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UNCERTAINTY ANALYSIS OF STRONG GROUND MOTION

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SUMMARY

Uncertainty modelling of strong ground motion is presented, emphasising engineering applications. The peak ground acceleration estimation equation is discussed, and implications for hazard and risk assessment are outlined. Currently, regression analysis provides by far the most common approach to establish ground motion estimation equations. These equations usually present an uncertainty measure, the total error, for the derivative variables, which depends on the uncertainty inherent in the basic data.

An alternative approach is presented, based on theoretical modelling, defining a functional relationship on a set of independent basic variables. Uncertainty in the derivative variable is then readily obtained when the inherent uncertainty of the basic variables has been defined. To simplify the presentation, shallow strike slip earthquakes with vertical fault planes are emphasised. In spite of this simplification, we believe that the methodology presented has a wider application.

The presented methodology is applied to interpret and re-assess the uncertainty of the derivative variable in the strong-motion estimation model. The result is that the uncertainty is approximately the same as given by the residuals typical for regression modelling. This finding seems to imply that uncertainty in attenuation modelling cannot be reduced below certain limits, which is in accordance with findings reported in the literature.

Finally, the implications of the presented methodology for hazard and risk analysis are discussed. It is well known that results obtained in hazard assessment are sensitive to the truncation of the error term commonly given as an integral part of strong-motion estimation equations. The presented approach does not suffer from this shortcoming and yields an apparently reasonable hazard curve without introduction of artificial constraints.

INTRODUCTION

In strong-motion engineering seismology, the variability, unpredictability, dispersion and scatter, in general, uncertainty in quantities seems to be the rule and not the exception. This applies especially to the so-called ground motion estimation equation [1] used for prediction of strong-motion at a given site

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induced by a seismic event with given characteristics. By such a relationship it is possible to transfer the seismicity of a given seismogenic region into the seismic action required for the design of structures and risk management. The uncertainties involved in this estimation process can be divided into two main categories, sometimes referred to as aleatory and epistemic uncertainties. The epistemic uncertainties are due to lack of knowledge used to describe the phenomenon. Obtaining new data and refining the modelling can reduce these uncertainties. Aleatory uncertainties, on the other hand, are related to the inherent unpredictability of earthquake processes. Such uncertainties cannot be reduced but are an intrinsic part of nature. It is important to be able to quantify these uncertainties correctly in the design process to ensure adequate safety and reliability of structures.

The objective of this paper is to discuss the nature of uncertainties connected with strong ground motion and quantify them. Furthermore, the aim is to give an example of uncertainty modelling and discuss the implications for the engineering design process. The following presentation is based on [2], where further details and equations are presented.

UNCERTAINTIES IN STRONG-MOTION MODELLING

The uncertainties related to the modelling of strong ground motion can be divided into two main classes:

(1) uncertainties related to the functional form of the model and

(2) uncertainties inherent in the input or basic variables applied in the modelling.

It is preferable to select the basic variables as independent in the probabilistic sense. The basic variables commonly used can be divided into three main categories:

(3) Variables describing the source, which include magnitude or seismic moment, epicentral location, depth and source dimensions. Furthermore, we believe that this category should also include the type of focal mechanism, which is not always recognised but is especially important for distance to the source less than four to five times the characteristic source dimension.

(4) Variables characterising the site. These include distance to the source, as well as variables describing the site conditions reflecting the local geology as well as local geography.

(5) Variables describing the wave propagation process and properties of the ray path from source to site. These variables include the mechanical properties of rock, including its damping characteristics.

It is common to treat some of the model variables as derivative variables rather than basic variables. In the modelling process there is a general tendency towards simplification. This is in accordance with the principle that the best scientific model is the model with the smallest number of basic variables that predict the derivatives with sufficient accuracy and reliability conforming to available data. From the engineering point of view, such a model is preferable as it simplifies design decisions and makes the design process more robust than is the case with more complex models.

Modelling based on regression analysis provides by far the most common approach to establishing ground motion estimation equations. Douglas [3] has given a comprehensive overview of these models encountered in the literature. The standard deviation of the residuals, the standard error, typically has values in the range 0.2 to 0.3 (assuming logarithm base 10).

It is found that the standard error is a function of the inherent uncertainty in the variables magnitude and source distance as well as other variables included in the ground motion estimation equations. This is evident as the standard error derived for a given data sample with uniform soil conditions is in general smaller than the standard error derived for a sample with mixed soil properties. The same applies to source mechanics and depth. Furthermore, the standard error obtained for a single event is smaller than the error derived from a sample containing many earthquakes, even in the case where influences from variables other than magnitude and distance are kept as small as possible. This has been pointed out by Brillinger and Preisler [4]. They found, applying a ground motion estimation equation with two variables (magnitude and distance) that the standard error could be split into two parts: (a) a contribution related to the variability between earthquakes, $\sigma_M = 0.2284$, and (b) a contribution related to variability between records from the same earthquake, $\sigma_R = 0.1223$. This gave a total error of $\sigma = \sqrt{0.2284^2 + 0.1223^2} = 0.259$.

This indicates that the total standard error can be assumed to be composed of contributions related to uncertainties inherent in the quantities governing the physical process and hence the variables of the mathematical model fitted to the data. It is therefore not obvious that increasing the number of model variables will lead to reduction of the total standard error. On the other hand, a refined model may better explain the sources of uncertainties than a simplified model.

MODELLING OF UNCERTAINTIES

Quantification of the uncertainties within the framework of regression modelling is chiefly through the total error, as discussed above. To be able to describe the uncertainties better and reveal their statistical interrelations, a more thorough analysis is needed. A suitable tool for this type of analysis is discussed in [2], using uncertainty modelling [5], the so-called safety index concept. To be able to apply this methodology, we need a well-defined set of basic variables and a functional relationship relating the derivative ground motion parameters to these basic variables. It is desirable that this functional relationship is derived from the basic principles of mechanics and reflects all main aspects and core ingredients needed for a theoretical description of the problem. The theoretical ground motion model adopted for our discussion here is described in detail by Olafsson [6]. It is based on the widely applied Brune source spectra [7] and is found valid for shallow strike slip earthquakes with approximately circular faults, i.e., the thickness of the seismogenic zone is not a significant constraint. One of the shortcomings of this model, from a practical point of view, is that it contains many variables, some of which may be difficult to obtain. A way out of this is to use constraint optimisation to define the parameters, provided we have reliable data. As pointed out [2], the lack of data prevents us from carrying this out, except for a limited number of special cases. Therefore, a less rigorous approach will be adopted, using statistical information when available and heuristic, a priori assumptions otherwise. This is done to illustrate the methodology rather than provide accurate statistical information.

Basic methodology

It is assumed that the behaviour of the earthquake-induced (ground) response can be modelled using a finite number of uncertain, measurable variables, termed basic variables and denoted by **X**. In the following, the basic variables are modelled as independent, stochastic variables. This implies that the variables are uncorrelated. Furthermore, it is assumed that the response can be described by a mathematical expression or function, called the response function of the system, exemplified by the strong-motion (response) estimation equation, expressed for simplification as:

$$A = f(\mathbf{X}) \qquad (1)$$

where, A is a derivative variable, for instance, peak ground acceleration.

It is elucidating to look at this function as a hyper-surface in an n-dimensional space of the basic variables. The response hyper-surface divides the space into two regions, that is, a region where $f(\mathbf{X}) > A$, and a region where $f(\mathbf{X}) < A$, which we could call, respectively, the exceedance and the non-exceedance region, assuming that A is a prescribed quantity. Furthermore, as the basic variables are assumed to be modelled as stochastic variables, the performance of the system can only be expressed in probabilistic settings as follows:

$$Pr\left[f(\mathbf{X}) \geq A\right] = C_p \tag{2}$$

Here, $Pr[\cdot]$ denotes the probability of exceedance, A is a prescribed reference value, and C_p is a number quantifying this probability.

Within the framework of the safety index approach [5], the basic variables, $\mathbf{X}$, are transformed to a normalised, Gaussian space, where the transformed variables, $\mathbf{u}$, are normally distributed with zero mean and unit standard deviation. Hence, the safety index can be obtained as:

$$\beta = \min\sqrt{\mathbf{u}^T\mathbf{u}} \qquad \text{for } \mathbf{u} \in \left\{\mathbf{u}\text{:}\ f\left(\mathbf{u}\right)\right\} \tag{3}$$

where, $\mathbf{u}$ denotes the vector of basic variables in the normalised, Gaussian space, and $a = f(\mathbf{u})$ is the corresponding response function. The point on the response surface with the highest probability density describes the ‘most likely’ performance of the system. The index β can be interpreted as the number of standard deviations that we have between the mean value and the border defined by the response surface. Furthermore, we have:

$$\Phi\left(-\beta\right) = C_P \tag{4}$$

where, Φ denotes the standardised normal distributions. If the response surface is well behaved, we assume that the above model applies with a reasonable degree of accuracy, which is the case when the response surface can be described with a hyper-plane in the vicinity of the performance point.

The basic variables used to describe the adopted strong-motion model can be selected in different ways. Without going into detail, we have selected the following basic variables, which we judge applicable for the presented case [2]:

1. magnitude or seismic moment
2. distance to source
3. depth
4. fault radius
5. shear wave velocity
6. density
7. spectral decay
8. peak factor

We assume, for the time being, that these variables can be treated as independent stochastic variables, and that other variables are either treated as stochastic derivative variables or approximated as deterministic.

Basic variables

The first variable mentioned above is magnitude. We find that the uncertainty in magnitude estimates tends towards normal distribution. However, the standard deviations obtained depend strongly on the number of stations as well as their azimuthal distribution. Based on [8] it was found for Iceland and the Iceland Region that the mean value of the standard deviations for individual events is 0.24, which is close to the values obtained for events during the last decade for which we have recordings from many stations (approximately 100). Hence, we can deduce that the standard deviation of magnitude estimates is quite high.

The ground motion model applied herein does not include magnitude as an explicit variable but the seismic moment, M_o. We therefore treat the seismic moment as a derivative stochastic variable. For magnitudes greater than 6, there is a small difference between the moment magnitude scale, M_w, and the surface-wave magnitude scale, M_S. In that case it is possible to use the Hank-Kanamori relation [9] to relate seismic moment and magnitude, i.e., $M_w = \frac{2}{3} log_{10}(M_o) - 10.7$ if $M_w > 6$.

To quantify the uncertainty in the seismic moment, let us assume that the magnitude has the mean value 7 and standard deviation 0.24, which gives a coefficient of variation equal to 0.0343. Applying these values gives a mean value of the seismic moment equal to 5.00×10^{26} dyn·cm and standard deviation equal to 4.97×10^{26} dyn·cm. This gives a coefficient of variation equal to 0.99, reflecting the great uncertainty inherent in the seismic moment. This great variability is in accordance with our experience in computation of seismic moments from individual records obtained from the same event [6]. In this context it is also worth pointing out the skewness of the moment magnitude distribution reflected in a modal value (i.e., the most probable value) equal to 1.78×10^{26} dyn·cm and a median value of 3.55×10^{26} dyn·cm.

The epicentral distance is Rayleigh distributed if we assume the coordinates of the epicentre and site location to be normal distributed. For distances in the far field, if the coefficient of variation is small, the distribution can be approximated as normal. In the intermediate field, however, the Rayleigh distribution is to be preferred. As pointed out [2], the uncertainty in distance depends on the source of information, ranging from a few hundred meters up to several kilometres. For source distances of intermediate range, it appears that the uncertainty is commonly in the range 1 to 5 km.

Depth is not a well-defined quantity. From a theoretical viewpoint it is seen that the distribution of depth must be defined on a closed interval, i.e., ranging from zero to the thickness of the seismogenic crust. A distribution that is easily adoptable to these constraints is the beta-distribution. In addition, it can take the form of a bell-shaped curve in cases where constraints from the boundaries are not significant. In such cases we believe that a normal approximation can be applied. In such cases we find that a coefficient of variation in the range 0.1 to 0.2 applies.

The fault radius is a quantity with great inherent uncertainty, which is difficult to quantify. It is also questionable whether the fault radius should be regarded as a basic variable, due to the fact that it is functionally related to the seismic moment, shear modulus of the rock and the slip. Here we have decided to treat the slip as a derivative variable, rather than the fault radius. By definition the fault radius must be greater than zero; furthermore, it seems natural to have some upper bounds on its length, for instance, half of the thickness of the seismogenic zone. This implies that we will not get surface fractures. Experience shows that the model adopted [6, 10] can be applied with reasonable accuracy even for events with surface faulting as long as the fault length is not much greater than the thickness of the seismogenic zone. In these cases we can define the radius for an equivalent circular area equal to the size of the fault. This may lead to a radius exceeding half of the thickness of the seismogenic zone by 10% to 20%. In view of this we suggest that the fault radius can be modelled by beta-distribution that may be approximated by a normal distribution if there are no significant constraints from the boundaries.

Mechanical properties like shear wave velocity and density are, in most cases, well-defined quantities, which we assume can be modelled by log-normal distribution. When doing so, we keep in mind that these quantities are positive by definition. The other mechanical properties needed in the adopted model for this study, like shear modulus, are defined as a derivative variable, using the shear wave velocity and the density.

The spectral decay parameter is applied to shape the high-frequency tail of the acceleration spectrum. By definition this variable must be positive, to secure a bounded integral defining the rms-acceleration. As this variable shows clear normal tendency, we suggest that it can be modelled by log-normal distribution. However, a normal approximation can also be adopted in cases where the values are far enough from zero.

The peak factor is last on the list of our suggested basic variables. It is defined in probabilistic settings as the ratio between the peak ground acceleration and the corresponding rms-value. The peak factor must hence be greater than 1. The distribution of this variable can be obtained using the theory of extremes [11]. However, for simplification it appears acceptable to approximate its distribution as log-normal distribution.

Other variables included in the adopted strong-motion model are treated as derivative variables or simply approximated as deterministic constants. It is important, also for the derivative variables, to investigate any physical boundary or constraints that may be connected with the variables. Furthermore, when the uncertainty analysis described above is exercised, it is necessary to check whether the critical events can be regarded as physically realisable. This means that all variables must be within reasonable physical limits.

APPLICATIONS TO GROUND MOTION ESTIMATION MODELS

The uncertainty analysis outlined above is readily applicable to peak ground acceleration and can be used to get estimates for the standard deviation that can be compared with the standard deviation of the residuals of the regression analysis. We can thereby assess whether it is probable that complex models can reduce the uncertainty of the derivative variables.

To illustrate our point, we use a simplified model for strike-slip earthquakes but exclude soil conditions commonly influencing site response. Hence we assume that the peak ground acceleration induced by shear waves in the near-field can be approximated by the expression put forward in [10].

The selected basic variables are displayed in Table 1, where the assumed mean values and coefficient of variance are also listed. As a first crude approximation all variables are taken to be normally distributed. Other variables are assumed to be derivatives or constants. This applies to the duration parameter, the dispersion and the partitioning factor. Furthermore, the seismic moment is derived from the moment magnitude applying the Hank-Kanamori relation.

The estimation of the standard deviation of the peak ground acceleration using the approach outlined above gave $\sigma = 0.239$ (corresponding to $\beta = 1$). This value is comparable in size to the standard deviations reported in the literature as a result of regression studies [3].

Table 3: Basic variables for the near-field model assumed normal distributed [2].

Name	*Symbol*	*Unit*	*Mean value*	*Coefficient of variation*
Magnitude	M_w	-	6.6	0.02
Fault radius	r	km	7.5	0.07
Shear wave velocity	v	km/s	3.5	0.10
Density	ρ	g/cm^3	2.8	0.07
Spectral decay	κ_o	-	0.02	0.12
Peak factor	p	-	2.94	0.15

The sensitivity factors are displayed in Figure 1. They represent the sensitivity of the standardised response surface at the performance point to changes in the basic variables [12]. A low sensitivity factor for a particular basic variable indicates that there is not a great need to increase statistical information on that variable. This may even suggest that this variable can be treated as deterministic rather than as a stochastic variable. For the data presented in Figure 1, the sensitivity factors indicate that the shear wave velocity, density and spectral decay could perhaps be treated as deterministic. The figure also shows that the improved statistical information is especially beneficial for the magnitude and the source radius. On the other hand, reduction of the uncertainties of these variables will increase the sensitivity factors of the other variables and thereby their importance.

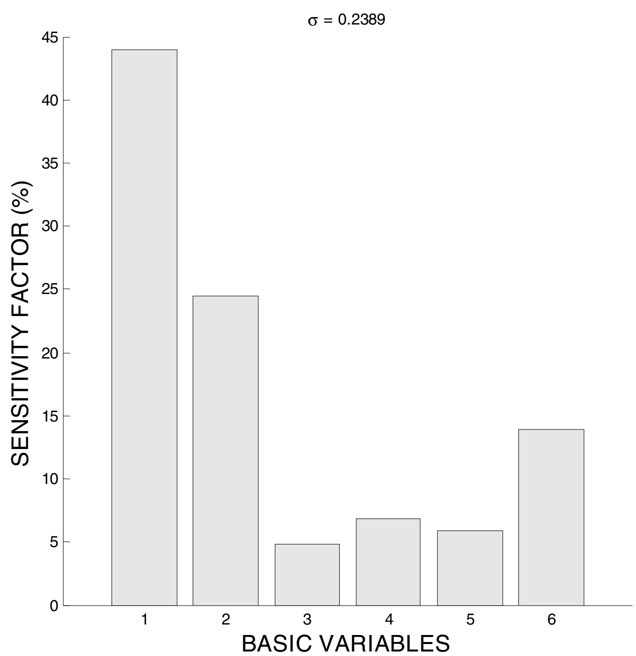


Figure 1: The sensitivity factors for the near-field model. Denotation of the basic variables: 1 - magnitude, 2 - fault radius, 3 - shear wave velocity, 4 - density, 5 - spectral decay, and 6 - peak factor [2].

As a further illustration let us look at the peak ground acceleration induced by shear waves in the far field, which we assume can be approximated by the model outlined in [6, 10]. The selected basic variables are listed in Table 2. At this stage, we assume that all the basic variables can be approximated by normal distributions with the parameters given in Table 2. Other variables are evaluated as derivatives, using the formulas given in the references [6, 10].

Table 2: Basic variables for the far-field model assumed normal distributed [2].

Name	*Symbol*	*Unit*	*Mean value*	*Coefficient of variation*
Magnitude	M_w	-	6.6	0.02
Distance to fault	D	km	variable	0.15
Depth	h	km	9.0	0.10
Fault radius	r	km	7.5	0.07
Shear wave velocity	v	km/s	3.5	0.10
Density	ρ	g/cm^3	2.8	0.07
Spectral decay	κ	-	0.04	0.12
Peak factor	p	-	2.94	0.15

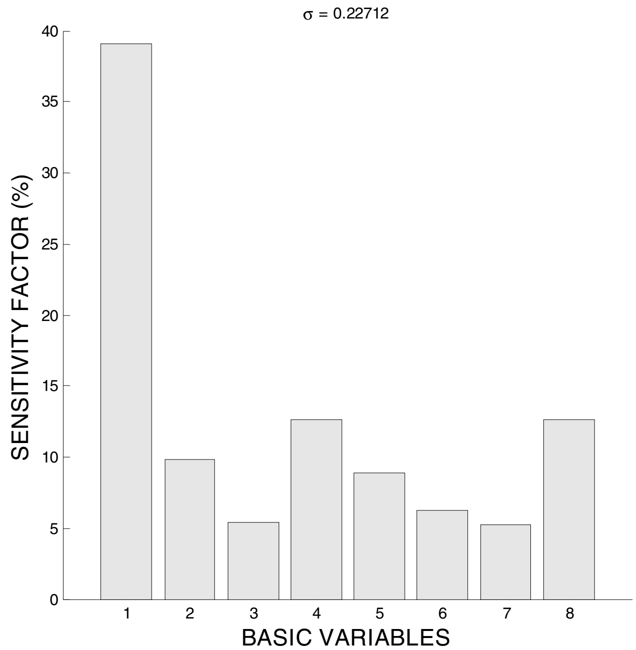
The obtained standard deviations of the peak ground acceleration for distance to fault equal to 10 and 50 km are 0.227 and 0.237, respectively (β = 1). The sensitivity factors are displayed in Figure 2. The uncertainty assigned to magnitude is the greatest single contribution, as was the case for the near-field data given in Figure 1. It is worth pointing out that the sensitivity factor for depth decreases from 5% for a 10-km source distance to almost zero for a 50-km distance. This seems in accordance with previous experience and expectance. Furthermore, this implies that for greater (epicentral) distances the effect of depth is negligible.

These results do not point towards reduction in uncertainty in the peak ground acceleration even if the adopted model accounts for more parameters than is usual in regression models. Therefore, it seems that complex models are not likely to decrease uncertainty. On the other hand, the complex model can explain the sources of uncertainties, and how they contribute to the uncertainty of the derivative response variable, better than can be done using models with few parameters. This study indicates in particular that the main source of uncertainty is attached to magnitude and its inherent uncertainty. The most obvious remedy to reduce uncertainty appears to be enhancement of magnitude determination or perhaps seismic moment.

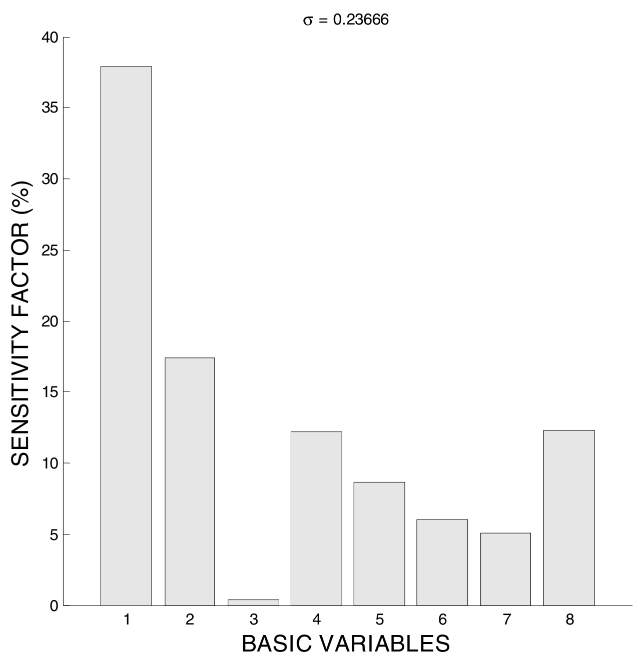
APPLICATIONS TO HAZARD AND RISK ASSESSMENT

In the above study of the ground motion estimation equation, it was assumed that all the basic variables followed a bell-shaped distribution. These distributions could be approximated by normal distribution, at least in cases where ‘tail sensitivity’ is not of importance. When applying the ground motion estimation equation in hazard and risk assessment, the distribution of magnitude and distance have to be redefined to reflect the statistical properties of the seismogenic area to be studied.

The distribution of epicentral distances for a particular site is derived from the distribution of epicentres, described in terms of geographical coordinates. For a line source with uniform seismic activity, it is common to treat the epicentres as uniformly distributed along the line. For an area source, on the other hand, it is most usual to assume the epicentres uniformly distributed within the area, even though more realistic models are available [13]. When assessing the distribution for fault distance, information on fault size and fault orientation is required in addition to the distribution of epicentres. In both cases this leads to distribution for distance that deviates significantly from the bell-shaped normal type distributions.



(a)



(b)

Figure 2: The sensitivity factors for the near-field model. Denotation of the basic variables: 1 - magnitude, 2 - distance to fault, 3 - depth, 4 - fault radius, 5 - shear wave velocity, 6 - density, 7 - spectral decay, and 8 - peak factor. (a) Distance to fault 10 km, (b) distance to fault 50 km [2].

The magnitude distribution is commonly assumed to be of the exponential type, often mapped on a closed interval ranging from the magnitude of the smallest earthquakes judged to have significant effect on structures to the magnitude of the largest earthquake that can credibly originate within the seismic zone in question. In addition, we need the number of earthquakes originating within the seismic zone that belong to the predefined magnitude interval. This leads to a magnitude distribution that is not of the bell type assumed in the previous sections.

The remaining basic variables can in principle be assumed to follow the distributions discussed earlier. On the other hand, some of the parameters of these distributions may be dependent on the earthquake magnitude. This applies especially to the size of the fault, which cannot be treated as independent of magnitude. In view of this, it can be argued that fault size should not be regarded as a basic variable. However, it is possible to overcome this difficulty by using the principles of conditional distribution. Other basic variables, discussed in the above section, appear to fulfil the requirements of independence and will therefore be retained as basic variables in the hazards assessment.

The methodology described above has been used to obtain hazard curves. The case considered refers to a site where the far-field approximation is assumed. The variables adopted and the corresponding distribution parameters conform to those used earlier, as discussed above. The data are summarised in Table 3. We assume a single seismic source area defined as follows: line source of length 50 km with uniformly distributed epicentres, parameters of the magnitude distribution, $M_{min} = 4$, $M_{max} = 6.3$, a = 10 and b = 1.57. The site is at the middle of the fault with the shortest distance to fault equal to 10 km.

Table 3: Basic variables for the strong-motion model describing a predefined source with assumed distributions.

Name	*Symbol*	*Unit*	*Distribution*	*Mean value*	*Coefficient of variation*
Magnitude	M_w	-	seismicity dependent[1]	-	-
Distance to fault	D	km	source zone	-	-
Depth	h	km	dependent[1]	9.0	0.05
Fault radius	r	km	normal	conditional[1]	0.07
S-wave velocity	v	km/s	normal	3.5	0.10
Density	ρ	g/cm^3	normal	2.8	0.07
Spectral decay	κ_o	-	normal	0.04	0.12
Peak factor	p	-	normal	2.94	0.15
			normal		

[1]See text

The results are given in Figure 3. It is seen that there is a great difference between the hazard curves obtained using mean values neglecting uncertainties, on the one hand (black curve), and the hazard curve we get, on the other, by using traditional methods based on mean values, but additionally introducing uncertainties in the form of residuals of the peak ground acceleration (red curve), especially for small exceedance probabilities. The results obtained, using the suggested uncertainty model, are shown by the blue curve. It is seen that this curve shows roughly the same behaviour as the 'mean' curve, the black one. Furthermore, it is seen that the 'mean' curve has an upper boundary, while the hazard curve, derived using the untruncated residual distribution, apparently does not have an upper boundary (red curve) as the probability of exceedance approaches zero. On the other hand, this appears to be the case for the presented uncertainty model (blue curve). The main advantage of this model, however, appears to be that it produces values that seem to be reasonable and in accordance with experience as far as can be inferred.

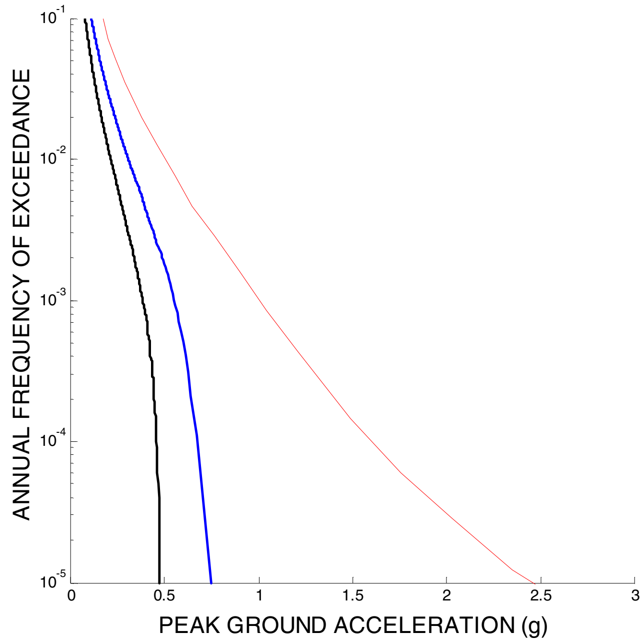


Figure 3: Hazard curve for peak ground acceleration derived using the far-field model. The properties of a seismic source area are described in the text. The following notation is used: (a) black curve based on mean values neglecting uncertainty, (b) blue curve based on suggested uncertainty modelling and data in Table 3, (c) red curve based on mean values and the introduction of residual distribution for the peak ground acceleration with σ = 0.25.

DISCUSSION AND CONCLUSIONS

Uncertainties in strong-motion modelling have been discussed both qualitatively and quantitatively. Emphasis has been put on shallow strike slip earthquakes and peak ground acceleration. It is found that the uncertainties in the peak ground acceleration can be explicitly related to uncertainties in a few basic variables, making it possible to quantify how much each basic variable contributes to peak ground acceleration or response spectra. It is found important to select basic variables that are statistically independent. If that is not possible, a transformation of dependent variables into independent ones is recommended. In some cases conditional distributions can be applied to simplify this process.
It is found that increasing the number of variables in the ground motion model for peak ground acceleration apparently does not decrease the standard deviation of the residuals. This is due to the intrinsic uncertainty of the basic variables. It is also found that the magnitude contributes most to the uncertainty in peak ground acceleration. It seems, therefore, that a method to reduce the uncertainty in magnitude or seismic moment would be a very beneficial remedy.

Even though multi-parameter analytical ground motion models, as put forward in this study, do not reduce the inherent uncertainty in ground motion, they are found useful in the analysis of uncertainties as they make it possible to quantify, to a certain extent, the contribution of individual parameters to the overall uncertainty in strong motion variables, like peak ground acceleration and response spectra.

Finally, the application of these models in hazard and risk analysis makes the treatment of uncertainties more realistic than in the traditional approaches. It is well known that results obtained in traditional hazard assessment are sensitive to the truncation of the error term commonly given as an integral part of ground motion estimation equations. The presented approach does not suffer from this shortcoming and yields apparently reasonable hazard curves without introducing artificial constraints.

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