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Bootstrapped Artificial Neural Networks for the seismic analysis of structural systems

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ABSTRACT

We look at the behavior of structural systems under the occurrence of seismic events with the aim of identifying the fragility curves. Artificial Neural Network (ANN) empirical regression models are employed as fast-running surrogates of the (long-running) Finite Element Models (FEMs) that are typically adopted for the simulation of the system structural response. However, the use of regression models in safety critical applications raises concerns with regards to accuracy and precision. For this reason, we use the bootstrap method to quantify the uncertainty introduced by the ANN metamodel. An application is provided with respect to the evaluation of the structural damage (in this case, the maximal top displacement) of a masonry building subject to seismic risk. A family of structure fragility curves is identified, that accounts for both the (epistemic) uncertainty due to the use of ANN metamodels and the (epistemic) uncertainty due to the paucity of data available to infer the fragility parameters.

1. Introduction

In the aftermath of the Fukushima nuclear accident, the 5-year project SINAPS@ (Earthquake and Nuclear Facilities: Ensuring and Sustaining Safety) has been launched in France in 2013. One of the key objectives of the project is the quantitative assessment of the behavior of Nuclear Power Plants (NPPs) under the occurrence of a seismic event. In the framework of this project, we made a preliminary study on the behavior of a structural system subject to seismic risk [1], with the aim of identifying the structure fragility curve, i.e., the conditional probability of damage of a component for any given ground motion level [2]. In this work, we complete the previous analysis with the estimation of the associated uncertainties.

Within the framework of analysis considered, in general the actions, events and physical phenomena that may cause damages to a nuclear (structural) system are described by complex mathematical models, which are then implemented into computer codes to simulate the behavior of the system of interest under various conditions [3,4]. In particular, computer codes based on Finite Element Models (FEMs) are typically adopted for the simulation of the system structural behavior and response: an example is represented by the Gefdyn code [5].

In practice, not all the system characteristics can be fully captured in the mathematical model. As a consequence, uncertainty is always present both in the *values of the model input parameters and variables* and in the *hypotheses supporting the model structure*. This translates into variability in the model outputs, whose uncertainty must be estimated for a realistic assessment of the (seismic) risk [6,7].

For the treatment of uncertainty in risk assessment, it is often convenient to distinguish two types: randomness due to inherent variability in the system behavior (aleatory uncertainty) and imprecision due to the lack of knowledge and information on the system (epistemic uncertainty). The former is related to random phenomena, like the occurrence of unexpected events (e.g., earthquakes) whereas the latter arises from a lack of knowledge of some phenomena and processes (e.g., the power level in the nuclear reactor), and/or from the paucity of operational and experimental data available [3,8–12].

For uncertainty characterization, two issues need to be considered: first, the assessment of the system behavior typically

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Nomenclature

a ground motion level
b index of the bootstrap training data sets or of the bootstrapped regression models, $b = 1, \ldots, B$
B number of the bootstrap training data sets or of the bootstrapped regression models
CP coverage probability
$D = \{(\boldsymbol{Y}_n, \delta_n), n = 1, \ldots, N\}$ entire data set
$D_{train} = \{(\boldsymbol{Y}_n, \delta_{FEM}(Y_n)), n = 1, \ldots, N_{train}\}$ training data set
$D_{train,b}$ bootstrap training data set, $b \in \{1, \ldots, B\}$
$D_{val} = \{(\boldsymbol{Y}_n, \delta_{FEM}(Y_n)), n = 1, \ldots, N_{val}\}$ validation data set
$D_{test} = \{(\boldsymbol{Y}_n, \delta_{FEM}(Y_n)), n = 1, \ldots, N_{test}\}$ test data set
E network performance (energy function)
$f(\boldsymbol{Y}_n, \boldsymbol{w})$ regression function
$f_b(\boldsymbol{Y}_n, \boldsymbol{w}_b)$ bootstrapped regression function, $b \in \{1, \ldots, B\}$
F fragility curve
F_b fragility curve built on the basis of the b-th bootstrapped regression function, $b \in \{1, \ldots, B\}$
$\underline{F}$ lower bound fragility curve due to the paucity of data
$\overline{F}$ upper bound fragility curve due to the paucity of data
$\underline{\underline{F}}$ lower bound fragility curve due to the model and the paucity of data
$\overline{\overline{F}}$ upper bound fragility curve due to the model and the paucity of data
h optimal number of hidden neurons
I_{Arias} Arias intensity
j index of the inputs $\boldsymbol{Y}$
L likelihood function
M number of input variables
n index of the data in a given set
N number of realization of the seismic event
NMW normalized mean width
N_{test} number of test data
N_{train} number of training data
N_{val} number of validation data
p coverage indicator; $p = 1$ if the output is included in the confidence interval; $p = 0$ otherwise
pgv Peak Ground Velocity
$PSA(T_{str})$ spectral acceleration at the first-mode period of the structure
$RMSE_{ANN}$ root mean square error of the ANN trained with the whole training data set D_{train}
$RMSE_{Boot}$ root mean square error of the bootstrap ensemble of ANNs
SI spectral intensity
T_m mean period
T_p predominant period
$Tstr$ fundamental period of the structure
V_{s30} average shear wave velocity in the upper 30 m
$\boldsymbol{w}$ vector of parameters of the regression functions
$\boldsymbol{w}_b$ vector of parameters of the b-th bootstrapped regression functions, $b \in \{1, \ldots, B\}$
X outcome of a seismic event (Bernoulli random variable)
x_n realization of the Bernoulli random variable X_n
$x = \{x_1, x_2, \ldots, x_n, \ldots, x_N\}$ vector of the realizations of the N Bernoulli random variable X_n, $n = 1, \ldots, N$
y ground motion IMs
$\boldsymbol{Y} = \{y_1, y_2, \ldots, y_i, \ldots, y_M\}$ vector of M uncertain input variables
$\boldsymbol{Z} = \{z_1, z_2, \ldots\}$ vector of system responses

Greek letters

α median ground motion intensity measure (IM)
$\hat{\alpha}$ estimate of α
$[\underline{\alpha}^{100(1-\theta)\%}, \overline{\alpha}^{100(1-\theta)\%}]$ 100(1 − θ)% confidence interval of α
β logarithmic standard deviation
$\hat{\beta}$ estimate of β
$[\underline{\beta}^{100(1-\theta)\%}, \overline{\beta}^{100(1-\theta)\%}]$ 100(1 − θ)% confidence interval of β
$1 - \gamma$ level of confidence for the bootstrap-based empirical PDFs
δ target, maximal structural top displacement
$\delta(\boldsymbol{Y}_n)$ model output (maximal structural top displacement) in correspondence of the n-th input vector $\boldsymbol{Y}_n$
$\delta_{ANN}(\boldsymbol{Y}_n)$ estimate of the maximal structural top displacement obtained by the ANN
$\delta_{Boot_b}(\boldsymbol{Y}_n)$ estimate of the maximal structural top displacement given by one of the b-th bootstrapped regression functions, $b \in \{1, \ldots, B\}$
$\bar{\delta}_{Boot}(\boldsymbol{Y}_n)$ average of the B estimates $\delta_{Boot_b}(Y_n)$, $b = 1, \ldots, B$
$\delta_{FEM}(\boldsymbol{Y}_n)$ true maximal structural top displacement computed by the FEM
δ^* damage threshold
$[\underline{\delta}^{100(1-\gamma)\%}(\boldsymbol{Y}_n), \overline{\delta}^{100(1-\gamma)\%}(\boldsymbol{Y}_n)]$ 100(1 − γ)% confidence interval of the quantity $\delta(\boldsymbol{Y}_n)$
$\varepsilon(\boldsymbol{Y}_n)$ Gaussian white noise
$1 - \theta$ level of confidence for parameters α and β
$\mu_\delta(\boldsymbol{Y}_n)$ nonlinear deterministic function
$\sigma^2_{Boot}(\boldsymbol{Y}_n)$ bootstrap estimate of the variance of $\sigma^2_f(Y_n)$
$\sigma^2_f(\boldsymbol{Y}_n)$ variance of the distribution of the regression function $f(\boldsymbol{Y}_n, \boldsymbol{w})$
$\sigma^2_\varepsilon(\boldsymbol{Y}_n)$ variance of $\varepsilon(\boldsymbol{Y}_n)$
$\Phi[\cdot]$ standard Gaussian cumulative distribution

Acronyms

ANN Artificial Neural Network
CDF Cumulative Distribution Function
CP Coverage Probability
FEM Finite Element Model
GA Genetic Algorithm
IM Intensity Measure
LGP Local Gaussian Process
NMW Normalized Mean Width
NPP Nuclear Power Plant
PGA Peak Ground Acceleration
PDF Probability Density Function
RMSE Root Mean Square Error
RS polynomial Response Surface
SA Spectral Acceleration
SPRA Seismic Probabilistic Risk Assessment
SVMs Support Vector Machines

requires a very large number (e.g., several hundreds or thousands) of FEM simulations under many different scenarios and conditions, to fully explore the wide range of uncertainties affecting the system; second, FEMs are computationally expensive and may require hours or even days to carry out a single simulation. This makes the computational burden associated with the analysis impracticable, at times.

In this context, fast-running regression models, also called metamodels (such as Artificial Neural Networks (ANNs) [13–17], Local Gaussian Processes (LGPs) [18,19] polynomial Response Surfaces (RSs) [7,20], polynomial chaos expansions [21,22], stochastic collocations [23], Support Vector Machines (SVMs) [24] and kriging [25–27], can be built by means of input-output data examples to approximate the response of the original long-running FEMs