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Seismic fragility analysis with artificial neural networks: Application to nuclear power plant equipment

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ABSTRACT

The fragility curve is defined as the conditional probability of failure of a structure, or its critical components, at given values of seismic intensity measures (IMs). The conditional probability of failure is usually computed adopting a log-normal assumption to reduce the computational cost. In this paper, an artificial neural network (ANN) is constructed to improve the computational efficiency for the calculation of structural outputs. The following aspects are addressed in this paper: (a) Implementation of an efficient algorithm to select IMs as inputs of the ANN. The most relevant IMs are selected with a forward selection approach based on semi-partial correlation coefficients; (b) quantification and investigation of the ANN prediction uncertainty computed with the delta method. It consists of an aleatory component from the simplification of the seismic inputs and an epistemic model uncertainty from the limited size of the training data. The aleatory component is integrated in the computation of fragility curves, whereas the epistemic component provides the confidence intervals; (c) computation of fragility curves with Monte Carlo method and verification of the validity of the log-normal assumption. This methodology is applied to estimate the probability of failure of an electrical cabinet in a reactor building studied in the framework of the KARISMA benchmark.

1. Introduction

The seismic probabilistic risk assessment (SPRA) methodology has been applied worldwide for the estimation of the seismic risk of nuclear power plants (NPPs) [1]. In the SPRA methodology, fragility curves are computed as conditional probabilities of failure of structures, or critical components, for given values of a seismic intensity measure (IM), such as the peak ground acceleration (PGA) [2]. The core damage frequency of the plant is, then, calculated by the convolution of the fragility curves with the hazard curves in fault tree and event tree analysis [2]. The computation of fragility curves requires a realistic estimation of the structure performance subject to seismic excitations via the quantification and the propagation of uncertainties existing in earthquake ground motions, structural material properties, etc. These uncertainties are categorized into two groups [3]: aleatory uncertainties, which reveal the inherent randomness of variables or stochastic processes, and epistemic uncertainties, which originate from the lack of knowledge about the model and provide a family of confidence interval curves for the fragility estimation.

In practice, a fragility curve is calculated as the conditional probability that the damage measure (DM) exceeds a critical threshold, for a given seismic IM [4,5]:

$$P_f(\alpha) = P(y > y_{\text{crit}}|\alpha) \quad (1)$$

where y is the DM, such as inter-story drift, y_{crit} is the failure threshold and α represents the seismic IM. This conditional probability can be evaluated pointwise for different α values with the Monte Carlo method [4,6], as well as with methods based on the log-normal hypothesis [3,7,8]. However, both methods require a few hundred heavy numerical simulations with the finite element method (FEM).

One way to improve the computational efficiency consists in building a metamodel to calibrate the statistical relation between seismic inputs and structural outputs. In fact, it is difficult to directly use stochastic ground motions to construct the metamodels, because the high-dimensionality of the inputs of such metamodels requires a very large size of training data to accurately approximate the input-output relation [9]. An alternative is to use seismic IMs as inputs of the metamodels to represent ground motions. Various functional models based on the calibration of IMs-DM relation have been proposed [10–12]. According to these works, a nonlinear regression metamodel seems more suitable to provide adequate nonlinearity in the IMs-DM relation. However, with this approach, the simplification of the continuous stochastic ground motion by a small set of IMs may not allow to describe

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all the random variability in the earthquake motion [13]. Therefore, it cannot ensure the performance of the metamodels.

Some studies regarding the application of metamodels in fragility analysis have been realized recently. Most works focus on using seismic IMs to characterize earthquake accelerations. Metamodels are constructed to calibrate the relation between DMs and uncertain inputs of the structural models, including IMs and material parameters. The construction of the metamodels is either achieved by decomposing the nonlinear input-output relation with high-dimensional model representation (HDMR) [13,14], or realized with polynomial regression [15–19] or other more advanced statistical tools, such as artificial neural networks (ANNs) [20–24], LASSO regression [25], Bayesian networks [26], merging multivariate adaptive regression splines, radial basis function network, support vector regression [27], Kriging [9,28], etc. On the other hand, earthquake accelerations are also used directly as inputs of the metamodel in [29] to predict structural response time histories. The construction of the metamodel is divided into two steps: the first step is to extract the characteristics of earthquake motions with nonlinear auto-regression; then the polynomial chaos expansion is applied to these characteristics to construct the metamodel. DMs are computed from the structural response time histories, and fragility curves can be thus obtained. Although this method seems different from the classical metamodeling with IMs, the idea remains the same: the nonlinear auto-regression serves as a tool to extract the features of earthquake motions and past values of the structural displacement, while these features are represented by the IMs in classical approaches. Besides regression methods, classification models like logistic regression, random forests and support vector machine are utilized in [30] to predict directly the probability of failure from the uncertain inputs. Despite the fact that seismic fragility analyses have been successfully performed with different types of metamodels, the following two points are rarely discussed: (i) Systematic selection of pertinent IMs to represent seismic ground motions. (ii) Quantification of the prediction uncertainty of the metamodels.

In this paper, a computationally efficient methodology for the application of ANNs to characterize the IMs-DM relation is proposed, from the selection of the most relevant IMs to the quantification of ANN prediction uncertainties. Most existing works take subjective choices of the IMs as inputs of metamodels according to their expertise (e.g. PGA or PGA with other IMs). One IM is obviously not sufficient to represent the seismic ground motion. More systematic approaches are proposed in [20,23] to guide the selection of IMs. Different sets of IMs are selected to train ANNs in [20] and the performances of the different sets of IMs are analyzed with respect to their corresponding ANNs median training errors. Ferrario et al. proposes a wrapper approach based on genetic algorithms in [23] to select the best subset of IMs. However, these approaches can be time-consuming, because it requires repeated trainings of the metamodel. A more efficient feature selection method is proposed in this work.

The uncertainty in the metamodel predictions is also investigated. The ANN prediction uncertainty is considered to be epistemic in [31] to quantify the impact of the size of the used data. The prediction uncertainty is determined by the bootstrap approach, in which retrainings of ANNs are necessary, and it provides confidence intervals of fragility curves. On the contrary, other works integrate the metamodel uncertainty completely into $P_f(\alpha)$ by modeling the standard deviation (Std) of the residual with a dual metamodel (quadratic response surface, HDMR or Kriging) [9,14,18,32]. The residual is sampled from a corresponding normal distribution, and it is added to the mean structural DM predicted by the primal metamodel. With this approach, the residual is an aleatory uncertainty, and the influence of the size of the training data is not accounted for. In addition, the number of FEM simulations required by the dual metamodel approach can be very large, because a number of FEM simulations should be performed at every design point with different stochastic motions to obtain the Std. Therefore, it may not be applicable to a very complex structure such as NPP. In this paper, a clearer insight of the ANN prediction uncertainty computed with the delta method is provided: it consists of an aleatory component from the simplification of the seismic inputs and an epistemic uncertainty due to the paucity of the training data. The former is considered in the computation of $P_f(\alpha)$, whereas the latter is used in the estimation of confidence intervals.

Among various types of metamodels, ANNs are chosen due to their adequate nonlinearity and their excellent universal approximation capability for continuous bounded functions [33,34] (e.g. compared to polynomial response surfaces). Firstly, rather than a classification model like a SVM classifier, which returns only binary failed or survived information for the conditions of structures, an ANN regression model provides predictive structural responses and offers more flexibility for the fragility analysis. Furthermore, the applicability of the ANN does not depend on the probability distribution of input data, so it is a versatile model with a very wide domain of application. Finally, a metamodel based on ANN is a regression rather than an interpolation model. If representative seismic IMs are used to characterize the continuous seismic motions as inputs of the metamodel, the IMs cannot fully represent the seismic randomness and this introduces a residual term. However, an interpolation model predicts identical outputs as the original ground motions for the training data: it may thus overfit the input-output relation. This point is addressed in detail in this work.

This paper is organized as follows: in the next section, the basis about simulation-based fragility analysis methods is briefly recalled. Section 3 presents the methodology for ANN-based fragility estimation. Feature selection techniques are highlighted in this methodology to select the most relevant seismic IMs for a better accuracy of the metamodels. ANN prediction uncertainties are separated into aleatory and epistemic components. These uncertainties are considered in the computation of the fragility curves and the related confidence intervals. An application of the proposed methodology to the Kashiwazaki-Kariwa NPP is demonstrated in Section 4 in the context of the KARISMA benchmark [35]. Conclusions are finally provided in Section 5. Only the ground motion record-to-record variability is considered in this paper, to better study the impact of the ANN prediction uncertainties on the fragility curves. In addition, without specification, the metamodel mentioned in this paper represents regression or interpolation models, instead of binary classification models.

2. Simulation-based fragility analysis

A simulation-based fragility analysis is composed of 3 main steps:

1. Structure modeling. This step consists in establishing a set of mathematical partial differential equations to describe the mechanical behavior of the underlying model.
2. Numerical simulation and calculation of the DM. Numerical simulations are performed to propagate the uncertainties and to compute the DM. FEM is the most widely used numerical resolution method.
3. Computation of the conditional probability of failure of the structure. This step is realized by applying a statistical analysis to the IM-DM data cloud (α,y) computed from the numerical simulation results.

In this section, the computation of the DM and the calculation of the conditional probability of failure are further discussed. The concept of the residual of the metamodel is introduced and emphasized. This concept will be later used throughout the next parts of the paper. Two commonly used methods for the computation of the conditional probability are presented. These two methods will be applied to calculate the fragility curves in an industrial complex case study in this paper.

2.1. Computation of the damage measure

2.1.1. Mechanical model

The mechanical model to compute the DM of a structure or a critical component can be described as

$$y = f(\boldsymbol{a}(t)) \tag{2}$$

where $\boldsymbol{a}(t)$ represents the seismic ground acceleration. The resolution of Eq. (2) is usually time-consuming, especially when the structural