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Derivation of New Equations for Estimating Earthquake Induced Peak Ground Acceleration and Velocity

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1-Introduction

Predicting ground motion equations is one of the most important components of earthquake risk evaluation. The most prominent seismology variables affecting the ground motion parameters are the effects of source, path and site. In this context, four parameters were used to model the equations of PGA and PGV prediction, including M_W (Moment magnitude of earthquake), R_{jb} (Joyner-Boore distance), V_{s30} (average shear-wave velocity to a depth of 30 meters), F (the mechanism of faulting, including normal, strike-slip, reverse and reverse oblique faults).

A subset of The Pacific Earthquake Engineering Research Center – Next Generation Attenuation Relationship (PEER-NGA) project database provided by Power, et al. was used as the database for development of GMPEs. The recordings, which lacked the required parameters as well as those being duplicate, were excluded from this study. Overall, from 3551 recordings, 2777 recordings of different types of faults (e.g. normal, strike-slip, reverse and reverse oblique) were used to develop the model.

2-Ground Motion Model

The aim of this study was to predict the peak ground acceleration (PGA) and peak ground velocity (PGV) using the regression-based tree algorithm known as M5. The M5 model creates a linear multivariable model of the data at each node of the tree model. The three main steps required for the setup of decision tree models are the development, pruning and simplification of the tree.

To better understand the equation and the effect of changes in each parameter in the final value of PGA and PGV, the natural logarithm of input and output parameters were used in the model, but they then were exponentiated.

$$\begin{matrix}\ln PGA \\ \ln PGV\end{matrix} = \alpha * \ln\ M_w + \beta * \ln R_{jb} + \gamma * \ln V_{s30} + C \quad (1)$$

$$\begin{matrix}PGA \\ PGV\end{matrix} = {M_w}^{\alpha} * \ {R_{jb}}^{\beta} * {V_{s30}}^{\gamma} * \exp C \quad (2)$$

The database was divided into two datasets: 80% for the training dataset and 20% for the testing dataset. The training dataset was used to train the algorithm and develop the model. The validation data were used as inputs for the model developed by the training dataset and the generalization ability of the models was assessed. Therefore, both training and validation datasets were used in the modeling process. To evaluate the function of models that were developed through M5, testing dataset, which did not contribute to the development of the model was used in the final model and the error rate and correlation coefficient were calculated. Multiple classifications of training and testing datasets were used to find the best classification. The training and testing datasets were selected so that the minimum, maximum, mean and standard deviation of parameters in the two datasets were matched.

The final equations for PGA and PGV shown in table 1 and figure 1 and 2 respectively.

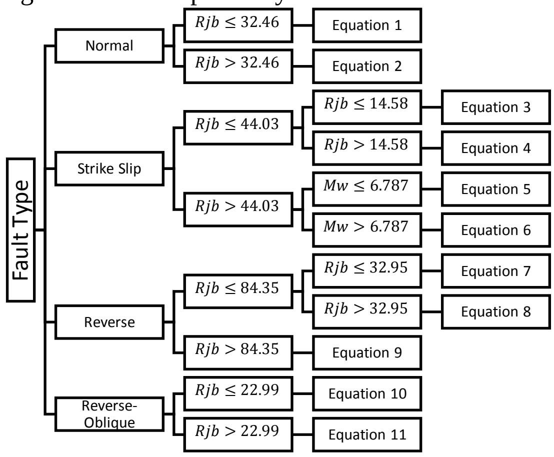

Fig.1 PGA Equations tree

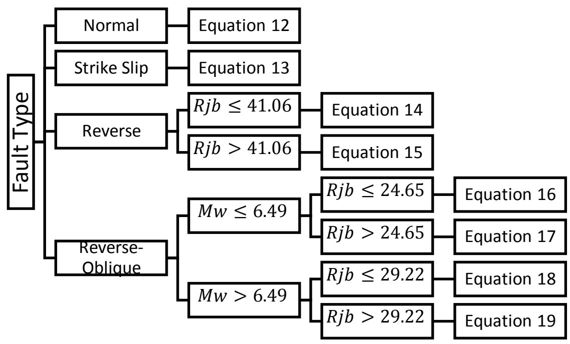

Fig.2 PGV Equations tree

Table 1. Equations Parameters

GMPE	Equation	M_w Power	R_{jb} Power	V_{s30} Power	C
PGA	1	2.752	-0.726	-0.564	1.757E-01
	2	3.138	-1.295	-0.091	3.272E-02
	3	0.444	-0.146	-0.031	1.653E-01
	4	0.444	-0.127	-0.031	7.608E-02
	5	0.708	-0.816	-0.457	2.444E+00
	6	0.840	-1.052	-0.052	1.666E+00
	7	3.893	-0.553	-0.025	6.69E-04
	8	6.602	-0.584	-0.331	2.1E-05
	9	3.834	-1.410	-0.327	1.022E-01
	10	0.529	-0.252	-0.023	1.461E-01
	11	1.079	-0.795	-0.304	1.194E+00
PGV	12	4.686	-0.956	-0.321	1.441E-01
	13	7.114	-0.689	-0.784	1.191E-02
	14	6.892	-0.425	-0.042	1.43E-04
	15	8.358	-0.840	-0.792	2.475E-03
	16	0.572	-0.305	-0.780	7.16E+02
	17	0.572	-0.760	-0.528	5.145E+02
	18	4.210	-0.241	-0.114	2.62E-02
	19	0.198	-0.472	-0.617	2.045E+03

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3-Regression Results and Comparison

Three PGA and PGV prediction models that have parameters similar to our model (i.e. those developed by Boore and Atkinson, Campbell and Bozorgnia, Gandomi) were used for the validation of the model based on the comparison of correlation coefficient (CC), root mean square error (RMSE) and mean absolute error (MAE) and the performance, reliability, parametric analysis and sensitivity of the model were evaluated. The advantage of our model was the calculation of PGA and PGV values rather than their natural logarithm, the simplicity of the model, and its better CC, RMSE and MAE for different types of faults regarding both training and testing datasets.

Table 2. PGA Model Comparison

Mech anism Class	Model / Error	Campbell-Bozorgnia - 2007	Boore-Atkinson - 2008	Gandomi-Alavi - 2011	M5
N	CC	0.8988	0.9404	0.8967	0.9373
	MAE	0.5582	0.4320	0.9574	0.0340
	RMSE	0.7450	0.4898	1.0856	0.0567
S	CC	0.8808	0.8505	0.8777	0.9106
	MAE	0.5163	0.6077	0.7430	0.0364
	RMSE	0.6038	0.7473	0.8953	0.0856
R	CC	0.7377	0.7778	0.7205	0.9531
	MAE	0.8121	0.9785	0.5161	0.0313
	RMSE	0.9573	1.1246	0.7055	0.2677
RO	CC	0.6810	0.5142	0.6075	0.8041
	MAE	0.3997	0.7165	0.6532	0.0327
	RMSE	0.5662	0.8016	0.8907	0.0662

Table 3. PGV Model Comparison

Mech anism Class	Model / Error	Campbell-Bozorgnia - 2007	Boore-Atkinson - 2008	Gandomi -Alavi - 2011	M5
N	CC	0.9015	0.9214	0.9491	0.9691
	MAE	0.6154	0.6023	0.5136	4.1675
	RMSE	0.7975	0.7694	0.6624	7.9640
S	CC	0.6651	0.8244	0.7922	0.8939
	MAE	0.5819	0.4762	0.5346	3.0824
	RMSE	0.8906	0.6146	0.6500	5.0869
R	CC	0.7119	0.7815	0.7679	0.8821
	MAE	0.5733	0.5059	0.5405	2.5625
	RMSE	0.7448	0.6690	0.6858	5.7484
RO	CC	0.4689	0.7857	0.7816	0.8560
	MAE	0.6366	0.4932	0.4796	6.7767
	RMSE	1.0323	0.6038	0.5990	9.5758

4-Sensitivity And Parametric Analysis

To better understand the effect of each input parameter in the model separately, sensitivity analysis was performed on all PGA and PGV prediction models that shown in table 4 and 5 respectively. In the PGA prediction model, it was shown that the R_{jb} distance highly influenced the model in different types of faults. When this parameter was omitted from the model, CC, RMSE and MAE were greatly affected. In normal and strike-slip faults, the second most important parameter in the model was the M_w and V_{s30}. Conversely, in reverse and reverse oblique faults, the V_{s30} and M_w were the second most important parameter in the model. The sensitivity analysis of PGV prediction models similarly showed that in different types of faults, R_{jb} distance had a substantial effect on the model, followed by M_w and V_{s30}.

Table 4. PGA Sensitivity Analysis

Mechanism Class	Model tree in absence of	CC	MAE	RMSE
Normal	-	0.9373	0.0340	0.0567
	Mw	0.8290	0.0372	0.0607
	Rjb	0.0000	0.0571	0.0999
	Vs30	0.8472	0.0296	0.0551
Strike-Slip	-	0.9106	0.0364	0.0856
	Mw	0.8903	0.0429	0.0909
	Rjb	0.1618	0.0702	0.1549
	Vs30	0.9089	0.0406	0.0865
Reverse	-	0.9531	0.0313	0.2677
	Mw	0.9545	0.0438	0.3962
	Rjb	-0.0939	0.0259	0.0301
	Vs30	0.9515	0.0320	0.2602
Reverse - Oblique	-	0.8041	0.0327	0.0662
	Mw	0.8208	0.0320	0.0687
	Rjb	0.3062	0.0480	0.0984
	Vs30	0.8069	0.0314	0.0663

Table 5. PGV Sensitivity Analysis

Mechanism Class	Model tree in absence of	CC	MAE	RMSE
Normal	-	0.9691	4.1675	7.9640
	Mw	0.8932	5.2204	9.5378
	Rjb	0.0000	6.6070	13.1714
	Vs30	0.9704	3.9900	7.2333
Strike-Slip	-	0.8939	3.0824	5.0869
	Mw	0.5975	5.2716	9.2373
	Rjb	0.3993	5.7575	10.5690
	Vs30	0.8229	3.7547	6.5424
Reverse	-	0.8821	2.5625	5.7484
	Mw	0.6774	3.2777	8.3848
	Rjb	0.5054	3.7534	9.5527
	Vs30	0.8785	2.7286	5.8157
Reverse - Oblique	-	0.8560	6.7767	9.5758
	Mw	0.6585	11.0747	15.7054
	Rjb	0.3377	11.3965	17.5614
	Vs30	0.8408	7.0653	9.9895

To evaluate the power of predictive equations in this study, parametric analysis was performed on the database and the models showed that PGA and PGV always increase with M_w, increase and decrease with R_{jb} and V_{s30}, respectively. These findings were expected from a geologic point of view, and suggested that the predictive models are powerful and can be confidently used for prediction in seismic risk evaluation studies.

5- Conclusions

The suggested GMPEs in this study show reliable estimates of PGA and PGV values and meet different intended conditions and criteria in their validation. Additionally, these equations are rather simple and efficient alternatives to the complex equations presented in previous studies. Since M5-based GMPEs are developed using a comprehensive database with a wide range of properties, they can be utilized confidently for practical design purposes.