A METHOD TO DETERMINE THE APPROPRIATE GMPEs FOR A SELECTED SEISMIC PRONE REGION

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SUMMARY:
Selection and ranking of ground-motion prediction equations (GMPEs) for probabilistic seismic hazard assessment (PSHA) of a region or a specific site is a developing research topic. In this paper the major features of the likelihood approaches of LH (Scherbaum et al., 2004), LLH (Scherbaum et al., 2009) and a newly proposed alternative procedure, EDR (Kale and Akkar, 2012) are investigated. A total of 14 candidate GMPEs from shallow active crustal regions are tested with a dataset that comprises of 984 accelerograms from Turkey. The comparisons between above methods are made using the performances of candidate GMPEs on the selected database. The performances of GMPEs are evaluated by considering various magnitude and distance bins extracted from the strong-motion database. As part of this study, evaluation of these methods lead to a set of GMPEs that can be applied confidently in PSHA studies for Turkey where the ground-motion data is collected.

Keywords: Ground-motion prediction equations, seismic hazard, likelihood methods, Euclidean distance

1. INTRODUCTION

Ground-motion prediction equations (GMPEs) are key ingredients for the probabilistic seismic hazard assessment (PSHA) in a region or site of interest. With the increasing size and quality of the ground motion databases, a significant amount of effort has been devoted to develop new models for properly reflecting the seismological features of the seismic prone regions. This effort results in increasing number of ground-motion models in all around the world. In essence, selecting the appropriate predictive models to calculate hazard in a site (or a region) of interest has become a popular topic in engineering seismology. The ground shaking in the target region must be well reflected by the selected GMPEs as ground motion variability directly affects the computed hazard in the study area.

Although there are various statistical methods (e.g., Chi-square, Kolmogorov-Smirnov, variance reduction, Pearson's correlation coefficient) to test the predictive models for their suitability at a given region, the procedures proposed by Scherbaum and his co-authors have attracted the attention of seismological community for selection and ranking of GMPEs. These maximum likelihood methods are called as LH (Scherbaum et al., 2004) and LLH (Scherbaum et al., 2009). Both methods calculate the similarity between spectral values obtained from observed and estimated ground-motion data in a statistical way. Scherbaum and his co-authors applied the LH method to the border region of France, Germany, and Switzerland for a small set of observed data (Scherbaum et al., 2004). Hintersberger et al. (2007) re-implemented the same method to the same region by extending the strong-motion dataset but keeping the same candidate GMPEs of Scherbaum et al. (2004). Hintersberger et al. (2007) obtained similar ranking results as of Scherbaum et al. (2004), which was interpreted as the stability of LH method. The applicability of the GMPEs developed in Next Generation Attenuation (NGA) project (Power et al., 2008) to Euro-Mediterranean region was also evaluated by applying LH methodology (Stafford et al., 2008). In a later study Scherbaum et al. (2009) proposed the information-theoretic LLH approach, which is stated as superior to LH because the older method depends on the data ground-motion size, it cannot consider the standard deviation of GMPEs in a consistent manner and there is a subjectivity of the chosen significance levels ranking that in turn are used for ranking the

GMPEs. The LLH method is also used as a robust selection and ranking technique in various studies (e.g., Delavaud et al., 2009; Delavaud et al., 2012a; 2012b) to identify suitable GMPEs for specific seismic prone regions.

Kale and Akkar (2012) pointed that both LLH and LH methods may suffer from a consistent handling of sigma associated with GMPEs. Amongst 2 ground-motion predictive models of similar median estimations these methods would favor the one with higher sigma. GMPEs associated with larger sigma values may result in considerably large seismic hazard at long return periods (Restrepo-Velez and Bommer, 2003). To this end, Kale and Akkar (2012) proposed an alternative ranking and selection methodology that is called as Euclidean Distance Based Ranking (EDR) method. This method also needs an observed ground-motion dataset as in the case of LH and LLH methods. It uses the Euclidean distance that is basically the absolute difference between the observed and estimated data. EDR considers sigma in a way analogous to consideration of ground-motion variability in conventional PSHA. The bias between the median ground-motion estimations and observed data is taken into account by a scheme similar to residual analysis. These concepts make it different with respect to the likelihood methods discussed in the text. Independency of ranking results from data size and a more rational consideration of sigma effect on the performance of GMPE are believed to be the advantageous sides of EDR method.

This study, first, details the fundamental features of the mentioned selection and ranking methods. Then, for a pre-selected set of local and global GMPEs, the ranking results of these procedures are compared by using a ground-motion database that consists of 984 recordings from 192 events recorded in Turkey. In the final part of this paper, the testing results are used to suggest a set of GMPEs that can be sued in the GMPE logic-tree applications for Turkey.

2. SELECTION AND RANKING METHODS OF GMPES

2.1. LH Method

LH method, which is proposed by Scherbaum et al. (2004), calculates the normalized residuals for a set of observed and estimated ground-motion data by considering that GMPEs are normally distributed in natural logarithm unit. The exceedance probabilities corresponding to calculated residuals are determined as LH values (Fig. 2.1.a). By following Scherbaum et al. (2004), this likelihood parameter can be expressed by Eqn. 2.1:

$$LH(|z_0|) = \mathrm{Erf}\left(\frac{|z_0|}{\sqrt{2}}, \infty\right) = \frac{2}{\sqrt{2\pi}} \int_{|z_0|}^{\infty} \exp\left(\frac{-z^2}{2}\right) dz \tag{2.1}$$

where z_0 represents the normalized residuals and Erf(z) is the error function while integrating the standard normal distribution. To describe the suitability of candidate GMPEs, the median LH values are reported as the resultant LH index that takes values between 0 and 1. For an optimum case, LH values are evenly distributed between 0 and 1, and the median of LH is about 0.5.

2.2. LLH Method

LLH method, which is an information-theoretic model selection method developed by Scherbaum et al. (2009) is based on log-likelihood approach to measure the distance between two continuous probability density functions f(x) and g(x). The function f(x) represents the distribution of an observed data point in the ground-motion dataset. The distribution of the estimated data point is described by g(x) and it is assumed as log-normal with the median and standard deviation of the considered GMPE. The distribution of f(x) is not known apriori and it is assumed to be log-normal with the same features of g(x). To obtain a model selection index, this approach calculates the average log-likelihood of the considered predictive model (Eqn. 2.2) using the observed dataset. An illustration of the probability consideration of LLH method is represented in Fig. 2.1.b.

$$\mathrm{LLH}(g, x) = -\frac{1}{N}\sum_{i=1}^{N}\log_2(g(x_i)) \tag{2.2}$$

In Eqn. 2.2, x_i represents the observed data for i = 1,…, N. The parameter N is the total number of data. A small value of LLH ranking index indicates a better relationship between the observed and estimated ground-motion data.

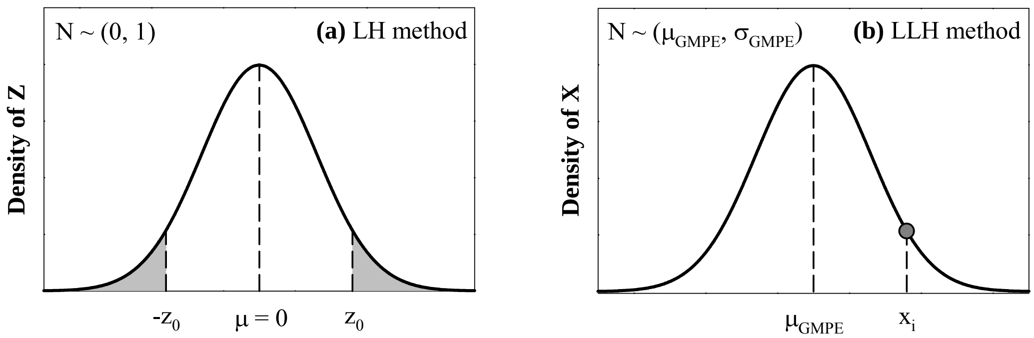

Figure 2.1. Illustrations of the probability calculations of (a) LH and (b) LLH methods. The summation of the shaded areas under the probability density function of Z is reported as LH index. Computation of LLH index is based on the occurrence probability of x_i by using median and sigma values of GMPE (μ_{GMPE} and σ_{GMPE}, respectively).

2.3. EDR Method

EDR method that is developed by Kale and Akkar (2012) proposes an alternative ground-motion model selection and ranking procedure. This method is based on Euclidean distance (DE) definition given in Eqn. 2.3 with some slight modifications to account for the influence of sigma on the estimated ground-motion data and existing trend between observed data and median estimations of predictive models. In Eqn. 2.3, square root of sum of squares of the differences between N number of (p_i, q_i) data pairs is calculated as Euclidean distance.

$$\mathrm{DE} = \sqrt{\sum_{i=1}^{N}(p_i - q_i)^2} \tag{2.3}$$

The consideration of sigma in EDR method is mimicked by the implementation of predictive models in PSHA. The logarithm of the ground-motion model is assumed to be normal with a mean, μ_{GMPE}, and standard deviation σ_{GMPE}. Thus, the ground-motion model yields a set of estimations with various levels of probability. The differences (D) between the logarithms of each observed data point and corresponding estimations for a range of σ_{GMPE} result in a normal distribution with mean, μ_D, and sigma, σ_D. From summation of random variables, μ_D is obtained by subtracting μGMPE from the observed data point. The summation of random variables dictates $\sigma_D = \sigma_{GMPE}$ (see Kale and Akkar, 2012 for details). EDR method considers this resultant distribution to obtain a model ranking index by making use of Euclidean distance concept. Distribution of D is shown in the left panel of Fig. 2.2 where d_j values represent the discrete values of D. This method considers only positive values since analogy is made between DE and D (see details in Kale and Akkar, 2012 for details). Accordingly, the distribution of D is converted to distribution of |D| as given on the right panel of Fig. 2.2. For a pre-selected sigma range, the Modified Euclidean distance (MDE) is obtained by using Eqn. 2.4.

$$\mathrm{MDE} = \sum_{j=1}^{n}|d_j|\,\Pr(|D| < |d_j|) \tag{2.4}$$

In Eqn. 2.4, Pr ($|D|<|d_j|$) is the occurrence probabilities of absolute differences, d_j, within an infinitesimal bandwidth, dd, for n discrete points.

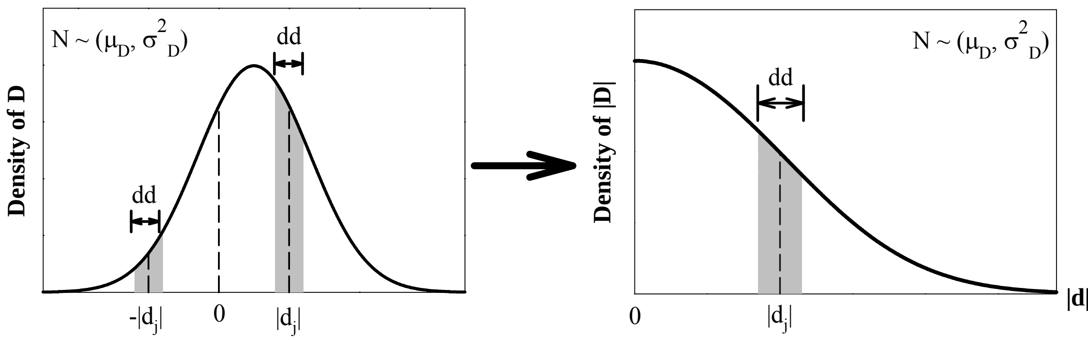

Figure 2.2. Illustrations of the probability definitions given in EDR method. Probability density function of D is given in the left panel. The right panel shows the probability density function of |D|. The gray shaded area represents the summation of the discrete probabilities, Pr ($|D|<|d_j|$), given in left panel of this figure.

The trend between the observed ground-motion data and corresponding median estimations is an indicator of bias for the considered predictive model. In EDR method, this bias is measured by the κ parameter given in Eqn. 2.5, which is the ratio of the original ($DE_{original}$) and corrected ($DE_{corrected}$) Euclidean distances. $DE_{original}$ is calculated from Eqn. 2.3 by considering p and q as the observed and median estimations of the considered predictive model, respectively. Both p and q are in natural logarithm units. $DE_{corrected}$ values are computed from observed data and corrected estimations that can be obtained by modifying the median estimations with the straight line fitted on the observed and estimated data. The ideal value of κ parameter is 1.0 (indicates observed data and corresponding median estimations overlap each other). Higher κ values indicate biased median estimations of GMPEs (Kale and Akkar, 2012).

$$\kappa = \frac{DE_{original}}{DE_{corrected}} \tag{2.5}$$

When the process explained for MDE is repeated for the entire ground-motion dataset of N recordings, the computed MDE values are combined with κ to obtain the EDR index (Eqn. 2.6). The computed MDE values are normalized by the total data number, N to make the EDR index independent of data size.

$$EDR = \sqrt{\kappa \cdot \frac{1}{N} \cdot \sum_{i=1}^{N} MDE_i^2} \tag{2.6}$$

A small value of EDR index is an indicator of the well representation of ground-motion dataset by the predictive model. The EDR index combines the effect of sigma and the level of trend between the observed data and median ground-motion estimations. These two components can be interpreted separately depending on the needs of the analysts.

3. TESTING OF GMPES USING LIKELIHOOD AND EDR METHODS

This section presents a case study about the implementation of investigated ground-motion selection and ranking procedures. The case study uses the Turkish ground motions that are compiled under the framework of the Earthquake Model of the Middle East (EMME) project. The case study tests 14 local and global GMPEs that are derived for different shallow active crustal regions around the world.

3.1. Ground-Motion Database

The strong-motion database considered in this study consists of the Turkish recordings from recently compiled EMME strong-motion database. The database includes 984 strong-motion accelerograms recorded from 192 events since 1976. The moment magnitudes (M_w) of the events are between 4.0 and 7.6. The Joyner-Boore distances (R_{JB}: closest distance to the horizontal projection of the fault rupture) and rupture distances (R_{RUP}: closest distance to the fault rupture) of the accelerograms are less than 200 km. These distances were calculated using the moment tensor solutions reported by the local and global seismic agencies. The acausal band-pass filtering procedure was applied to the recordings in the database by following the procedures explained in Akkar and Bommer (2006) and Akkar et al. (2011). Computation of finite-fault distance metrics (i.e., R_{JB} and R_{RUP}) from actual fault-plane solutions and individually filtered ground-motion data increase the reliability of the database. Fig. 3.1 shows M_w vs. R_{JB} scatter plots of strong-motion recordings in terms of style-of-faulting (SoF) and site classification. The strike-slip, normal and reverse ground-motion records given in the left panel of Fig. 3.1 are abbreviated as S, N and R, respectively. The data scatter with respect to different site classes are shown on the right panel of Fig. 3.1. The site classes are in accordance with Eurocode 8 (CEN, 2004). This code uses V_{S30} (average shear wave velocity of top 30 m layer of the soil profile) intervals such that EC8-A, B, C and D soil classes correspond to V_{S30} > 800m/s, 360 < V_{S30} ≤ 800m/s, 180 < V_{S30} ≤ 360m/s and V_{S30} ≤ 180m/s, respectively. The numeric information for the number of data corresponding to SoF and site classification is denoted next to each legend in the related figures.

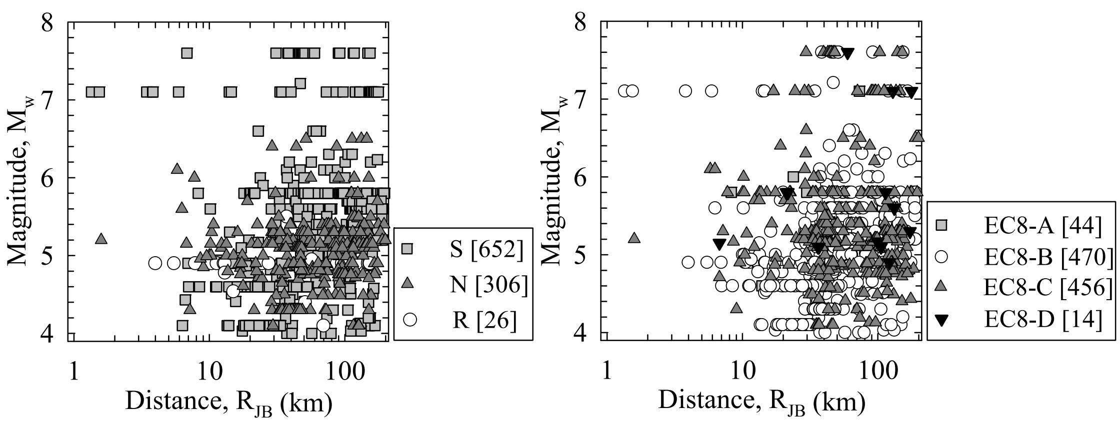

Figure 3.1. M_w vs. R_{JB} scatters of the database in terms of SoF (left panel) and site class (right panel).

3.2. Selection and Testing of Candidate GMPEs

Pre-selection of the local and global GMPEs is done by following the criteria described in Cotton et al. (2006) study. This method suggests that the GMPEs should be eliminated if 1) the model is from irrelevant tectonic regime, 2) the predictive model is not PEER-reviewed, 3) the documentation and dataset is insufficient, 4) the model has been superseded, 5) the period range is not appropriate, 6) the functional form is inappropriate, 7) the regression method or coefficients are inappropriate.

The list of 14 GMPEs tested in this study and their acronyms are given in the first two columns of Tables 3.1 and 3.2. This pre-selected candidate ground-motion model set is the same as that used in the model selection and ranking work package of EMME project. The reader is referred to Kale and Akkar (2012) for general features of the candidate GMPEs.

Tables 3.1 and 3.2 display the average testing results of GMPEs in terms of EDR components and actual EDR index. Tables 3.1 and 3.2 also list the corresponding LH and LLH ranking indices. Each table shows a different approach implemented during the testing of GMPEs. The test results given in Table 3.1 are obtained by considering the limitation of each GMPE in terms of magnitude and distance. In other words, the number of recordings used in the testing of each predictive model is different because of the magnitude and distance limitations imposed by each model developer. Table 3.2 presents testing results that are computed using the entire database without considering the magnitude and distance limitations of the predictive model. In this case, the number of recordings used for testing is the same for all GMPEs. The average results given in these tables represent the overall performance of GMPEs for a spectral period band that comprises of T=0.0s (PGA), 0.1s, 0.2s, 0.5s, 0.75s, 1.0s, 1.5s and 2.0s. The general performance of predictive models at each selected period is shown in Fig. 3.2 when all accelerograms in the dataset is used (case described for Table 3.2). A similar plot for the results summarized in Table 3.1 is not given due to the spacing limitations.

Table 3.1. Performance of candidate GMPEs in terms of EDR components, EDR, LH and LLH indices by considering the magnitude and distance limitations of each predictive model. Top 4 best performing models are shown in bold.

GMPEs	**Acronym**	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\mathrm{MDE}_i^2}$	$\sqrt{\kappa}$	**EDR**	**LH**	**LLH**
Akkar and B.ommer (2010)	AB10	1.12	1.23	1.39	**0.38**	2.31
Akkar and Çağnan (2010)	AC10	**1.04**	**1.09**	**1.13**	**0.53**	**1.81**
Ambraseys et al. (2005)	Aetal05	1.21	1.22	1.49	0.37	2.47
Abrahamson and Silva (2008)	AS08	1.21	1.28	1.55	0.26	2.81
Boore and Atkinson (2008)	BA08	1.20	1.32	1.59	0.18	3.06
Bindi et al. (2010)	Betal10	**1.06**	**1.10**	**1.17**	**0.49**	**1.88**
Campbell and Bozorgnia (2008)	CB08	1.27	1.39	1.76	0.12	3.65
Cauzzi and Faccioli (2008)	CF08	**1.09**	**1.12**	**1.22**	**0.45**	**2.03**
Chiou and Youngs (2008)	CY08	1.12	1.17	1.32	0.30	2.50
Fukushima et al. (2003)	Fetal03	1.26	1.35	1.72	0.23	2.88
Ghasemi et al. (2009)	Getal09	1.28	1.32	1.69	0.29	2.67
Kalkan and Gülkan (2004)	KG04	1.59	1.75	2.78	0.10	3.83
Özbey et al. (2004)	Oetal04	**1.05**	1.16	**1.22**	0.34	**2.20**
Zhao et al. (2006)	Zetal06	1.11	**1.13**	1.26	0.36	2.26

Table 3.2. Performance of candidate GMPEs in terms of EDR components, EDR, LH and LLH indices by using the entire ground-motion database. Top 4 best performing models are shown in bold.

GMPEs	**Acronym**	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\mathrm{MDE}_i^2}$	$\sqrt{\kappa}$	**EDR**	**LH**	**LLH**
Akkar and Bommer (2010)	AB10	**1.04**	**1.10**	**1.14**	**0.42**	**2.06**
Akkar and Çağnan (2010)	AC10	**1.04**	**1.05**	**1.09**	**0.54**	**1.82**
Ambraseys et al. (2005)	Aetal05	1.26	1.23	1.56	0.32	2.48
Abrahamson and Silva (2008)	AS08	1.30	1.34	1.74	0.17	3.10
Boore and Atkinson (2008)	BA08	1.20	1.32	1.59	0.18	3.06
Bindi et al. (2010)	Betal10	1.14	**1.04**	**1.19**	**0.46**	**2.06**
Campbell and Bozorgnia (2008)	CB08	1.27	1.39	1.76	0.12	3.65
Cauzzi and Faccioli (2008)	CF08	**1.05**	**1.09**	**1.14**	**0.46**	**1.92**
Chiou and Youngs (2008)	CY08	1.12	1.17	1.32	0.30	2.50
Fukushima et al. (2003)	Fetal03	1.83	1.72	3.14	0.03	5.44
Ghasemi et al. (2009)	Getal09	1.21	1.26	1.52	0.29	2.47
Kalkan and Gülkan (2004)	KG04	1.57	1.74	2.74	0.10	3.78
Özbey et al. (2004)	Oetal04	1.24	1.12	1.39	0.25	2.75
Zhao et al. (2006)	Zetal06	**1.07**	1.13	1.22	0.37	2.15

The test results given in Tables 3.1 and 3.2 show that EDR, LH and LLH methods generally yield similar rankings. One particular advantage of EDR is that it not only provides an idea on the overall performance of tested predictive models but also informs the analyst about the individual contributions of sigma (i.e., the level of aleatory variability) and bias in median estimations to overall performance of GMPEs. For example, when testing results of entire database is of concern, Zetal06 performs better in terms of aleatory variability (smaller MDE component in EDR). However, Betal10 supersedes Zetal06 when the overall EDR is considered. Accordingly, as indicated before, EDR offers different levels of information to the analyst for considering the aleatory uncertainty, degree of bias between observed and median estimations and combination of these two components.

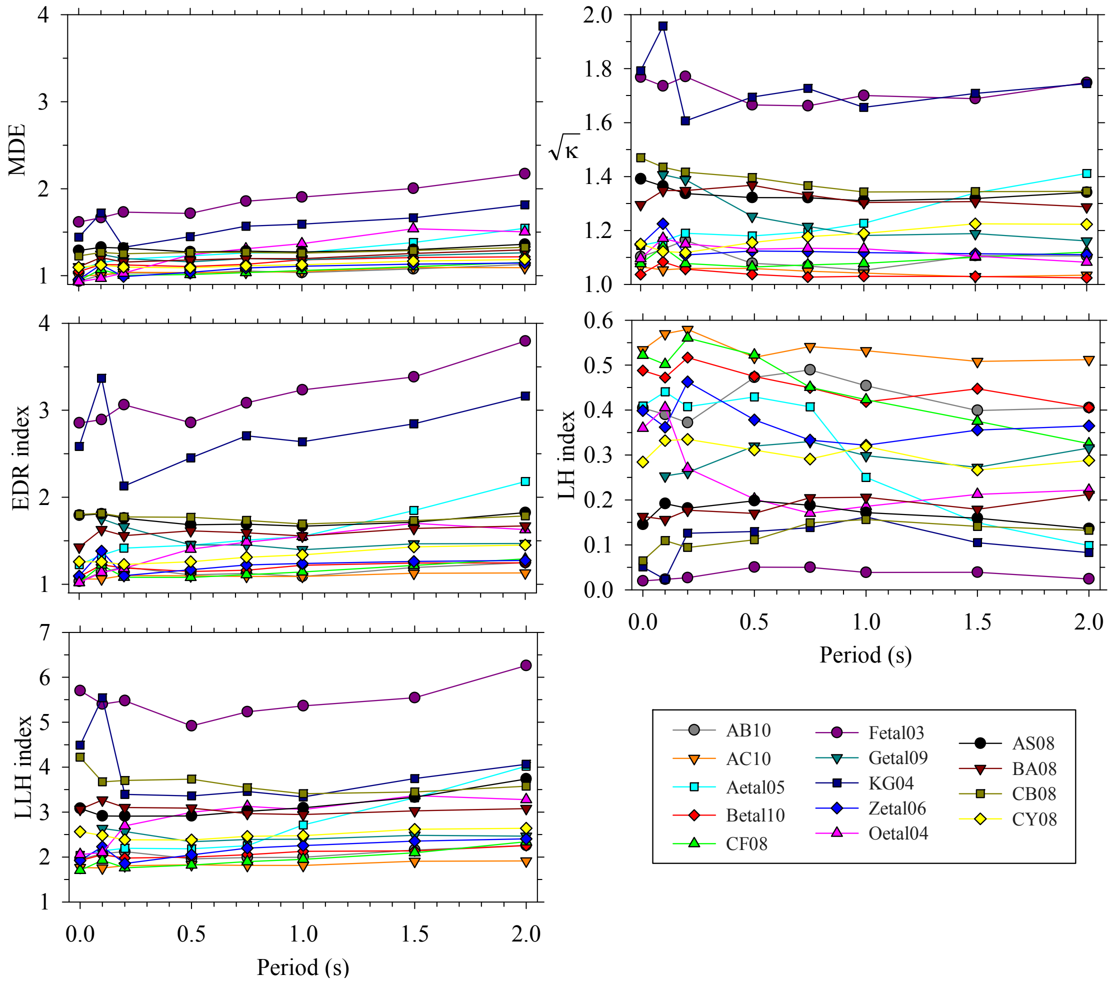

Figure 3.2. Performances of candidate GMPEs at the selected period levels when the entire database is used for testing of GMPEs. Top row shows the components of EDR index ($\sqrt{\frac{1}{N}\sum_{i=1}^{N}MDE_i^2}$ and $\sqrt{\kappa}$), middle row shows the actual EDR and LH indexes and bottom row shows the LLH index.

When model limitations are considered, AC10, Betal10, CF08 and Oetal04 perform better according to EDR and LLH procedures. LH method reports AB10 model instead of Oetal04 among the best four performing GMPEs while rest of the models are same with the rankings of EDR and LLH procedures. When the entire database is used for all GMPEs, all ranking methods select the same four GMPEs: AB10, AC10, Betal10 and CF08. When all the ranking results are considered from these 2 cases, the better performing GMPEs are AB10, AC10, Betal10, CF08, Oetal04 and Zetal06.

The above six GMPEs can be reduced further, if ground-motion variability is accepted to be addressed by 4 predictive models in GMPE logic-tree applications. The strong-motion database is divided into different M_w and R_{JB} bins. The bins range from small to large magnitude earthquakes with various R_{JB} intervals spanning near- to far-distance accelerograms. Fig. 3.3 shows the generated bins as well as the number of accelerograms in each bin. The M_w - R_{JB} bins are called with the numbers given in the horizontal axis of this figure. The individual performances of the six GMPEs are re-evaluated using these M_w - R_{JB} bins. The bin-dependent performances of the GMPEs are also important as the PSHA disaggregation results would identify different magnitude and distance values depending on the level of activity and proximity of seismic sources.

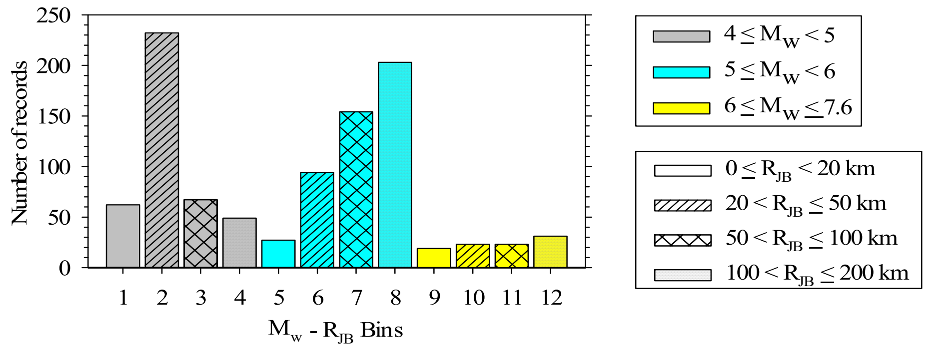

Figure 3.3. The generated M_w - R_{JB} bins. Intervals of M_w and R_{JB} are given next to each legend. Different magnitude intervals are represented by different colors while different patterns identify the distance intervals. For example, the 7th bin (i.e., No.7) represents the data for $5 \leq M_w < 6$ and $50 < R_{JB} \leq 100$ km.

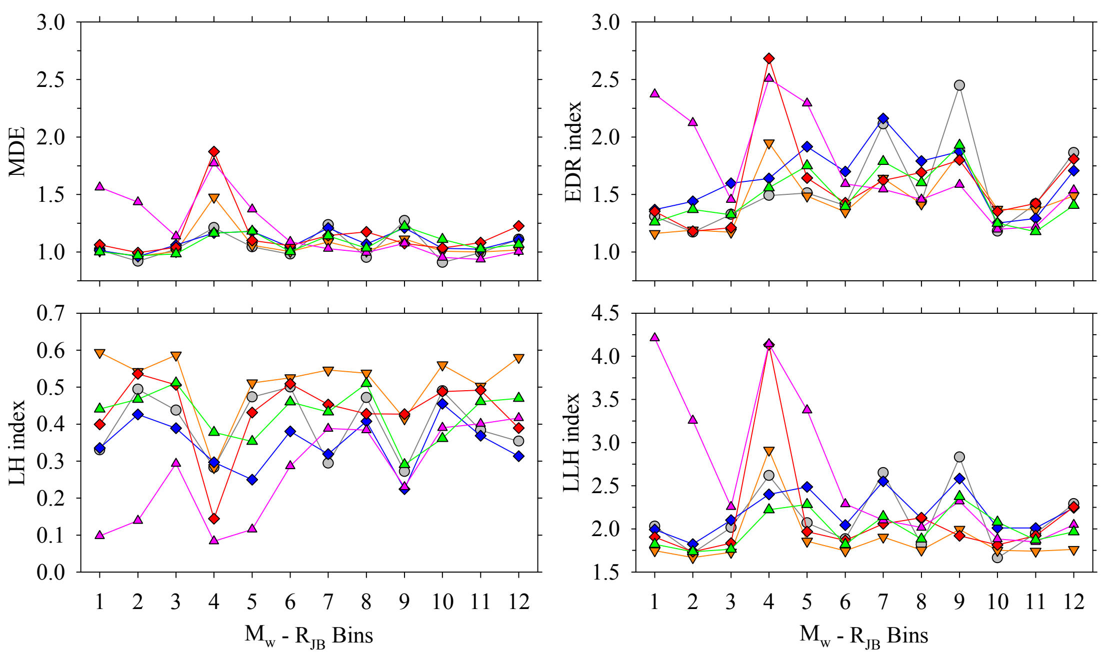

Figure 3.4. Performances of AB10, AC10, Betal10, CF08, Oetal04 and Zetal06 GMPEs for different M_w - R_{JB} bins. Legends of this figure is the same as in Fig. 3.2. Top row shows the MDE component of EDR (i.e., $\sqrt{\frac{1}{N}\sum_{i=1}^{N} MDE_i^2}$) and the actual EDR index. Bottom row shows LH and LLH ranking indices.

The GMPEs that show fairly stable ranking results for bin-based data as considered here can be used in the GMPEs logic-tree applications for the considered region. Fig. 3.4 shows the average testing results of six GMPEs to assess their bin-based performances. The first row panels in Fig. 3.4 show the performance of GMPEs in terms of MDE component of EDR (left panel) and EDR index (right panel). The second row panels show similar comparisons for LH (left panel) and LLH (right panel) methods. Among the considered GMPEs for bin-based performance, Oetal04 and Betal10 do not perform stable behavior especially for the small-magnitude - far-distance bin (i.e., No.4). Oetal04 model also shows relatively poor performance for bins of small and moderate magnitudes and near-distance recordings (i.e., No.1, No.2 and No.5). Another interesting observation from the presented results is the unstable performance of AB10 for close-distance – large-magnitude recordings (i.e., No.9). However, this model shows fairly good performance for the rest of the bins. AC10, CF08 and Zetal06 predictive models perform relatively better for all the bins. Under the light of these observations, GMPE logic-tree applications in Turkey can consider AB10, AC10, CF08 and Zetal06 for consistent hazard results.

4. CONCLUSIONS

In this study, different testing methods (i.e., LH, LLH and EDR) that are used for selection and ranking of ground-motion models are described with their essential features. The LH method (Scherbaum et al., 2004) uses the exceedance probabilities of normalized residuals to assess the candidate GMPEs. The information-theoretic LLH approach (Scherbaum et al., 2009) supersedes the LH method and it computes the occurrence probabilities of the empirical ground-motion data using the median and sigma values of GMPEs to develop a ranking index. These methods, in probability computations, normalize the residuals with standard deviation of the GMPEs. This fact may result in favoring of GMPEs associated with larger sigma in ranking (Kale and Akkar, 2012). The last investigated procedure, EDR that is proposed by Kale and Akkar (2012) handles the consideration of sigma in a different way: it considers a range of sigma values instead of normalizing the residuals with sigma as done by both likelihood methods.

A case study is conducted to compare the main features of the LH, LLH and EDR methods as well as the associated components of EDR index, which account for the effect of sigma and existing trend between observed data and median estimations. The case study also serves for proposing a set of consistent and reliable GMPEs for GMPE logic-tree applications in Turkey. The compared selection and ranking methods generally give similar ranking results. AB10, AC10, CF08 and Zetal06 are the proposed predictive models for GMPE logic-tree applications after evaluating different testing schemes on the pre-selected candidate GMPEs.

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