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Parameterized Seismic Fragility Functions For Gravity Dams: An Approach Including The Effect Of Updated Model Parameter Knowledge

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ABSTRACT

With the increasing knowledge in seismicity, a growing number of dams fail to meet revised safety criteria that incorporate this new seismic hazard information. Therefore, the validity of the original design requirements needs to be revised. Probabilistic methods allow a wide variety of configurations to be considered, constituting the basis of more adequate design and assessment procedures. Multivariate fragility functions have become popular in assessing dams under seismic loads, as they offer efficient posterior uncertainty propagation and the ability to explore sensitivities and design parameter variation. This study aims to develop a procedure to generate parameterized seismic fragility functions that reduces uncertainty in the analysis when new information on parameters becomes available. A sequential approach is employed to highlight the impact of additional information related to each parameter and prioritize its comprehensive study. A verbal mapping scheme based on expert judgment is established to assign exceedance probabilities to seismic events with different return periods to determine whether or not target performance limit states are attained. Although the availability of additional information may not have a substantial impact on reducing the uncertainty in the fragility estimates, the proposed methodology allows for the identification of such cases and considers the anticipated value of further efforts to reduce uncertainty as a factor in selecting a course of action. The proposed methodology is applied to a case-study gravity dam located in eastern Canada, and the results show that efforts should be reoriented to perform a thorough seismic hazard analysis at the dam site and more exhaustive drainage efficiency controls.

Keywords: Seismic fragility analysis, uncertainty reduction, seismic scenario, gravity dams, safety factor, probabilistic analysis.

INTRODUCTION

As the understanding of seismic activity grows, more and more dams are falling short of newly established safety standards that take this updated seismic hazard knowledge into account. Consequently, there is a need to re-evaluate the original design criteria to ensure their safe and continued operation [1]. Requirements for the stability of concrete dams in the current regulations are based on simplifications, which, in many cases, are very conservative. Concrete dams in Canada, as in most of the world, are designed and assessed based on a deterministic framework using safety factors (SFs). Among the main drawbacks of this method are the equal treatment of loads and the identical consideration of strength and capacity uncertainties [2]. Furthermore, present-day safety assessments and/or rehabilitation projects involve higher safety requirements than do the traditional standards. Design criteria have evolved according to technological advances in engineering, and with the growing societal awareness of risk, these criteria are more demanding than ever before. As a consequence, unnecessary rehabilitation works may be carried out on dams that are safe but do not meet the safety requirements. Thus, there is interest in moving towards more refined methods, such as probabilistic methods, that allow a wide variety of configurations to be considered, and constitute the basis of more adequate design and assessment procedures [3].

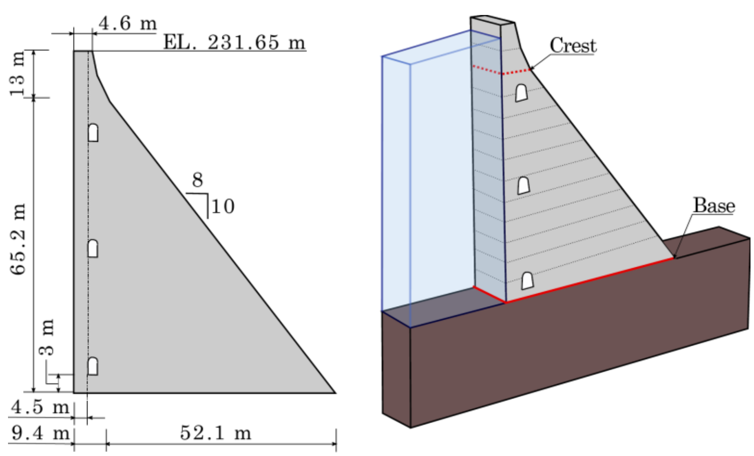
In contrast to the deterministic approach, the probabilistic approach requires the treatment of each parameter as a random variable (RV) with an associated probability density function (PDF). This PDF allows variables to be treated as uncertain inputs by directly incorporating a possible range of values into the model instead of a single value [4]. To implement this type of analysis, the emphasis must be placed on the quality of the input parameters [2] especially of the seismic demand of the structural systems [5]. Probabilistic assessment, no matter how sophisticated, can still lead to very different solutions for a given problem because of the complex choices of RVs, characteristic values, PDFs, and bounds, which can largely influence final results [6]. Fragility functions have become increasingly popular for the probabilistic assessment of dams, particularly under seismic loads [7]. However, these functions are frequently generated using a single parameter related to the expected damage, rendering the analysis highly dependent on the conditioning intensity measure (IM). As a result, multivariate models are increasingly being utilized to predict the response of a certain structure [8–9] despite requiring a large number of simulations. Hence, the analysis is generally not updated in light of new information due to the time-consuming re-evaluation and the lack of flexibility in the methods regarding including modified PDFs and bounds. Thus, there is a need to develop simplified and more expeditious methods for analyzing the safety of dams within a probabilistic framework. With this in mind, using a parameterized formulation, where the fragility of the system can be described by a fairly simple equation is preferred. Noted advantages of these parameterized multivariate fragility functions include the potential for efficient posterior uncertainty propagation and exploring sensitivities or the influence of design parameter variation.

Accordingly, the main objective of this study is to develop a procedure to generate parameterized seismic fragility functions while jointly reducing the uncertainty in the analysis when new information on the parameters becomes available. To explicitly account for the effect of improved parameter knowledge, multidimensional integration is implemented to update the fragility functions so that recommendations can be formulated to achieve the expected seismic performance. This requires varying the probability density function of the input parameters and then examining the resulting effects on the fragility estimates. In order to accomplish this, a sequential approach is employed to highlight the impact of additional information related to each parameter and prioritize its comprehensive study. In addition, a verbal mapping scheme based on expert judgment is established to assign exceedance probabilities to seismic events with different return periods to determine whether or not target performance limit states are attained.

CASE STUDY

Numerical Model

The present study is focused on a case study of a concrete gravity dam in Quebec, Canada with a maximum crest height of 78 m (Figure 1a). The tallest monolith of the dam, with lift joints each 6 m, was modeled with the computer software CADAM3D [10] (Figure 1b), which performs stability analysis on gravity dams using the limit equilibrium method. Only one loading case was analyzed; this case includes the self-weight of the block, seismic loads, the hydrostatic and hydrodynamic load exerted by the reservoir on the block and the uplift pressures at the concrete-rock foundation. The uplift pressure distribution was defined according to the United States Army Corps of Engineers (USACE) [11]. A nonlinear analysis that allows to consider the crack propagation along the lift joints is used to analyze the system response, where if the base crack extends beyond the drain, the full uplift pressure is considered in the crack. The seismic loads were evaluated using the pseudo-static method (seismic coefficient) [12]. Given that this method does not recognize the oscillatory nature of seismic loads, it is generally accepted that stability calculations can, therefore, be performed using a sustained acceleration ranging from 0.67 to 0.5 times the peak acceleration [13]. In the context of this study, a reduction factor of 0.5 was applied to the horizontal peak ground acceleration (PGA) to account for the effect of sustained accelerations. Finally, the hydrodynamic pressure acting on the dam was modeled as added masses using Westergaard's formulation [11].



(a) *(b)*

Figure 1. Case study dam: (a) cross-section, (b) CADAM3D numerical model.

Seismic hazard and earthquake scenarios

The choice of return period (RP) for seismic analysis of a dam depends on several factors, including the importance of the dam, the consequences of failure, and the potential for seismic hazard in the region. Generally, dams with higher consequences of failure or located in regions with high seismic hazard would require a higher return period for the seismic analysis. In general, the seismic analysis of a dam should consider a seismic event with a return period of at least 2475 years [14]. However, if the dam is located in a region with a high seismic hazard or has a high consequence of failure, it may be appropriate to use a return period of 10,000 years [14]. Moreover, it should be mentioned that Canada's national mapping efforts have moved from qualitative assessment towards probabilistic assessment, reflected in the different editions of the National Building Code of Canada (NBCC) [15]. Table 1 presents PGA values for different RP at the dam site according to the last four editions of the NBCC [16–19] as well as the value considered in the dam owner's internal seismic guidelines for a deterministic analysis.

Table 1. PGA values in (g) for the different editions of the NBCC.

Return Period (yrs)	Deterministic analysis	NBCC			
		2005	2010	2015	2020
100	-	0.027	0.014	0.015	0.019
475	-	0.058	0.031	0.036	0.054
975	-	0.083	0.050	0.053	0.081
2475	0.23	0.125	0.080	0.080	0.131

From Table 1, it can be observed that the values prescribed in the 2010 and 2015 editions are comparable, as are the values in the 2005 and 2020 editions. Returns periods greater than 2475 years are beyond the scope of the NBCC. However, it's possible to extrapolate the values provided for the required return period. The 2020 edition of the NBCC [19] was used to determine the PGA value at the dam site for RP=10000 years, as shown in Figure 2, which corresponds to 0.32 g. Accordingly, the seismic scenarios considered in the analysis of the case study dam included events with return periods between 500 and 10,000 years, which corresponded to PGA values within the 0.05-0.35 g range.

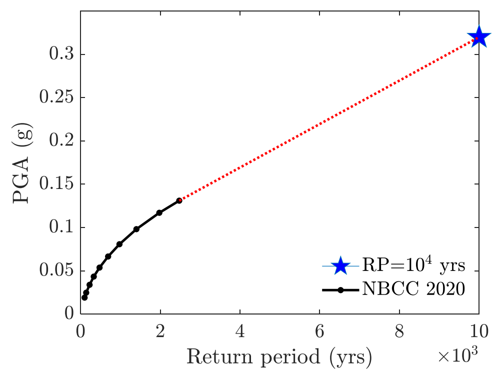


Figure 2. NBCC 2020 hazard curve at the dam site for PGA

Modeling Parameters

Each parameter was defined either as a fixed value or as an RV, for which the uncertainty or likelihood of occurrence was formally included through their PDF. Table 2 presents all the RV parameters considering the input parameters in the CADAM3D numerical model. Their respective distributions were defined using empirical data from similar dams and values found in the literature [20]. All the RVs were assumed to be uniformly distributed mainly because the available information was limited to the maximum and minimum values and because it defines equal probability over a given range [21]. All the remaining input parameters were held constant and represented by their best estimate values. In addition, Table 2 contains the values used in a deterministic stability assessment of the dam adopted for this case study.

Table 2. Modeling parameter as RV

Variable	Uniform distribution parameters		Deterministic analysis
	Lower	Upper	
Cohesion, c (kPa)	0	3000	500
Angle of friction, ϕ (°)	42	55	45
Drain efficiency, η (%)	0	67	50
Reservoir elevation, H (m)	225	231	228
PGA (g)	0.05	0.35	0.23

PARAMETERIZED SEISMIC FRAGILITY FUNCTIONS

The first step in a seismic fragility analysis is the identification of the damage states that are relevant to the system performance. When subjected to strong ground motion, gravity dams may be damaged in different ways. In recent years, typical damage modes that could lead to the potential collapse of dams after a seismic event have been identified, and seismic damage levels have been established. The overall stability of concrete retaining structures is verified by imposing performance criteria on predefined indicators to ensure that a sufficient margin of safety against failure exists for each of the failure mechanisms considered for the body of the system. Preliminary analyses have identified sliding as the critical failure mode for the case study dam; other failure modes would only occur after sliding has already been observed. As a result, the performance indicator considered in this study is sliding safety factor (SF).

Design of experiments

To optimize the cost of running computer model simulations while analyzing an adequate number of loading conditions and structural system configurations, an appropriate experimental design method should be used. The uncertainties due to the variables in Table 2 were propagated in the analysis using Progressive Latin hypercube sampling (PLHS) [22] due to its ability to sequentially generate sample points while progressively preserving the distributional properties of interest and to ensure that the set of samples reflects the entire range of the parameters, as demonstrated in past applications to earthquake engineering [5]. The final experimental design matrix **X** has dimensions of $10^4 \times 5$, where the columns are the parameters of Table 1 and the rows are the number of permitted simulation runs as a trade-off between the available computational resources and time. Finally, 10^4 training points were generated (one for each row of the design matrix), where the output of interest is the sliding SF.

Multivariate fragility functions

Logistic regression (LR) is commonly chosen to derive probabilistic tools because it provides a closed-form equation for estimating failure probabilities, which can be useful for practical applications. While LR is not a state-of-the-art approach, its prevalence, historical importance, and simple formulation make it a good choice for fragility-based safety assessments [23]. The principle of this classification algorithm is to transform the system response, $g(\mathbf{X})$, into the interval (0, 1) describing the probability $P\ (g(\mathbf{X}) = 1 \mid \mathbf{X})$. We can transform the output of a linear model into the interval (0, 1) by passing it through a sigmoid function. In this study, LR was used to generate parameterized multivariate fragility functions to determine the probability of not reaching a certain SF, for given material and loading conditions. To this end, for each row of the experimental design matrix **X**, the SF is predicted using the CADAM3D. Target peak sliding SF (SF_i) for extreme cases based on the Federal Energy Regulatory Commission (FERC) [14] guidelines were used. These guidelines propose SFs considering the level of knowledge in the strength parameters, where the required SFs are larger if no material tests are available. As such, two sliding SF at the base joint were considered for seismic loading: (i) SF=1.3 if material tests are available and (ii) SF=1.1 otherwise. Accordingly, two LR models were generated, one for each target SF. A binary vector $\mathbf{Y}_{CLS}$ was used to determine the condition of the structure, if the capacity is greater than the demand ($SF > SFi$), there is no undesirable behavior, and $\mathbf{Y}_{CLS} = 0$; otherwise, $\mathbf{Y}_{CLS} = 1$. The two final LR models are functions of the same parameters **X**, but have different explanatory functions. The general expression of the two LR models is presented in Eq. (1), but since the two models were generated for different SFs, the coefficients for each parameter are different.

$$\mathrm{P}(\mathrm{SF} \leq SF_i | \mathrm{c}, \phi, \eta, H, PGA) = \frac{\exp(g(\mathrm{c}, \phi, \eta, H, PGA))}{1+\exp(g(\mathrm{c}, \phi, \eta, H, PGA))} \tag{1}$$

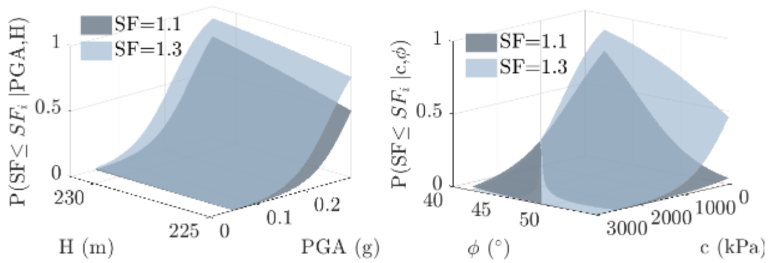
A confusion matrix was used to evaluate the performance of the LR algorithm by comparing the actual versus the predicted class of data. The confusion matrix reports the numbers of true positives (unseating), true negatives (survival), false positives (false prediction of unseating), and false negatives (false prediction of survival). Therefore, any off-diagonal elements represent misclassification. The misclassification error (ME), defined as the ratio of the number of incorrectly classified samples to the total number of samples in the validation data, provides a simple measure of accuracy of the trained model. Table 3 presents the confusion matrices resulting from 10-fold cross-validation. The algorithm for SF = 1.1 and SF = 1.3 perform well, as is evident from the relatively small MEs of 7% and 8%, respectively.

Table 3. Confusion matrix from 10-fold CV.

True Class	**Predicted class SF=1.3**		**Predicted class SF=1.1**	
	Survival	Failure	Survival	Failure
Survival	0.92	0.10	0.93	0.19
Failure	0.08	0.90	0.07	0.81

Multidimensional integration

The generated multivariate fragility functions can be used to evaluate the vulnerability of the case study dam. Eq. (1) depicts the capability the structure to withstand a specified event given a determined system configuration setting. Notably, the vulnerabilities of different components given the material and loading parameters can be found by simple substitution. Similarly, the sensitivity of fragility estimates to a specific parameter or combination of different parameters can be studied by varying some parameters while holding the others constant. This is shown in Figure 3 where fragility surfaces as a function of H-PGA and as a function of ϕ-c were generated, while keeping all of the other parameters constant and equal to the values used in the deterministic analysis (Table 2).



(a) *(b)*

Figure 3. Fragility surfaces as a function of: (a) H-PGA and (b) ϕ-c

Additionally, for a particular set of conditioning parameters, if some or all of the remaining parameters are probabilistic in nature, the multivariate fragility function may be estimated by explicitly accounting for the effects of parameter uncertainties via integration [23]. This multidimensional integration strategy is applied as follows:

$$\mathrm{P}(\mathrm{SF} \leq SF_i|[\mathbf{x}_\mathrm{n}, \ldots, \mathbf{x}_{\mathrm{n-k}}]) = \int_{\mathbf{x}_1} \ldots \int_{\mathbf{x}_{n-k-1}} \frac{\exp(g(\mathbf{X}))}{1+\exp(g(\mathbf{X}))} \times f(\mathbf{x}_1) \ldots \times f(\mathbf{x}_{\mathrm{n-k-1}}) \mathrm{d}\mathbf{x}_1 \ldots \mathrm{d}\mathbf{x}_{\mathrm{n-k-1}} \tag{2}$$

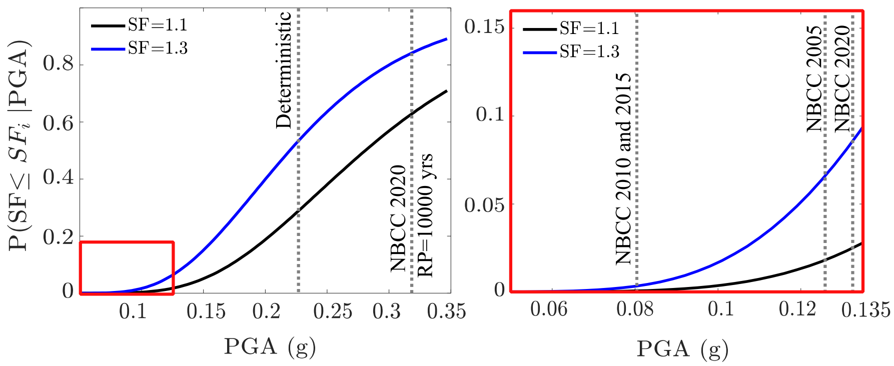
where $\mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_n]$ denotes the parameters involved in the calculation of the LR algorithm, $[\mathbf{x}_\mathrm{n}, \ldots, \mathbf{x}_{\mathrm{n-k}}]$ is the subset of conditioning parameter in the fragility function, and $f(\mathbf{x}_1)\cdots\times f(\mathbf{x}_{\mathrm{n-k-1}})$ are the associated PDFs of the remaining parameters $[\mathbf{x}_1, \ldots, \mathbf{x}_{\mathrm{n-k-1}}]$. Statistical independence is assumed between the predictor variables while conducting the multidimensional integration shown in Eq. (2). However, certain degree of correlation might be expected among the predictor variables, especially between the material properties [9]. The proposed methodology allows the possibility of efficiently including posterior uncertainty propagation by convolving the fragility function with updated probability density functions, as depicted in Eq. (2).

SAFETY ASSESSMENT

In cases where the safety standard is set too low, the stability of the structure may be inadequate to prevent disastrous consequences in the event of a failure. Conversely, if the standard is set too high, the project may not produce the expected economic benefits, resulting in wastage of water resources and incurring production and investment losses. Given the parametric fragility functions proposed in the previous section, it is important to understand the level of risk to which the structure is subjected. To evaluate the seismic performance of the studied structure under seismic events, the probability of not reaching a target SF was estimated for the PGA values in Table 1 corresponding to a 2475 and 10,000-year return period. Thus, for a given PGA prescribed by the NBCC [16–19], the corresponding probability shown in Table 4 was extracted from the fragility curves in Figure 3. The main outcome of this expedited safety assessment is that slightly different SFs, coupled with an outdated hazard model, yield very different estimates, which can have a direct impact on the application of safety guidelines and eventual decision making.

Table 4. Probabilities of exceedance conditioned on PGA.

Probability	**RP (yrs.)**	**Deterministic analysis**	**NBCC**			
			2005	**2010**	**2015**	**2020**
P(SF<1.1)	2475	0.301	0.017	0.000	0.000	0.023
P(SF<1.1)	10000	-	-	-	-	0.661
P(SF<1.3)	2475	0.540	0.064	0.003	0.003	0.081
P(SF<1.3)	10000	-	-	-	-	0.856



(a) *(b)*

Figure 3. Seismic fragility curves: (a) 0.05<PGA<0.35 g and (b) 0.05<PGA<0.135 g

Verbal mapping scheme

In situations where there isn't enough statistical data or probabilistic models for risk analyses of dams, it's possible to make qualitative estimates of the quantitative risk by considering expert engineering judgments about the probabilities of relevant events related to the specific failure mode. To do this, subjective probability methods based on the degree of belief can be used to estimate or assign probabilities. Table 5 presents the verbal mapping scheme for the safety analysis based on the United States Bureau of Reclamation (USBR) guidelines [24]. The following section provides the results of combining this scheme with the generated parameterized multivariate fragility functions to define acceptable range of values and parameter combinations that provide probabilities of not reaching a specific SF in line with the verbal mapping scheme.

Table 5. Adopted verbal mapping scheme.

Event likelihood	Assigned probability
Virtually certain	0.999
Very likely	0.900
Likely	0.750
Neutral	0.500
Unlikely	0.200
Very unlikely	0.100
Virtually Impossible	0.001

Updating knowledge on model parameters and its impact

When making decisions about future actions, it's important to consider a variety of factors such as risk estimates, the confidence in those estimates, the most influential issues affecting the risks, how the risks might be affected by specific inputs, the cost of taking further action, and the potential for decreasing uncertainties [9]. To reduce uncertainties, it may be necessary to undertake additional measures such as gathering more data, monitoring or conducting surveillance, or carrying out a more in-depth analysis of natural hazards. However, there may be instances where these efforts do not lead to a significant reduction in uncertainty or alter the estimate of fragility.

In this study, parameterized fragility functions were implemented together with the multidimensional integration strategy presented in the previous sections to measure the sensitivity of the fragility estimates to changes in the key input assumptions. First, it is of interest to know how collecting additional information would affect the fragility estimates. One way to investigate this issue is to vary the input parameter PDFs and then examine the resulting effects on the fragility estimates. In light of new information, the PDFs presented in Table 6 were considered.

Table 6. Updated model parameters' PDFs

Variable	Distribution	Distribution parameters	
		Mean	Standard deviation
Cohesion, c (kPa)	Lognormal	500	15
Angle of friction, ϕ (°)	Lognormal	49	3
Drain efficiency, η (%)	Uniform	0.4 (min)	0.7 (max)
Reservoir elevation, H (m)	Normal	227.5	0.57
PGA (g) RP=2475 yrs	Lognormal	0.12	0.42
PGA (g) RP=10^4 yrs	Lognormal	0.28	0.33

The PDFs for cohesion and angle of friction were adjusted by incorporating more comprehensive field measurements and literature values from structures sharing similar geological features. As for the reservoir and drain efficiency, their PDF underwent revision through a statistical examination of past data. For the PGA, the PDF was modified based on the distribution of a series of 50 ground motion records selected for the dam site considering return periods of 2475 and 10,000 years consistent with the NBCC 2020 [19], as shown in Figure 4. Further information concerning the record selection method can be found on Segura et al. (2019) [5].

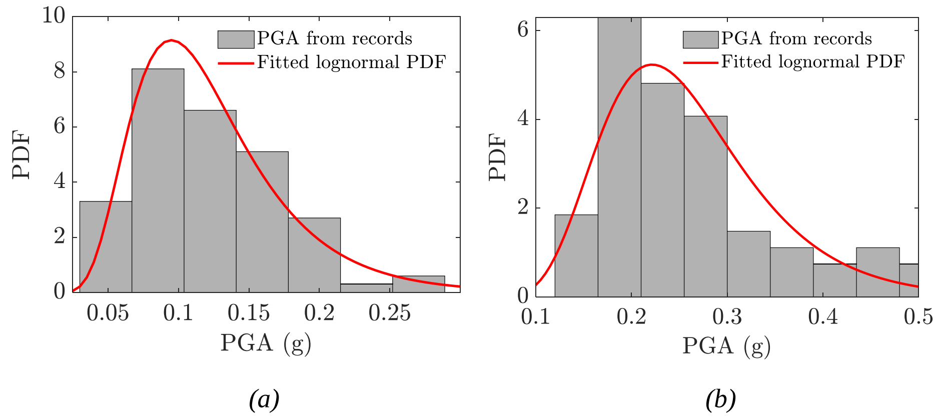


Figure 4. PGA probability density function: (a) RP= 2475 yrs and (b) RP=10000 yrs

Using the integration method outlined in Eq. (2), fragility curves were created by propagating the uncertainties in the updated parameters, without having to re-evaluate the structure. A step-by-step approach was implemented to prioritize a thorough examination of each parameter's additional information on the fragility estimates. Figure 5 illustrates the resulting fragility curves that consider the effect of the updated parameters for seismic events with 2475 years return period. Since cohesion is one of the most uncertain parameters in the seismic stability analysis of dam-type structures [25], the fragility curves are conditioned on its values. The red curve in Figure 5 represents the fragility function obtained from the multidimensional integration when there is no new information available, and all the parameter PDFs are uniformly distributed (Table 2). The remaining curves show the PDFs updated with one parameter at a time. Figure 5 reveals that the knowledge of PGA and drain efficiency has a significant impact on reducing the fragility estimates, while the effects of angle of friction and reservoir elevation are negligible.

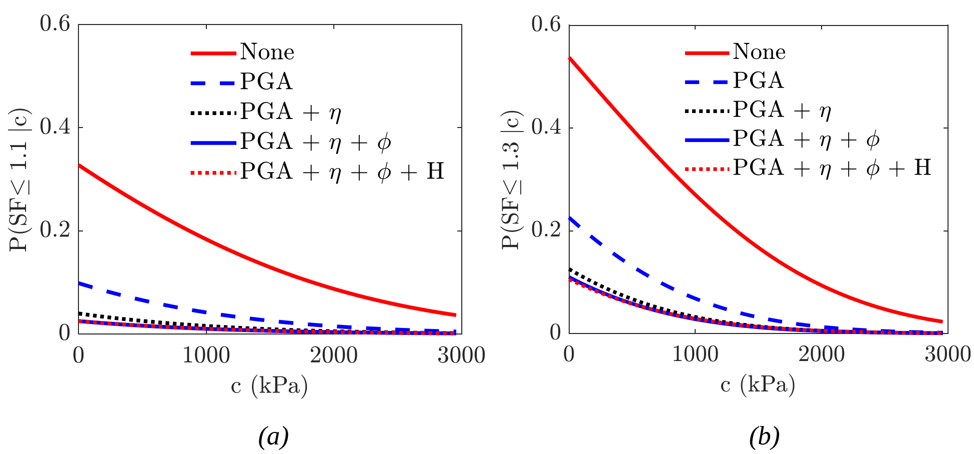
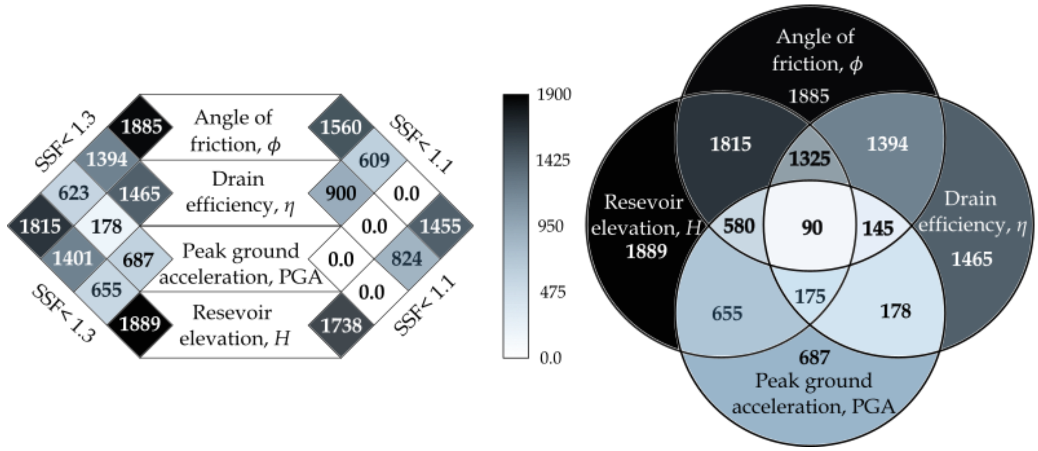


Figure 5. Updated fragility curves: (a) SF= 1.1 and (b) SF=1.3

In the same manner, by updating the PDFs of two and three parameters at the time in the integration scheme and taking into account the target probability of 10% for a 'very unlikely' seismic event (Table 5), minimum cohesion values can be determined to provide a probability of not reaching an SF lower than 10%. As shown in Figure 5, when no additional information is available, the minimum cohesion values for a 10% probability are 1823 kPa and 1942 kPa for SF=1.1 and SF=1.3 respectively. In Figure 6 (a), the matrices with the minimum cohesion values in line with the target probability are presented if only one or two parameters are updated at the time. All the matrix values are lower than the minimum cohesion values if no additional information is available, reflecting the advantage of collecting new information. Additionally, Figure 6(a) indicates that for SF=1.3 acquiring information regarding PGA-η and PGA-ϕ yields cohesion values of 178 kPa and 623 kPa, respectively, while

H-ϕ shows almost no improvement in the analysis. Likewise, if only the information of one parameter is updated at the time, PGA provides the lowest cohesion value, followed by the drain efficiency, angle of friction and lastly the reservoir. The same conclusions are observed for SF=1.1. Similarly, Figure 6(b) presents the minimum cohesion values for SF=1.3 if three parameters are updated at the time. It can be observed that improving the knowledge of PGA-η-ϕ will require a cohesion value equal to 145 kPa to respect the 10% probability threshold, while improving the knowledge of all parameters at the time, will reduce this value to 90 kPa.



(a) *(b)*

Figure 6. Cohesion minimum values (kPa) for a target probability of 10%: (a) two parameters variation and (b) three parameters variation

CONCLUSIONS

The analysis of dams' stability is subject to uncertainties, particularly in defining loading conditions and material properties. To obtain more realistic results, it is essential to account for these sources of uncertainty using a probabilistic-based framework. Thus, this study aimed to create parameterized multivariate fragility functions to assess seismic safety. The PLHS method was utilized to generate 10,000 samples of the numerical model, which were then used to train a logistic regression algorithm to build fragility functions based on various loading and model parameters. Compared to traditional single-parameter models, multidimensional fragility models have several advantages, such as their ability to efficiently update and estimate fragility estimates with new data obtained through field instrumentation. Furthermore, a verbal mapping scheme was established based on expert judgment to assign target probability of exceedance for a seismic event with different return periods. This helped to provide recommendations regarding the minimum values of conditioning parameters needed to achieve the expected performance when considering 2475 years return periods and a fixed target probability of 10%. However, additional information may not significantly reduce uncertainty in fragility estimates. The proposed methodology can identify such cases and consider the value of additional effort to reduce uncertainty in selecting a course of action. It is noteworthy that for the studied structure, efforts should be directed towards conducting a comprehensive seismic hazard analysis representative of the dam site and effectively controlling drain efficiency to reduce the uncertainty in the cohesion. Similarly, if only one parameter could be modified, it would be more prudent to prioritize investments in increasing seismicity knowledge at the dam site. Finally, the use of parameterized fragility functions along with multidimensional integration was found to be an efficient and effective method for safety assessment, offering unique advantages over other conventional hazard- or structure-specific approaches. Ultimately, improved prediction of dam instability events can lead to better safety margins, increased resource efficiency, and minimized delays and shutdowns.

REFERENCES

[1] Li, Z. (2020). “Global Sensitivity Analysis of the Static Performance of Concrete Gravity Dam from the Viewpoint of Structural Health Monitoring”. *Arch. Comput. Methods Eng*., 28,1611-1646(2021)

[2] Segura R., Miquel B., Paultre P., and Padgett J. (2021). “Accounting for uncertainties in the safety assessment of concrete gravity dams: A probabilistic approach with sample optimization”. *Water*, 13(6),885.

[3] Westberg Wilde, M., Johansson, F. (2013). Probability-based guidelines for design and assessment of concrete dams. In Safety, Reliability, Risk and Life-Cycle Performance of Structures & Infrastructures. Taylor & Francis Group, London, UK, pp. 5187–5210.

[4] Kalinina, A., Spada, M., Marelli, S., Burgherr, P., and Sudret, B. (2016). *Uncertainties in the Risk Assessment of Hydropower Dams: State-of-the-Art and Outlook*. Report No RSUQ-2016-008, ETH Zurich: Zürich, Switzerland.

[5] Segura, R., C. Bernier, R. Monteiro, and P. Paultre. (2018). "On the seismic fragility assessment of concrete gravity dams in eastern Canada." *Earthquake Spectra*. 35 (1): 211–231.

[6] Escuder-Bueno, I., Mazza, G., Morales-Torres, A., and Castillo-Rodriguez, J.T. (2016). "Computational Aspects of Dam Risk Analysis: Findings and Challenges". *Engineering*, 2(3):319–324.

[7] Hariri-Ardebili, M. and Saouma, V. (2016). "Seismic fragility analysis of concrete dams: A state-of-the-art review". *Eng Struct*, 128:374–99.

[8] Segura, R., Padgett, J. and Paultre, P. (2020). "Metamodel-based seismic fragility analysis of concrete gravity dams". *Journal of Structural engineering*, 146(7):04020121.

[9] Segura, R., Fréchette, V., Miquel, B., and Paultre, P. (2022). "Dual layer metamodel-based safety assessment for rock wedge stability of a free-crested weir". *Engineering Structures*, 268(1):114691.

[10] CADAM3D (2023). Version 2.5.10. MLT Technology Inc. http://www.cadam3d.com/

[11] U.S. Corps of Engineer – USACE (1995). *Gravity Dam Design*. Technical Report EM 1110-2-2200, Washington, DC, USA.

[12] Fenves, G. and Chopra, A.K. (1986). *Simplified analysis for earthquake resistant design of concrete gravity dams*. Report No UCB/EERC-85/10, Earthquake Engineering Research Center, University of California, Berkeley, CA.

[13] Chopra, A. K. (2014). "Earthquake Analysis of Concrete Dams: Factors to be Considered". In *10th U.S. National Conference on Earthquake Engineering*, Anchorage, USA.

[14] Federal Energy Regulatory Commission - FERC. (2018). Engineering g*uidelines for evaluating seismic hazards at hydropower projects*. Washington, DC, USA.

[15] Adams, J., Allen, T., Halchuk, S. and, Kolaj, M. (2019). "Canada's 6th generation seismic hazard model, as prepared for the 2020 national building code of Canada". In: *12th Canadian conference on earthquake engineering*. Quebec, QC.

[16] National Research Council of Canada – NRCC (2005). National building code of Canada. Prepared by the NRCC, Ottawa, ON.

[17] National Research Council of Canada – NRCC (2010). National building code of Canada. Prepared by the NRCC, Ottawa, ON.

[18] National Research Council of Canada – NRCC (2015). National building code of Canada. Prepared by the NRCC, Ottawa, ON.

[19] National Research Council of Canada – NRCC (2020). National building code of Canada. Prepared by the NRCC, Ottawa, ON.

[20] Kreuzer, P. and Leger, P. (2013). "The adjustable factor of safety: A reliability-based approach to assess the factor of safety for concrete dams". *Int J Hydropower Dams*, 20(1):67–80.

[21] Murphy K.P. (2012). *Machine learning a probabilistic perspective*. The MIT Press, London, UK.

[22] Sheikholeslami, R., and Razavi. S. (2017). "Progressive latin hypercube sampling: An efficient approach for robust sampling-based analysis of environmental models". *Environ Model Softw* 93(July):109–26.

[23] Kameshwar, S., and Padgett, J. (2014). "Multi-hazard risk assessment of highway bridges subjected to earthquake and hurricane hazards". *Eng Struct* 78:154–66.

[24] U.S. Bureau of Reclamation and U.S. Army Corps of Engineer (2019). *Best practices in dam and levee safety risk analysis*. Technical report version 4.1.

[25] Chopra A. (2020). *Earthquake engineering for concrete dams: analysis, design and evaluation*. Wiley, Oxford, UK.