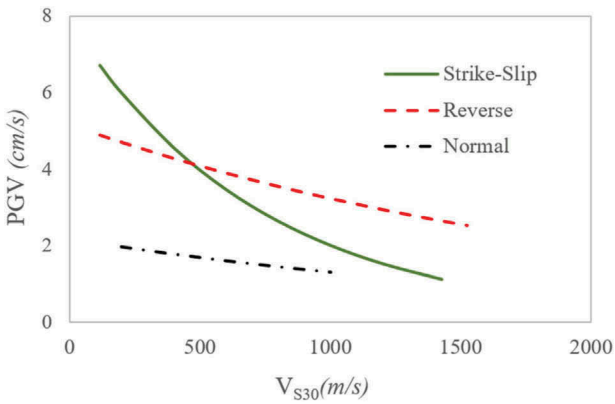

Figure 7. Variations of PGV with respect to V_{s30} for strike-slip, normal and reverse faulting mechanism; R_{jb} =70 *km and M=6.5*

Furthermore, it can be seen in Figure 5 that the changes in PGV due to changes in distance follow the same general trend for strike-slip, normal and reverse fault mechanisms. As it was expected, for all three faulting mechanisms the rate of change in the predicted PGV is maximum within the distance of 50 km from the source and becomes negligible beyond that point. In addition, according to Figure 7 the rate of change of PGV due to change in V_{s30} for strike-slip fault type is higher compared to the other faulting mechanisms.

6 CONCLUSIONS

Peak Ground Velocity (PGV) is one of the most important ground motion parameters used in many applications such as seismic analysis (design and assessments) of structures and buried pipelines, assessment of liquefaction potential, and as an indirect indicator of potential of damage to structures. Therefore, the precise prediction of PGV is of great importance in geotechnical and earthquake engineering.

In this study, Genetic Programming (GP) has been used to develop PGV attenuation relationships as functions of earthquake magnitude, source to site distance and shear wave velocity for three fault types (i.e., strike slip, normal and reverse). The database of strong ground motion of shallow crustal earthquakes for 1436 records of 60 mainshocks released by Pacific Earthquake Engineering Research center (PEER) has been used. The values of coefficient of determination, root mean square error and mean absolute error calculated for the proposed equations for each training and validation sets are consistent and demonstrate the ability of GP proposed models in predicting unseen/untrained cases. Furthermore, the comparison with the other PGV attenuation relationships in literature demonstrates the superior performance of the proposed GP models. The results of parametric study reveal that PGV increases as earthquake magnitude increases while it decreases by increase in source to site distance and shear wave velocity.

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