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PRELIMINARY RESULTS ON THE DEVELOPMENT OF AN ADJUSTABLE BACKBONE APPROACH FOR GROUND-MOTION PREDICTION WITHIN THE UK

Ilaria MOSCA[1], Brian BAPTIE[2], Richard FOWLER[3] & Peter STAFFORD[4]

Abstract: *The ground motion model (GMM) used in seismic hazard studies describes the value(s) of the ground motion parameter of interest at the site from all possible earthquake scenarios. However, choosing a GMM can be challenging because it has a strong influence on the hazard estimates, both in terms of estimated median prediction and the aleatory uncertainty, i.e. the random variability. In the last five years, the backbone approach has emerged as a way to more rigorously capture the epistemic uncertainties in the median prediction of the GMM. It is based on the selection of one or more ground motion prediction equations (GMPEs), which is referred to as the 'backbone model'. The median predictions of the backbone model are then scaled up and down to capture the epistemic uncertainties in the median ground motion using available observations from the target region. This approach has been successfully applied at a regional and local scale. We developed a methodology to adapt the backbone approach proposed by Stafford et al. (2022) to predict ground motion in the United Kingdom (UK). The GMPE of Chiou and Youngs (2014) is used as the backbone model. This is adjusted for source and path characteristics to account for the host-to-target differences using the available data in the target region. To achieve this, considerable effort has been spent to compile a database of existing metadata for ground motion recordings available for the UK, including event and station information, a dataset of homogeneous strong motion data, stress drop parameters recorded for British earthquakes and existing anelastic attenuation models. Here, we will give an overview of this database, whereas we will show preliminary results on the initial Fourier spectral inversion of the backbone model to estimate the key source and path parameters for the target region at the conference.*

Introduction

Capturing the uncertainty in ground motions from possible future earthquakes is a significant challenge for earthquake hazard assessment, particularly in intraplate regions with low levels of seismicity, such as the UK, where there are limited data.

The traditional approach to develop the ground motion model in seismic hazard analysis is the selection of multiple ground motion prediction equations (GMPEs) in a logic tree formalism to account for the centre, body, and range of technically defensible interpretations of the ground motion model (Budnitz et al., 1997; Atkinson et al., 2014). The variability in the ground motion is captured by including alternative models and parameters in the logic tree where weights are assigned to each branch using expert judgement and/or data-driven approaches to reflect the relative confidence in the models and parameters (Coppersmith and Bommer, 2012). This often introduces a certain degree of judgement making the process to define the logic tree weighting scheme opaque. Moreover, Bommer and Scherbaum (2008) argue that because the alternative models selected to populate the ground motion logic tree are often derived from the same dataset, they do not fully capture the epistemic variability in the median prediction of the ground motion model. Last but not least, even GMPEs that are derived in regions with abundant recordings appear not to be fully adequate to capture the full range of epistemic uncertainty in the ground motion (Al Atik and Youngs, 2014).

To overcome the shortcomings of the multi-GMPE approach, the backbone approach has emerged as a more transparent way to capture the epistemic uncertainties in the median prediction of the ground motion model (e.g. Atkinson et al., 2014; Bommer and Stafford, 2020). It

[1] Dr, British Geological Survey, Edinburgh, United Kingdom, imosca@bgs.ac.uk
[2] Dr, British Geological Survey, Edinburgh, United Kingdom
[3] Principal Inspector, Office for Nuclear Regulation, Cheltenham, United Kingdom
[4] Prof, Imperial College London, London, United Kingdom

is based on the selection of one, or more, GMPE, which is referred to as the 'backbone model'. The median predictions of the backbone model are then scaled (or adjusted) up and down to describe the range of epistemic uncertainties in the median ground motion (e.g. Atkinson et al., 2014; Douglas, 2018). The scaling factors can be considered as host-to-target adjustments to adapt the source, path, and site components of the backbone model that was derived for a host region to the target region (e.g. Stafford et al., 2020). The backbone approach has been successfully applied at a regional scale (e.g. Goulet et al.; 2017; Akkar et al., 2021; Weatherill et al.; 2020, Stafford, 2022) and a local scale (e.g. Coppersmith et al., 2014; Bommer et al., 2015; Kowsari and Ghasemi, 2021; Boore et al, 2022).

In this work, we develop a methodology to adapt the backbone approach proposed by Stafford et al. (2022; here referred to as SBYB22) to predict ground motion in the UK where the GMPE of Chiou and Youngs (2014) is the host backbone model. In the following sections, we describe the database of metadata for UK ground motion recordings and the uniform processing of ground motion recordings to obtain Fourier amplitude and response spectra.

Features of the BGS ground motion dataset

The UK national seismic monitoring network operated by the British Geological Survey (BGS) currently consists of about 75 stations, of which 28 have strong motion sensors, mostly co-located with broadband sensors. This network developed with time since the 1970's and reached a peak of over 140 stations in the late 1990s. We select 1521 observations from 53 low-to-moderate (3.5 ≤ ML ≤ 5.4) earthquakes that occurred in the UK and the North Sea between July 1984 and December 2022. Figure 1 shows the location of the 53 earthquakes and the recording stations, whereas the distribution of the strong motion data as a function of epicentral distances (up to 500 km) and local magnitude is displayed in Figure 2. The majority of the data are weak motion recordings for earthquakes of magnitude lower than 4 ML and distances larger than 50 km. The largest earthquake, for which strong motion records are available, is the 5.2 ML Market Rasen earthquake on 27 February 2008. Note that in this first phase, we have selected a broad dataset of earthquakes and stations that may be reduced when all the waveforms are inspected and the Fourier spectral inversion is performed.

Most of the BGS monitoring stations are uncharacterised in terms of local site conditions and often little information is available on the geological conditions where the stations are located. For further information see the SECED conference paper ID57 by Mosca et al. (2023).

The stations, earthquakes and waveform metadata are stored in the SEISAN format (Haskov et., 2020). The data is organized in a database-like structure using the file system. The smallest basic unit is the S- file, which is expressed in the Nordic format and contains the source parameters (e.g. date and time, location, depth, and magnitude) and original phase readings (arrival times, amplitude, period, azimuth, and apparent velocity) for one event. The metadata for the stations are also in SEISAN format and include station name and code, network name, location and altitude as well as instrument response (Ottemöller et al., 2021).

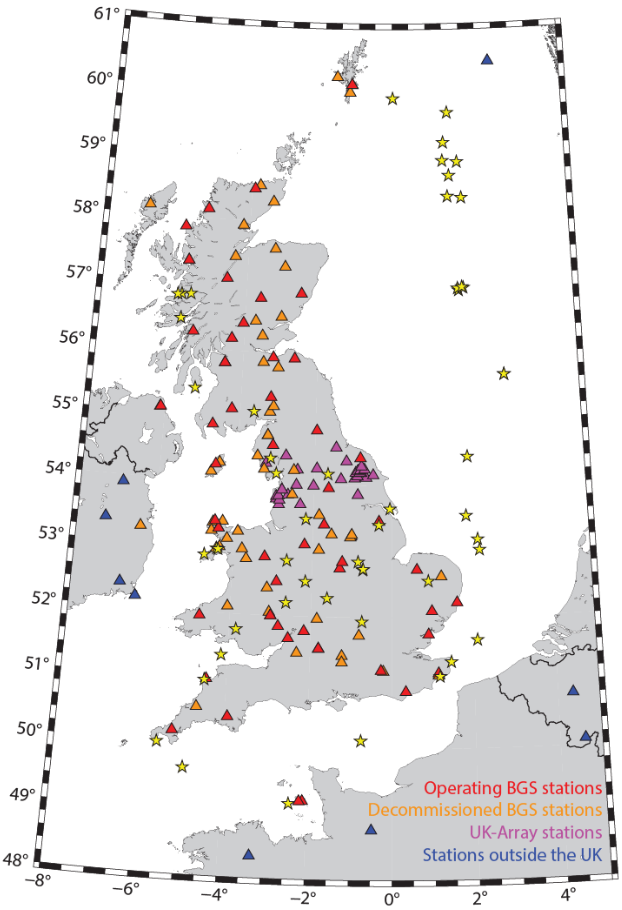

Figure 1. Location of the seismic monitoring stations (triangles) and earthquakes (stars) for which the strong motion observations were recorded.

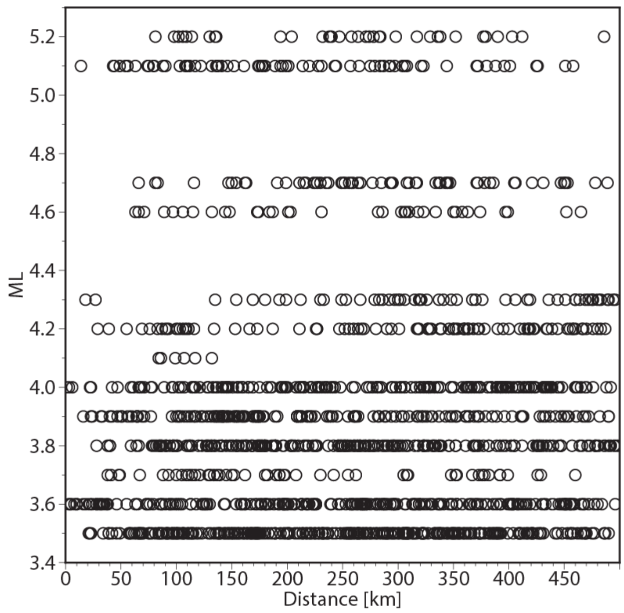

Figure 2. Distribution of the UK ground motion data in terms of distance and magnitude (for distances up to 500 km).

Record processing

We develop an automatic workflow to ensure that the UK strong motion data are processed uniformly. This is based on the data processing developed for the European Engineering Strong Motion (ESM) Database (Lanzano et al., 2019) to select and process uncorrected acceleration time series and derive several products, including processed acceleration time series, displacement and acceleration response spectra. Care is taken to remove high- and low-frequency noise through filtering since this can affect weak motion data. The processing workflow consists of a set of Python scripts.

The main steps of the processing are the following.

- Read the S-file for an event and a selected station and look for the corresponding acceleration time series in the BGS waveform archive.
- Remove the instrument response after applying a bandpass pre-filter. This pre-filter defines the four corner frequencies of a cosine taper and aims to prevent amplifying the noise during the deconvolution between the signal and the station response. The pre-filter is designed to include as much signal as possible without losing information.
- Window the time series to identify the starting and ending time of the waveform.
- Baseline correction to remove the linear trend using a least square method.
- P- and S-wave arrival picking.
- Identification of the portion of signal and noise that is selected before the occurrence time of the event.
- Signal-to-noise ratio (SNR) for each acceleration component is defined as the ratio between the smoothed Fourier amplitude spectrum (FAS) of the signal and the noise. The FAS smoothing is computed using the Konno and Ohmachi (1988) log-scale smoothing with a smoothing factor of b = 40. The SNR is used to define the usable frequency range. This corresponds to the continuous frequency window with SNR above 4 by a visual inspection.
- Application of a cosine taper with a 5% tapering rate at both sides of the time series and padding with zeroes. This step avoids the possible ringing effects that can occur in the time domain after applying acasual filters (Boore, 2005; Boore and Bommer, 2005).
- Application of the 8th order acasual (zero phase) frequency domain Butterworth filter to the 3-component acceleration time series (Edwards and Ntinalexis, 2021).
- Computation of the spectral acceleration and displacement for the 50th percentile of the response spectra over all non-redundant rotation angles (RotD050).

Figure 3 shows an example of the FAS and SNR for the two horizontal components of the original and processed acceleration time series recorded by station MCH1 for the 5.2 ML 17 February 2018 earthquake in South Wales, together with spectral acceleration and displacement for the RotD050.

Towards the Fourier spectral inversion

We follow the SBYB22 approach where the (host) backbone model is the GMPE of Chiou and Youngs (2014). The GMPE of Chiou and Youngs (2014) has been identified as the most adaptable backbone model of current GMPEs to target regions with crustal earthquakes, having a functional form that closely mimics the theoretical scaling implicit in stochastic simulations and including terms that can be individually adjusted for host-to-target region differences in source, path, and site characteristics (Bommer and Stafford, 2020; Stafford et al., 2022).

The SBYB22 methodology is based on the inversion of empirical target data and the backbone model to define the Fourier spectral parameters for source and path characteristics for the UK. This is done using the Hybrid Empirical Method of Campbell (2003). We will present the results of the Fourier spectral inversion at the conference.

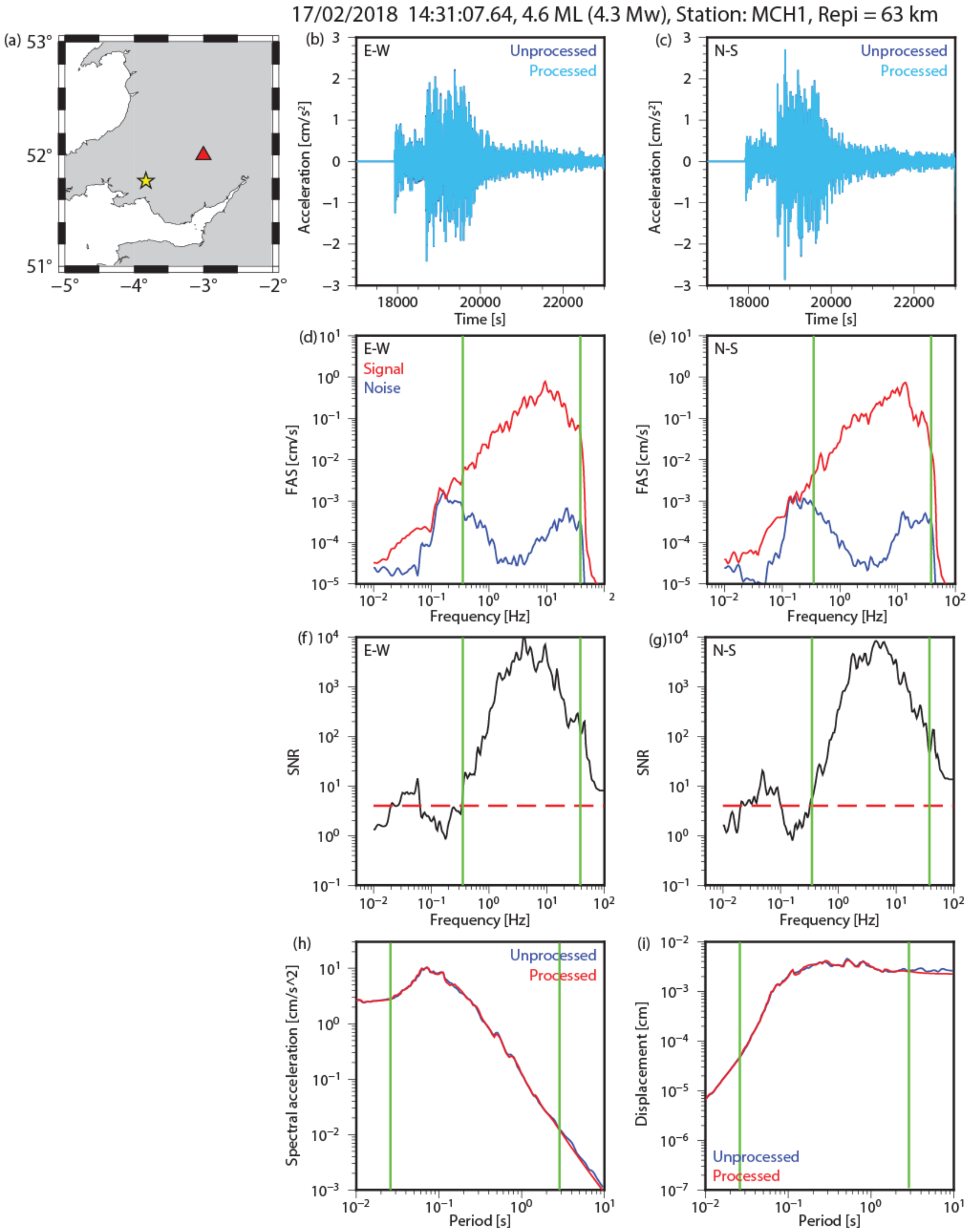

Figure 3. (a) Geographical location of the earthquake epicentre (yellow star) and the station MCH1 (red triangle). (b, c) Raw and processed acceleration time series for the two horizontal components. (d, e) Fourier amplitude spectra (FAS) of the signal and noise portions for the two horizontal components. (f, g) Signal-to-noise ratio (SNR) for the horizontal components. (h, i) Pseudo spectral acceleration and spectral displacement for the 50th percentile of the response spectra over all non-redundant rotation angles. The dashed red lines in (f, g) indicate the SNR threshold of 4. The green vertical lines in (d-i) described the usable frequency range and the corresponding usable period range.

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