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Quantification of model uncertainty and variability in Newmark displacement analysis

Wenqi Du[a], Duruo Huang[b], Gang Wang[c,*]

[a] Institute of Catastrophe Risk Management, Nanyang Technological University, 50 Nanyang Avenue, Singapore
[b] Department of Hydraulic Engineering, Tsinghua University, Beijing, China
[c] Department of Civil and Environmental Engineering, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong

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ABSTRACT

Newmark displacement model has been extensively used to evaluate earthquake-induced displacement in earth systems. In this paper, model uncertainty and variability associated with the Newmark displacement analysis are systematically studied. Fourteen Newmark displacement models using scalar or vector intensity measures (IMs) as predictors are compared in this study. In general, model uncertainty for the vector-IM models is found smaller than that of the scalar-IM models, and remains consistent over different earthquake magnitude, distance and site conditions. Yet, the model uncertainty of these Newmark displacement models is still much larger than that of the ground-motion prediction equations (GMPEs) for IMs, indicating further development of the models is much needed. Considering the variabilities contributed from both GMPEs and Newmark displacement models, the total variability of the predicted Newmark displacements is rather consistent among the scalar- and vector-IM displacement models, due to extra sources of variability introduced by incorporating additional IMs. Finally, a logic tree scheme is implemented in the fully probabilistic Newmark displacement analysis to account for the model uncertainty and variability. Sensitivity analysis shows that specific weights would not significantly influence the displacement hazard curves as the results may be dominated by outlier models. Instead, selecting appropriate GMPEs and Newmark displacement models is more important in using the logic-tree framework.

1. Introduction

Since its introduction in the 1960s, Newmark's sliding block [1] and other related models have been widely used to estimate earthquake-induced displacements in natural slopes, earth dams, and solid-waste landfills, *etc*. The Newmark model assumes the sliding mass is rigid during earthquakes, and the deformation of the mass can be neglected. Sliding occurs on a well-defined failure surface when the input acceleration exceeds a critical acceleration (a_c), and the block continues to slide until the relative velocity between the block and ground reaches zero. The permanent displacement of the sliding block, namely the Newmark displacement, is then calculated by integrating the velocity time history of the sliding block (Fig. 1). The critical acceleration a_c represents the resistance of the mass against sliding, and it can be determined by the strength, unit weight of the material and slope angle [2]. The Newmark displacement has been widely used as an index to categorize landslide hazard [3], or to evaluate earthquake-induced shallow sliding in natural slopes, e.g. [4–7].

The first empirical equation to estimate the Newmark displacement was proposed by Newmark [1], which is a function of a_c, peak ground acceleration (PGA) and peak ground velocity (PGV) based on regression analysis of empirical data from four earthquakes. Throughout years, many researchers [8–11] proposed various empirical equations using different ground motion intensity measures (IMs) as predictor variables, including PGA, moment magnitude of the earthquake (M_w), PGV and spectral acceleration (Sa). Arias intensity (Ia) is also a commonly used predictor, as it can effectively incorporate the cumulative effect of an acceleration time history [12,13]. Hence, the Newmark displacement can be predicted based on a single IM, termed as the scalar-IM model, or multiple IMs, termed as the vector-IM model. In general, the vector-IM models are advantageous over the scalar-IM models in that predictions using multiple IMs can better satisfy the efficiency and sufficiency criteria [14]. In other words, a vector-IM model usually yields a smaller standard deviation, which is not much dependent on moment magnitude (M_w) and rupture distance (R_{rup}) of scenario earthquakes. For example, Saygili and Rathje [10] reported that the Newmark models using two IMs generally result in 40–60% reduction in the standard deviations compared with the scalar-IM models.

Recently, Douglas [15,16] and Douglas et al. [17] studied the model uncertainty and consistency of ground motion prediction equations

* Corresponding author.
E-mail address: gwang@ust.hk (G. Wang).

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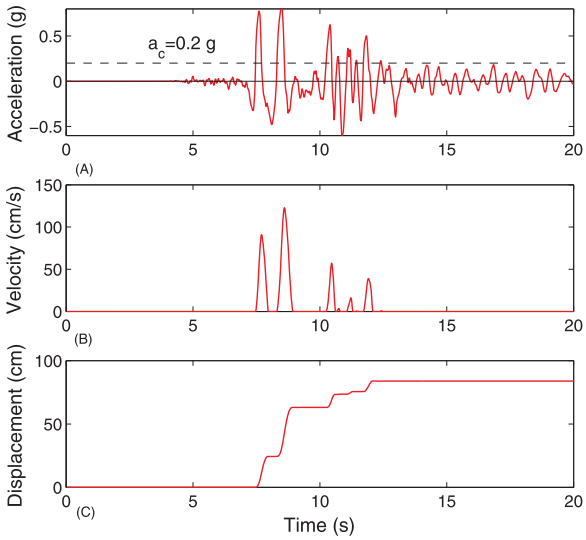

Fig. 1. Computing Newmark displacement with critical acceleration $a_c = 0.2$ g. (A) Earthquake acceleration-time history. (B) Velocity of sliding block versus time. (C) Displacement of sliding block versus time.

(GMPEs) for various IMs (e.g., PGA, PGV, Ia, significant duration) developed during the past four decades. Compared with the ground-motion IMs, two levels of model uncertainties are associated with the Newmark displacement predictions, including uncertainties in the estimation of IMs from GMPEs and uncertainties in the predictions of the Newmark displacement models based on IMs. Because different strong-motion databases and functional forms were used in developing the Newmark displacement models, it is not surprising that these models would yield widely divergent predictions for some scenarios. Yet, uncertainties associated with various levels of the Newmark displacement prediction have not yet been systematically quantified

Uncertainty and variability in a prediction model have been widely discussed in the literature (e.g., [18]). Model uncertainty due to limited knowledge is epistemic. In principal, it can be reduced if more data becomes available or the predictive models are improved. Aleatory variability, on the other hand, represents inherent randomness of the prediction that cannot be reduced. It is usually quantified by the variation of the observed data against model predictions. In this study, uncertainties and variabilities of various Newmark displacement models are quantified under several representative earthquake scenarios. The model uncertainty is approximately evaluated by the dispersion of different prediction models, which employs different predictors, functional forms and databases. The model variability, on the other hand, is approximately by the standard deviation of residuals reported in a prediction model. Although the model variability is reportedly reduced in a vector-IM model as discussed before, inclusion of an additional IM would inevitably induce additional variability associated with the prediction of this IM. Therefore, the total variability of the Newmark displacement prediction is still not clearly studied. The present study will clarify how the model uncertainty and variability in the GMPEs and Newmark models are added up together in the Newmark displacement predictions. Then a logic-tree approach [19] is implemented into a fully probabilistic Newmark displacement analysis [20] to incorporate the uncertainties and variabilities associated with GMPEs and the Newmark displacement models.

2. Selection of Newmark displacement models

In the past, many Newmark displacement models have been proposed by different scholars. A total of eight groups of Newmark models are listed in Table 1. It is seen that the models developed recently (typically later than 2006) were based on much more earthquake events and strong-motion records than earlier models. Fourteen Newmark displacement models proposed since 1988 are used in this study and listed as follows. Among these equations, the unit of the Newmark displacement D is cm; PGA, Sa and a_c are in the unit of g; PGV is in the unit of cm/s; and I_a is in the unit of m/s.

1. [PGA] AM88 model by Ambraseys and Menu [8]:

$$\begin{aligned}\log_{10}(D) &= 0.215 + 2.341\log_{10}\left(1-\frac{a_c}{PGA}\right) - 1.438\log_{10}\left(\frac{a_c}{PGA}\right);\\ \sigma_{\log_{10}D} &= 0.3\end{aligned} \tag{1}$$

2. [PGA Ia] R00 model by Romeo [21]:

$$\begin{aligned}\log_{10}(D) &= 0.607\log_{10}\left(\frac{I_a}{100}\right) - 3.719\left(\frac{a_c}{PGA}\right) + 0.852;\\ \sigma_{\log_{10}D} &= 0.365\end{aligned} \tag{2}$$

3. [PGA, Sa(T = 1)] WA06 model by Watson-Lamprey and Abrahamson [22]:

$$\begin{aligned}\ln D &= (5.47 + 0.451(\ln(S_a(T=1s)) - 0.45)\\ &\quad + 0.0186(\ln(S_a(T=1s)) - 0.45)^2\\ &\quad + 0.596(\ln(A_{RMS}) - 1) + 0.656(\ln(S_a(T=1s)/PGA))\\ &\quad - 0.0716(\ln(S_a(T=1s)/PGA)^2)\\ &\quad + 0.802(\ln(Dur_{a_c}) - 0.74) + 0.0763(\ln(Dur_{a_c}) - 0.74)^2\\ &\quad - \frac{1}{0.581(\ln(PGA/a_c) + 0.193)}\\ \sigma_{\ln D} &= 0.53\end{aligned} \tag{3}$$

where A_{RMS} is the root mean square of acceleration (unit in g) and Dur_{ac} is the duration (unit in s) that the acceleration is greater than the critical acceleration. Prediction equations for A_{RMS} and Dur_{ac} are provided as follows [22]

$$\ln(A_{RMS}(g)) = -1.167 + 1.03\ln(PGA); \tag{4}$$

$$\begin{aligned}\ln(Dur_{a_c}(s)) &= -2.775 + 0.956\ln(PGA/a_c) - \frac{1.554}{\ln(PGA/a_c) + 0.390}\\ &\quad - 0.597\ln(PGA) + 0.381\ln(S_a(T=1s)) + 0.334M_w\end{aligned} \tag{5}$$

4. [PGA] J07 model by Jibson [9]:

$$\log_{10}(D) = 0.215 + 2.341\log_{10}\left(1-\frac{a_c}{PGA}\right) - 1.438\log_{10}\left(\frac{a_c}{PGA}\right);$$

$$\sigma_{\log_{10}D} = 0.51 \tag{6}$$

5. [PGA, M_w] J07 model by Jibson [9]:

$$\begin{aligned}\log_{10}(D) &= -2.71 + 2.335\log_{10}\left(1-\frac{a_c}{PGA}\right) - 1.478\log_{10}\left(\frac{a_c}{PGA}\right)\\ &\quad + 0.424M_w;\\ \sigma_{\log_{10}D} &= 0.454\end{aligned} \tag{7}$$

6. [Ia] J07 model by Jibson [9]:

$$\begin{aligned}\log_{10}(D) &= 2.401\ \log_{10}(I_a) - 3.481\log_{10}(a_c) - 3.23;\\ \sigma_{\log_{10}D} &= 0.656\end{aligned} \tag{8}$$

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