CALIBRATING THE BACKBONE APPROACH FOR THE DEVELOPMENT OF EARTHQUAKE GROUND MOTION MODELS

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Abstract. The backbone approach is becoming increasingly employed to develop ground-motion models for use within probabilistic seismic hazard assessments, particularly for nuclear facilities. The backbone approach has a number of attractions, including: transparency over the level of uncertainty implied by the ground-motion model, a clearer understanding of the meaning of the weights of the logic tree (because each branch is mutually exclusive and collectively exhaustive) and an ability to make the model specific for a given site. This is in contrast to the classic method of selecting (using various approaches) a suite of ground motion prediction equations from the literature, which may appear easier but suffers, for example, from the difficulty of understanding whether epistemic uncertainty in future ground motions at the site is sufficiently captured.

One of the principal challenges in applying the backbone approach is its calibration so that the branches of the ground-motion logic tree capture the appropriate level of epistemic uncertainty. This is particularly difficult for regions with limited strong-motion data, which are generally areas of lower seismicity. In this article, I summarize previous uses of the backbone approach in the literature before investigating calibration using the stochastic method, which is particularly useful when there are few or no local strong-motion records. I show that the scaling factors developed from the stochastic models roughly imply the expected variations in epistemic uncertainty given the amount of data available from different tectonic regimes.

Key Words: seismic hazard, ground-motion model, backbone approach, epistemic uncertainty.

1. INTRODUCTION

The development of ground-motion logic trees for use within seismic hazard assessments is a critical step within these assessments. As shown in many previous studies (e.g. [1]) the uncertainty in the ground-motion model is often the most important factor controlling the uncertainty in the final hazard curves. Therefore, there is considerable research and practical interest in methods for the construction of ground-motion logic trees; and various proposals have been made [2]. These proposals fall into two main categories (although there are studies applying aspects of both these techniques): populating the branches of the logic tree with previously published ground motion prediction equations (GMPEs), which is the traditional approach; or using fewer GMPEs (in the extreme case, just a single model) and populating the branches with scaled versions of this GMPE. This so-called backbone technique [3] has become increasingly popular, particularly for site-specific seismic hazard assessments for nuclear facilities. This increased use is because it captures epistemic uncertainties in a more transparent manner, which is particularly important in a highly regulated environment such as nuclear safety. In addition, the results of the hazard calculations are easier to interpret as the behaviour of each of the logic tree branches is often more understandable when using a backbone over a multiple GMPE approach.

Despite its use in a number of recent nuclear-related projects [4, 5, 6], there is still a need to investigate methods for the calibration of the backbone method, particularly in areas with few local strong-motion data from hazard-controlling earthquakes (generally magnitudes greater than 5 and distances less than about 100km). The objectives of this article are: firstly, to summarise previous studies applying the backbone approach and, secondly, investigate the calibration of the method using the stochastic method (e.g. [7]). The stochastic method is potentially more useful than a direct observational approach in low seismicity regions. Douglas [2] surveys observational approaches and proposes a method directly based on data.

2. Summary of previous studies

Table 1 summarises those studies in the public literature using the backbone approach to construct a ground-motion logic tree. Haendel et al. [8] propose using a mixture of GMPEs as the backbone model with the weights in the mixture defined by the fit between the individual GMPEs and the observations. They do not specify how this backbone should be scaled to construct a full logic tree so it is not included here. More details are given in [2] for most of the studies listed in Table 1.

TABLE 1: PREVIOUS APPLICATIONS IN THE PUBLIC LITERATURE OF THE BACKBONE APPROACH FOR CRUSTAL EARTHQUAKES.

Study	**Brief description of method**
Toro et al. [9]	Use a single backbone model, which is branched into four versions to account for uncertainty in median stress drop and modelling.
EPRI [10, 11]	Use four backbone models (weighted averages of component GMPEs derived using similar assumptions for the simulations used in their derivation) with branches capturing the variation between GMPEs within each cluster.
Atkinson [12]	Similar technique to [13] but she employs an unconventional split between aleatory variability and epistemic uncertainty.
Atkinson and Adams [13]	For active regions: use a single backbone and add branches to match the spread in the predictions from various GMPEs as well as averages of observed ground motions in well-recorded earthquakes. Use this spread as a lower limit on the branches for stable regions.
Al Atik and Youngs [14]	Use five backbone models and add branches to account for the statistical uncertainty (based on the covariance matrix) in the regression curves due to a lack of data.
Coppersmith et al. [4]	Use a single backbone model, which is representative of a set of selected GMPEs for hazard-critical scenarios, which adjust for shear-wave velocity (V_s) and kappa and branch out based on uncertainty in anelastic attenuation and magnitude scaling.
Petersen et al. [15, 16]	Use five backbone models to which they add additional branches that account for the number of earthquakes used to derive the models in different magnitude-distance bins.
Bommer et al. [5]	Use three backbone models, which in addition to applying a V_s-kappa adjustment, they scale by four factors reflecting uncertainty over the average stress drop in the region.
GeoPentech [6]	Similar technique to [17].
García-Fernández et al. [18] & Gehl [19]	Similar approach to [13] but applied to Europe and the Middle East.
Goulet et al. [17]	This is different to the other approaches as rather than branching out from a backbone GMPE, they extend the suite of the available GMPEs to a continuous distribution, which is visualised using a Sammon's map. Models are chosen from this Sammon's Map based on the expected epistemic uncertainty.
Douglas [2]	Uses a single backbone model with three regional anelastic attenuation terms, which he scales by three factors related to the observed differences in average ground motions in different countries/regions (from data and published GMPEs).

3. Calibration

When applying the backbone approach two principal choices have to be made: firstly, which GMPE (or GMPEs) is used as the backbone? And, secondly, how should this backbone model be scaled up and down? These two questions are discussed in the following, with a focus on the second.

3.1. Choice of backbone model (or models)

The ground motions predicted by published GMPEs can show considerable differences, even when considering only models that pass quality-assurance criteria (e.g. [20, 21]). These differences will manifest themselves in the final ground-motion models if the same scale factors are applied to different backbone GMPEs. There should be stability of hazard results if a different backbone model is used. Therefore, it is important that particular care be taken when choosing the backbone GMPE.

One important criterion for the backbone GMPE is that it provides robust predictions for all magnitudes and distances of interest to the seismic hazard assessment, even for those scenarios that are outside the GMPE's 'comfort zone' [20]. This criterion means that it may be better to use a global rather than local GMPE, even if the local model is for the region of interest.

To minimise the impact of the choice of the backbone GMPE, it may be best to choose the GMPE that provides predictions that are roughly in the middle of all considered models (e.g. [13]). Because the relationship (e.g. which one is highest and which lowest) between the predictions from different GMPEs depends on magnitude, distance and other independent parameters, it may be appropriate to use a Sammon's map [22, 23] to assess which model is the most representative of the potential choices.

Once they had winnowed down the choice of potential backbone models through application of the criteria of [20] and seismological arguments, Bommer et al. [5] sought diversity in the predictions from the three GMPEs they selected. This diversity was judged using simple seismic hazard assessments using the various backbone candidates and choosing those that led to separate hazard curves so as not to narrow unintentionally the modelled epistemic uncertainty. This led to the exclusion of some candidate GMPEs that produced similar hazard results.

3.2. Calibration of scale factors

In this section, I propose two approaches to calibrate the scale factors: firstly, an empirical approach based on recorded strong-motion data and, secondly, an approach based on published stochastic ground-motion models, which is discussed in more detail as it is the focus of this article.

3.2.1. Empirical

The simplest method of calibrating the scale factors is to use the approach of [13]. In this approach the spread in predictions from a set of GMPEs for magnitudes and distances of hazard-critical scenarios are examined visually, a representative GMPE is chosen, and scale factors estimated that when applied to that GMPE lead to lower and upper models that roughly cover the spread in the predictions from other GMPEs. In addition, Atkinson and

Adams [13] also examine observations from a set of well-recorded earthquakes for which the event terms (between-event residuals) are robust to also judge how much higher or lower the median GMPE could be. The scale factors can be magnitude and/or distance dependent. A Sammon's map representation of the spread of GMPEs could be used to make this approach more objective and better take account of many magnitudes and distances. The measure of the spread in GMPEs used in [1] and [14], i.e. $\sigma_{\ln y}$, which equals the standard deviation between predictions, perhaps averaged over magnitude and distance, could also be used to make this approach more objective.

Although this method is simple, it assumes that the available GMPEs provide a good model of the epistemic uncertainty in ground-motion prediction at the site in question. This assumption may be true for regional hazard mapping, which was the focus of [13], and for tectonic regimes (e.g. shallow crustal active) where there are many well-calibrated and independent GMPEs available. For site-specific studies and particularly those for tectonic regimes (e.g. stable continental) with limited data (and hence GMPEs), however, this approach would not be feasible or the scale factors would be difficult to justify. This width of the branches assessed using this approach for data-rich regimes can be used, as they are in [13], as a lower bound on the uncertainties that should be captured for data-poor regimes.

Douglas [2] computes the average residuals with respect to a single backbone GMPE computed using data from a magnitude-distance interval (**M** 5-6 and 20-60km) and three countries (Italy, Greece and Turkey) with considerable data. He also computes the average residual between the backbone GMPE and local GMPEs that provide robust predictions at least for that limited magnitude-distance range. Consequently, he proposes scaling factors that would capture the spread in the observed average residuals, which he suggests captures the 'regional' uncertainty related to differences in the average stress drop between regions. Using the residuals with respect to the chosen backbone model means that the scale factors would adjust automatically if a different backbone model were chosen.

If it is assumed that there was no regional dependency in ground motions for a given tectonic regime and a GMPE derived using all available data and a state-of-the-art derivation technique were available then this model could be chosen as the backbone model. Then the scale factors should equal those from the statistical uncertainty in the regression. This is the proposal of [14], although because the NGA West 2 GMPEs show between-model differences they propose that these differences are also captured within the final logic tree.

3.2.2. Stochastic

Stochastic models (e.g. [7]) provide a useful method of predicting earthquake ground motions for areas with limited strong-motion data because the input parameters related to the path (principally, geometric decay and anelastic attenuation, Q) and site (principally, site amplification and attenuation, kappa) can be assessed using weak-motion data and geological/geophysical/geotechnical information. The remaining inputs, i.e. those related to the source (principally, source spectral shape and stress drop/parameter), can be estimated from weak-motion data, although there remains uncertainty on the applicability of these parameters for strong ground motions (e.g. [24]). The use of the stochastic method to derive scale factors for the backbone approach is the focus of the rest of this article.

Because parameters of the stochastic model trade off (e.g. [25]) it is not possible to compare stress drop/parameters estimates for different regions from various studies unless the rest of the parameters (e.g. geometric decay function and Q) are the same. Therefore, the variation in predictions from stochastic models are used in the same way as variations in observed ground motions were by [2].

The twenty stochastic models considered in [26] are used for the calculations presented here. Since publication of [26] a number of stochastic models have been proposed for other regions [27] but the general trends demonstrated by these twenty models are unlikely to have changed significantly. Douglas [26] separates the models into three tectonic regimes based on average strain rates, roughly corresponding to: low (stable continental regions), intermediate (intraplate, plate boundary related) and high (interplate), which has been retained here to examine whether the variations between models depends on the tectonic regime.

In agreement with the approach of [2], the variations between the stochastic models at **M** 5.5 and a hypocentral distance of 50km are examined. Again for consistency with [2] the base GMPE (i.e. the model without the regional terms) of [28] is used to compute the residuals. Figure 1 shows the computed residuals [i.e. natural logarithm of predictions from the stochastic model – natural logarithm of predictions from the GMPE of [28]] for peak ground acceleration (PGA) and pseudo-spectral acceleration (PSA) at 1s. From this graph it can be seen that the spread of the predictions becomes narrower as the strain rate increases for both intensity measures, which is probably mainly related to stress drop/parameters showing larger variations in low strain regimes (differences in attenuation is unlikely to be a predominant factor at 50km). Some of this variation may be due to large epistemic uncertainties in assessing the parameters of the stochastic model in low strain (and consequently low seismicity) regions. This variation in the spread of the residuals is confirmed by the standard deviations within each regime: for PGA, 0.74, 0.91 and 1.39 for high, intermediate and low strain, respectively; and for PSA(1s), 0.43, 0.78 and 0.92 for high, intermediate and low strain, respectively.

Comparing the width of the branches that would be required to span the spread of the residuals for each of the regimes with those proposed by [2] shows that a wider spread is necessary based on the stochastic models for intermediate and low strain regions. For high regions the spread of 1.4 (in terms of natural logarithms) for PGA and 1.0 for PSA(1s) proposed by [2] is consistent with the spread seen in the predictions from the stochastic models (if the Erzincan model is excluded).

Assuming a constant value of kappa, the stress drop/parameter is the most important effect influencing the predictions from the stochastic models for the magnitude-distance range of most interest for seismic hazard assessment. Therefore, the considerable recent work on variability in stress drops can be used as a constraint on the width of the branches. This is useful as often articles publish only estimates of stress drop/parameters from many earthquakes rather than complete stochastic models (e.g. [29]). Note that, because of the trade-off in the parameters within stochastic models mentioned above, only the spread in stress drop/parameters rather than the actual values are examined here.

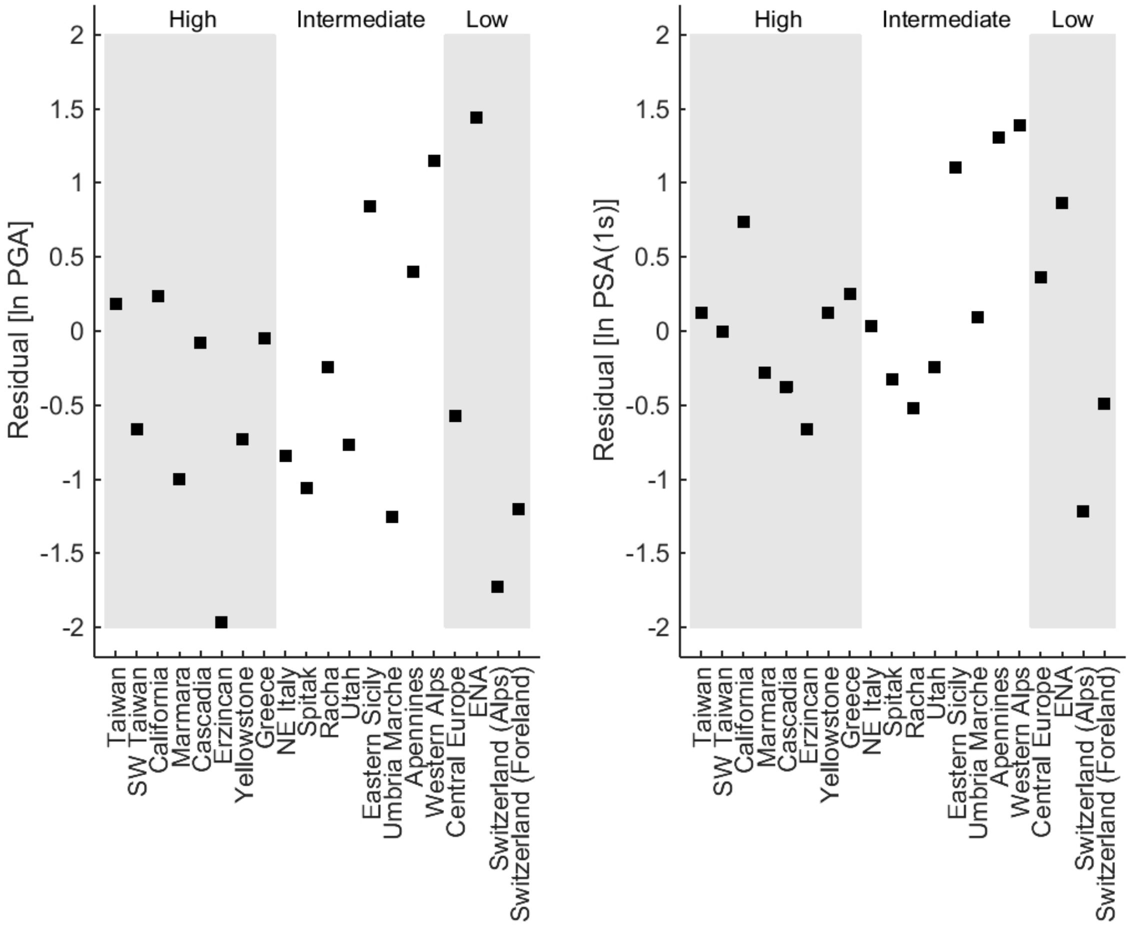

FIG. 1. Residual between various stochastic models and the base model of [28] evaluated at ***M*** *5.5 and hypocentral distance of 50km for PGA (left) and PSA at 1s. A vertical fault and a hypocentral depth of 10km is assumed when evaluating [28].*

Cotton et al. [30] discuss the variability in stress drops/parameters, which they capture by the standard deviation (sigma). There are two end members of the spread in average stress drop using their estimates of sigma, which can be used to assess the scaling factors for the backbone approach. Firstly, the sigma of the stress drop is an estimate of the possible variation in average stress drop between regions (using sigma as if it were a standard error) or, secondly, the average sigma is the same everywhere (with a standard error of zero) and the reported sigma is a reflection of the global standard deviation. In the first case, high stress-drop earthquakes in areas of low to moderate seismicity (e.g. Saguenay, Canada, 1988; Market Rasen, UK, 2008; St Die, France, 2003) would provide estimates of the average stress drop for that region in the absence of other data. In the second case, the high stress drops in these events would be seen as simply part of the natural variability of a lower average and a relatively high standard deviation. The reality is probably somewhere been these extremes. It is informative, however, to assess these lower and upper bounds on possible scaling factors.

Table 2 reports the standard deviations and standard errors in the natural logarithms of the stress drop/parameter (assuming that $\Delta\sigma$ is lognormally distributed) from some recent studies: [29] for global intraplate events (their Table 1); [31] for predominantly Italy and Turkey (their Table 3 for earthquakes recorded by at least seven stations); [32] for Switzerland (their equations 10 and 11); and [33] for Japan (their Figure 2). Next, I assume a simple ground-motion logic tree with lower, middle and upper branches. The middle branch uses the median

$\Delta\sigma$ within a stochastic model. The lower and upper branches reflect the uncertainty in this median by using the 5^{th} and 95^{th} percentiles of the confidence interval using the reported standard error. The weights of the lower, middle and upper branches would be 0.185, 0.63 and 0.185, respectively, following the approach of [14].

The $\Delta\sigma$ adjustment equation of Atkinson and Boore [34, 35; their equation 6] can be used to estimate the impact of this uncertainty in the median $\Delta\sigma$ on ground motions predicted by the stochastic model. The ratios in the predicted ground motions between the upper and middle branches of ground-motion logic trees constructed using this approach are reported in Table 2 for PGA and PSA for a natural period of 1s assuming a moment magnitude of 6.

TABLE 2: STANDARD DEVIATION (S.D.) AND STANDARD ERROR (S.E.) OF ln($\Delta\sigma$), WHERE $\Delta\sigma$ IS THE STRESS DROP/PARAMETER, FROM VARIOUS STUDIES. ALSO GIVEN ARE THE RATIOS BETWEEN THE UPPER AND MIDDLE BRANCHES OF A GROUND-MOTION LOGIC TREE CONSTRUCTED USING THESE S.D.s AND S.E.s (SEE TEXT FOR DETAILS).

Reference	**Subset**	**Median $\Delta\sigma$ (MPa)**	**S.D. of ln($\Delta\sigma$)**	**PGA**	**PSA(1s)**	**S.E. of ln($\Delta\sigma$)**	**PGA**	**PSA(1s)**
Allmann and Shearer (2009)	Intraplate	6.0	1.22	3.79	2.43	0.157[1]	1.19	1.12
Bora et al. (2017)	All	7.9	0.91	2.70	1.94	0.139	1.16	1.11
	Italy	3.7	0.52	1.77	1.46	0.139	1.16	1.11
	Turkey	8.2	0.90	2.67	1.93	0.176	1.21	1.14
	M≥5	6.1	0.82	2.45	1.82	0.145	1.17	1.11
Edwards and Fäh (2013)	Foreland	0.2	0.81	2.42	1.80	0.147	1.17	1.11
	Alpine	0.1	0.62	1.97	1.57	0.076	1.09	1.06
Oth et al. (2017)[2]	All	~2	1.10	3.32	2.23	0.025	1.03	1.02
	Kyushu	~9	0.91	2.70	1.94	0.054	1.06	1.04
	Honshu	~1	0.84	2.50	1.84	0.021	1.02	1.02

The results presented in Table 2 suggest that the epistemic uncertainty in the predictions of median ground motions is quite small when considering the standard error of ln($\Delta\sigma$), especially when there are many earthquakes available from which to compute the median $\Delta\sigma$ and its standard error (e.g. in Honshu). This is only true within the region, however, because of the large variations in median $\Delta\sigma$ between regions, e.g. compare median $\Delta\sigma$ for the alpine region of Switzerland (0.1MPa) and Kyushu (Japan) (~9MPa). Because the data from Switzerland used to estimate $\Delta\sigma$ is all from small events, whose relevance to the prediction of ground motions from moderate and large earthquakes is difficult to assess, it could be argued that these data should not be considered when calibrating the backbone approach. This reduces considerably the spread in $\Delta\sigma$. However, as noted above, values of $\Delta\sigma$ from different

[1] The standard error of the *median* $\Delta\sigma$ in this article is reported as '±1.01' rather than as a ratio, which would be correct if they were computed using the logarithms of $\Delta\sigma$. The standard error report is converted to natural logarithms thus: ln[(5.95+1.01)/5.95], where 5.95 is the reported median $\Delta\sigma$ (in MPa).

[2] The values of median $\Delta\sigma$ are not explicitly given in this article. The median was estimated by eye from the histogram provided.

studies should not be compared in isolation unless the other parameters in the stochastic model are identical.

A large epistemic uncertainty is implied by using the standard deviation of $\ln(\Delta\sigma)$ to assess the width of the lower and upper branches. As discussed above, this makes a strong assumption on the meaning of the variability in stress drop/parameter between earthquakes and hence it is unlikely to provide appropriate scaling factors.

4. Conclusions

In this article, firstly, I have provided a brief overview of the backbone approach [3] for the construction of ground-motion models for use in seismic hazard assessments and, secondly, I proposed two techniques to calibrate this technique. The backbone approach has advantages over the classic multiple GMPEs approach when developing ground-motion models that transparently and rigorously capture epistemic uncertainties. Nevertheless, the calibration of this technique for different regions and sites requires considerable care and further research to capture not just what we know but what we *do not* know about strong ground motions that could affect nuclear installations.

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