NARSIS

New Approach to Reactor Safety ImprovementS

WP4: Applying and comparing various safety assessment approaches on a virtual reactor

D4.4 – Applicability of model reduction strategies in safety analyses

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Primary Author: Giuseppe Rastiello (CEA)

Other contributors:

Deliverable Review:

Reviewer#1: Cyril Feau (CEA)

Reviewer#2: Evelyne Foerster (CEA)

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1 Executive Summary

The Probabilistic Safety Assessment (PSA) of Nuclear Power Plants (NPPs) raises a need for advanced and efficient numerical approaches to derive the required decision-making information (e.g., fragility curves) related to complex structures and equipment with moderate (reasonable) computational efforts.

High-fidelity Finite Element (FE) models can accurately predict the response of structures, systems and components (SSCs) under various loadings. However, they are highly demanding from a computational viewpoint and challenging to use in practice, as assessing safety margins and taking into account the variability of the reference problem parameters lead to making this numerical effort for a series of simulations (or models).

Within the NARSIS project, two families of computationally less expensive strategies to model SSCs were developed and tested for seismic risk assessment: metamodelling techniques (i.e., surrogate models) and numerical solvers including model reduction.

Constructing a metamodel consists in developing a simplified expression between model input (Intensity Measures, IMs) and output (e.g., Engineering Demand Parameters, EDPs). Accordingly, probabilistic and sensitivity analyses can be performed at an affordable computational cost. In NARSIS deliverable D4.2 (Feau et al., 2020), two non-intrusive metamodelling strategies were proposed:

- One based on Support Vector Machines (SVMs) coupled with an Active Learning algorithm;
- A 2nd one using Artificial Neural Networks (ANN).

Another solving strategy was proposed for non-linear seismic problems as well. It was recently developed in the PhD works of Rodriguez-Iturra (2021) and is summarized in NARSIS deliverable D4.3 (Charbonnel, 2022). This strategy naturally includes model reduction since it is based on the LATIN (LArge Time INcrement) and Proper Generalized Decomposition (PGD) methods. Its implementation in a FE software is intrusive since the solving process differs from the standard Newton-like approach with Newmark-like time discretization schemes.

These methodologies have successfully applied to different test cases and proven to reduce computational costs associated with probabilistic analyses (e.g., fragility curves). Their applicability to the safety assessment of a whole nuclear facility is still to be demonstrated. This report aims at providing some information on this topic.

2 Introduction

The probabilistic Safety Assessment (PSA) procedures for Nuclear Power Plants (NPPs) raises a need for advanced and efficient numerical approaches in order to derive the required decision-making information (e.g., fragility curves) related to the complex structures and equipment with moderate (reasonable) computational efforts.

High-fidelity Finite Element (FE) simulations can be highly demanding from a computational viewpoint. The complexity and richness of the numerical models used to predict the often non-linear behaviour of structures, systems and components (SSC) may induce computation times of several days for the simulation of a single seismic event using classical Newmark-like incremental methods. Furthermore, assessing safety margins and taking into account the variability of the reference problem parameters (mechanical parameters, loading) lead to making this numerical effort for a series of simulations (or models).

Within the NARSIS project, two families of computationally less expensive strategies to model SSC were developed and tested for seismic risk assessment: metamodelling techniques (i.e., surrogate models) and numerical solvers including model reduction.

Constructing a metamodel consists of developing a simplified expression between model input (Intensity Measures, IMs) and output (e.g., Engineering Demand Parameters, EDPs). Accordingly, probabilistic and sensitivity analyses can be performed at an affordable computational cost. In NARSIS deliverable D4.2 (Feau et al., 2020), two metamodelling strategies were proposed:

- The first one (Sainct et al., 2020) is based on Support Vector Machines (SVMs) coupled with an Active Learning algorithm.
- The second one (Wang et al., 2018) uses Artificial Neural Networks (ANN).

Since high-fidelity FE simulations are used only for building and training metamodels, and can be done with a simulation program distinct from the code used for constructing metamodels (i.e., FE codes are used as “black boxes”), these techniques can be defined as *non-intrusive*.

Another solving strategy was proposed for non-linear seismic problems as well. It was recently developed in the PhD works of Rodriguez-Iturra (2021) and is summarized in NARSIS deliverable D4.3 (Charbonnel, 2022). This strategy naturally includes model reduction since it is based on the LATIN (LArge Time INcrement) and Proper Generalized Decomposition (PGD) methods. Its implementation in FE software requires substantial numerical code modifications since the solving process differs from the standard Newton-like approach with Newmark-like time discretization schemes. In that sense, this technique can be defined as *intrusive*.

These methodologies have been applied successfully to different test cases and proven to reduce computational costs associated with probabilistic analyses (e.g., fragility curves). Their applicability to the safety assessment of a whole nuclear facility is still to be demonstrated. This report aims at providing some information on this topic.

The document is structured as follows:

- Section 2 presents metamodels for seismic risk assessment, focusing on the main aspects of the different formulations proposed.
- Section 3 focuses on the LATIN-PGD formulation.
- Section 4 discusses the applicability of each strategy to the safety analysis of the NARSIS model plant (Brunèliere et al., 2018; Lo Frano et al., 2022) after presenting some representative examples.

Some conclusions close this document.

3 Non-intrusive model reduction methods – Metamodels for seismic risk assessment

3.1 SVM-based methodology

Sainct et al. (2020) proposed a methodology based on SVMs coupled with an Active Learning algorithm. SVMs are used to classify (binary classification) structural responses relative to a limit threshold of exceedance (or a failure criterion). Since the SVM output is not binary, but a real-valued score, a probabilistic interpretation of this score is introduced to estimate fragility curves efficiently. Indeed, the score function can be viewed as an optimal seismic IM since a perfect classifier would lead to a fragility curve in the form of a unit step function when the problem is linearly separable.

Modelling phases. The first step involves generating a large set of artificial seismic signals and computing the different IM indicators of interest. This step is not time-consuming compared to non-linear mechanical calculations. In this work, it was chosen to enrich a set of acceleration records selected in a real ground motion database using magnitude and distance criteria (Ambraseys et al., 2000). To this end, the parameterized stochastic model of modulated and filtered white-noise process defined in Rezaeian et al. (2010) has been implemented. This model efficiently addresses both temporal and spectral non-stationarities of seismic signals and has been used in several recent works.

The second step consists of building an SVM-based classifier by optimally selecting the mechanical calculations to perform by active learning. A probabilistic interpretation of the real-valued score given by the classifier is used in a third step to estimate fragility curves very efficiently as score functions.

Sainct et al. (2020) showed that the classifier could also be used to predict the scores and probabilities associated with several new input parameters[1] to estimate fragility curves as functions of the classical seismic IMs (e.g., Peak Ground Acceleration, PGA).

3.2 ANN-based methodology

Wang et al. (2018) developed a methodology based on ANNs for constructing metamodels. ANNs (Figure 1) were chosen due to their adequate nonlinearity and excellent approximation capability for continuous bounded functions (Bishop, 1995; Reed, 1999).

Modelling phases. The proposed methodology allows for constructing vector-valued fragility curves. The main modelling phases can be summarized as follows:

1. Preparation of data set by performing FE simulations of the considered structures, systems, and components;
2. Feature selection to extract the most important IMs as inputs of the ANN;
3. ANN training and validation;
4. ANN uncertainty quantification;
5. Computation of fragility curves with ANN simulation results.

The construction of the ANN requires conducting a series of FE simulations, eventually taking into account soil-structure interaction. The number of simulations needs to be limited due to the computational complexity of FE analyses involving models with many Degrees of Freedom (DOFs) and accounting for material nonlinearities.

Once the ANN is built, the fragility curves can be evaluated point-by-point through direct Monte Carlo (MC) simulation or by assuming a log-normal model and applying linear regression techniques. The quantification and investigation of the ANN prediction uncertainty is computed with the delta method. It consists of an aleatory component from the simplification of the

[1] *Those which have not been selected for the definition of the classifier or others generated from new simulations of the ground motion model.*

seismic inputs and an epistemic model uncertainty from the limited size of the training data. The aleatory component is integrated into the computation of fragility curves, whereas the epistemic component provides the confidence intervals.

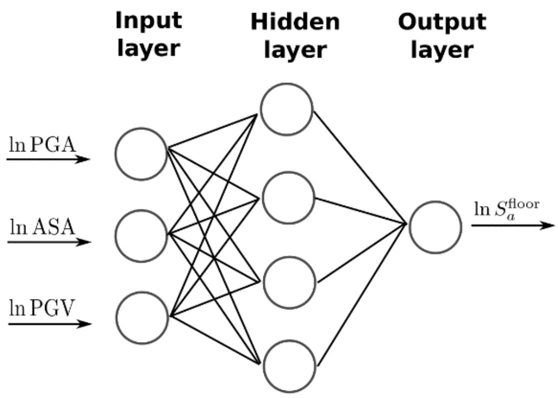

Figure 1 – ANN-based metamodel – ANN to establish a link between IMs (e.g., PGA, Peak Ground Velocity PGV) and EDPs.

The ANN then allows for the computation of fragility curves with the MC method and verification of the validity of the log-normal assumption. In the numerical simulations, a set of N time histories is used to obtain a sample of N EDPs. The collection of corresponding IMs is determined from the time histories. This data is used to train the ANN. Once the ANN is trained, new data can be simulated at negligible cost by sampling IMs (e.g., using Ground Motion Prediction Equations, GMPEs) and determining the respective EDPs. The whole procedure is summarized in Figure 2.

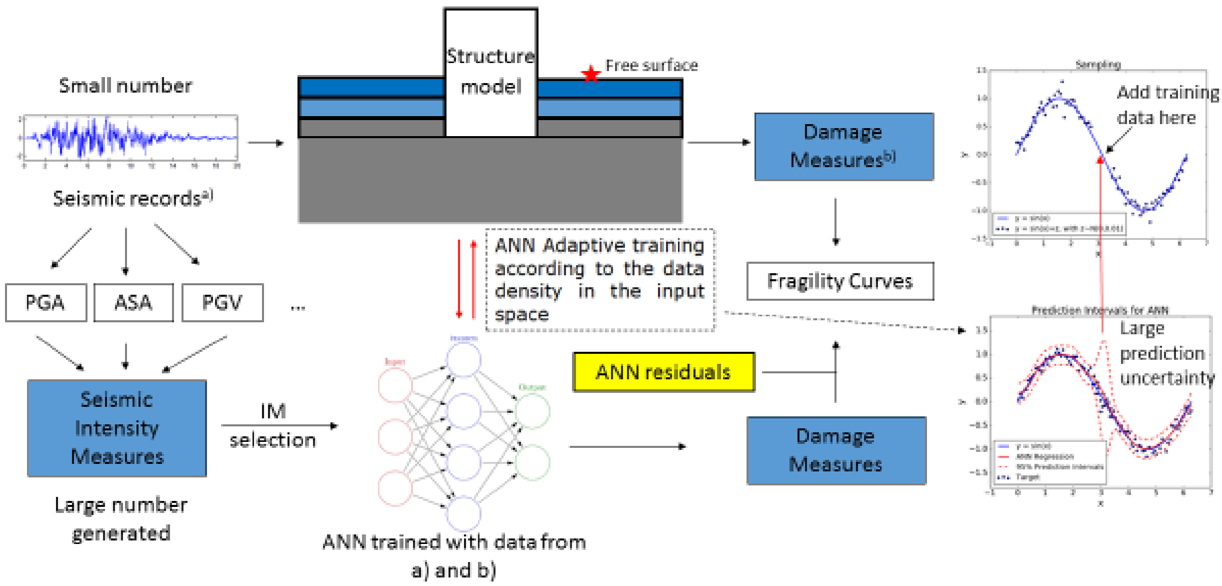

Figure 2 – ANN-based metamodel – Schematic representation of the methodology.

4 Intrusive model reduction methods – LATIN/PGD methodology for seismic analyses

Building metamodels implies a repetitive computation of the response of the structure of interest, taking into account the variability of the input parameters (mechanical characteristics, loading parameters). This task can sometimes be highly demanding from a computational viewpoint, particularly when considering complex structures (e.g., confinement structures and the associated systems and equipment) and non-linear material behaviours are taken into account.

In the framework of the NARSIS project, a considerable effort has been made to develop a novel computationally efficient solving method for computing parametric solutions for non-linear dynamics in a low-frequency range (seismic signals with frequency contents below 50 Hz).

Model ingredients. The proposed approach is based on two main elements:

1. the LATIN method, a general strategy for resolving non-linear problems. Despite what is done in Newton-like solvers based on Newmark-like time integration schemes, the complete time-space solution is computed at once and progressively corrected to fulfil kinematic/dynamic admissibility and the constitutive equations (Figure 3).

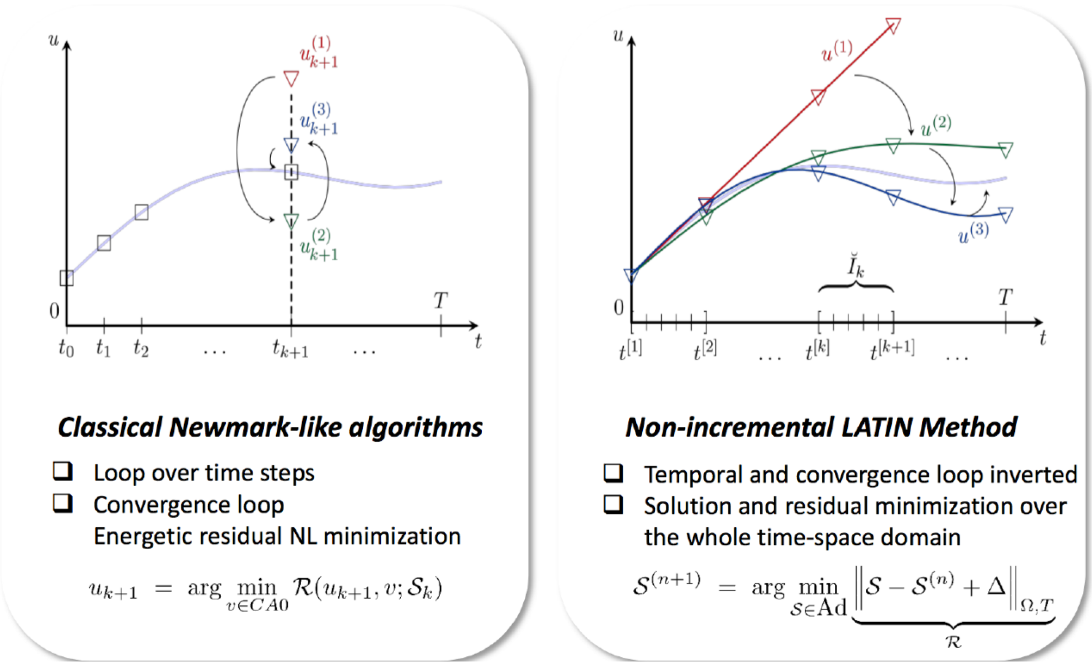

Figure 3 – LATIN-PGD approach – Classical Newmark-like algorithms vs LATIN method.

2. the PGD [Ladevèze, 1999], a model-order-reduction technique that offers a framework for obtaining parametric solutions in the linear range (see, e.g., Ammar et al., 2006; Gunzburger et al., 2007; Chevreuil & Nouy, 2012). Thanks to the PGD, the proposed approach intrinsically contains model reduction, which becomes essential to reduce computational costs, particularly when computing parametric solutions. The leading idea of model-order reduction methods, such as the PGD, is to exploit information redundancy in the parametric solution to propose an approximated and numerically efficient problem resolution. The solution of the reference problem is thus approached by a sum of *M* terms, each of them being a product of functions with separate variables. Moreover, the approximation space (i.e., the basis containing the separate variables functions) is built incrementally and enriched progressively.

Solving process. According to the LATIN method, the problem solution is achieved iteratively through a sequence of linear and non-linear stages (Figure 4).

The sought solution S_i associated with a vector θ_i parameterizing the constitutive relations is at the intersection of a manifold $\boldsymbol{\Gamma}_i$ (on which constitutive relations are fulfilled) and an affine space $\boldsymbol{Ad}$ (where the kinematic and dynamic admissibility is fulfilled).

At each linear stage, one solves a global space-time problem expressing the system's equilibrium. At iteration $n+1$ of the solving process, the non-linear correction $\Delta S^{(n+1)}$ is sought by minimizing a global residual integrated on the time (T) and space (Ω) domain:

$$\Delta\mathcal{S}^{(n+1)} = \arg\min_{\mathcal{S}\in\mathrm{Ad}} \underbrace{\left\|\Delta\mathcal{S} - \mathcal{S}^{(n)} + \Delta\right\|_{\Omega,T}}_{\mathcal{R}} \tag{1}$$

where $S^{(n)}$ denotes the solution at iteration *n* and Δ defines the loading for each linear stage.

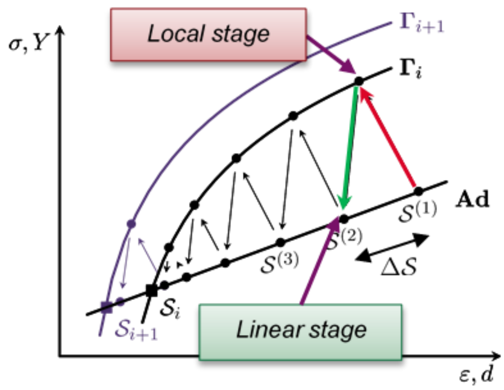

Figure 4 – LATIN-PGD approach – Overview of the solving strategy.

The PGD is used to provide a reliable and numerically economical low-rank approximation of the solution $\Delta S^{(n+1)}$ by seeking the corrections under the form:

$$\Delta\mathcal{S}^{(n+1)}(t,x) = \sum_{m=1}^{M} \alpha_m(t)\ \phi_m(x) \tag{2}$$

where the time- and space-modes (α_m and ϕ_m, respectively), are computed using a fixed-point strategy with alternate search directions.

In seismic mechanics, a potentially critical point is the length of the time-domain on which the solution has to be computed. Seismic signals are typically composed of thousands of points, quickly leading to high computation time. The CPU time spent solving the sequence of linear stages within the LATIN/PGD methodology can thus be significant and can penalize the method's efficiency. In Rodriguez-Iturra (2021), a particular effort was made to take advantage of the multi-frequency nature of the seismic input. A new decomposition of the residual Δ figuring in eq. (1) was proposed. Δ is written as a sum of periodic contributions or modes, each mode being associated with a single frequency and an envelope function. A coarse macro time-scale for each mode can then be defined. The correction related to each mode can be computed using a reduced number of Gauss points for time integration. The "remeshing" stage in time is quick and automated and enables to decrease the numerical cost associated with time integration and computation of corrections (terms $(\alpha_i)_{i=1}^{M}$ figuring in eq. (2)). This improvement was tested on an elasto-viscoplastic case. It allowed a 38% time saving for the computation of time corrections for the considered seismic loadings.

Additional developments were made to improve the non-linear stage resolution, where the constitutive relations $C(x_i, t_j)$ have to be solved at each Gauss integration point (j in time and

i in space). Once again, a separate variables representation of the constitutive relations on the manifold $\boldsymbol{\Gamma}$ was sought as follows:

$$C(x,t) \approx \sum_{k=1}^{N} a_k(t)\, b_k(x) \tag{3}$$

In practice, reference points are chosen to characterize the manifold $\boldsymbol{\Gamma}$, and a posteriori Proper Orthogonal Decomposition (POD) is performed to find the time and space contributions $(a_k, b_k)_{k=1}^{N}$. Once this decomposition is obtained in a preliminary computation stage, solving the constitutive relations can be significantly accelerated. An approximated expression of the tangent operators can be obtained and used as optimized search directions in the LATIN strategy. This last ingredient was also tested for elasto-viscoplastic problems, showing encouraging results with significant (up to 50%) computation time saving for the non-linear stages.

In addition to previous developments, an incremental time resolution strategy was developed based on the Time Discontinuous Galerkin Method (TDGM). It allows to efficiently solve the temporal PGD functions since it reduces the size of the operators needed to be inverted for the enrichment and preliminary steps of the LATIN-PGD method. This provides an advantage over the classically used methods, which correspond to a continuous formulation in time using the Time Continuous Galerkin Method (TCGM), especially when the time domain is large. In these situations, the continuous formulation requires the assembly and inversion of large matrices for the temporal resolution, which decreases the efficiency of the LATIN-PGD method. On the other hand, in the case of the discontinuous formulation using the TDGM, the temporal PGD functions are computed element by element of the temporal FEM discretization, avoiding the construction and inversion of large assembled matrices thus increasing the efficiency of the LATIN-PGD method.

Computing parametric solutions. The proposed approach can be highly convenient to compute parametric solutions. The solution S_{i+1} for a set of parameters θ_{i+1} close to θ_i can be initiated to the already converged solution S_i . This allows for decreasing the number of LATIN iterations needed for convergence. Moreover, the space basis $(\phi_i)_{i=1}^{M}$ can be reused throughout the numerical process, making the general methodology particularly efficient. In other words, the PGD allows capturing the non-linear solution's redundancies in both space and time, allowing a considerable simulation time reduction. An enrichment stage can be performed if the convergence criterion is not met.

5 Applicability of model reduction strategies

Within the NARSIS project, a generic so-called GEN III-based (1300 MWe) NPP model with large dry containment was developed for large-scale numerical simulations (mainly in WP2 to WP4). In this section, for each model reduction strategy presented in the previous sections, we provide representative examples and discuss their potential application to the safety assessment of the NARSIS-NPP.

5.1 The NARSIS-NPP model

Based on the definition provided in NARSIS deliverable D4.1 (Brunèliere et al., 2018) of a simplified reference NPP, representative of the European fleet, the so-called NARSIS-NPP, a FE model of a double-wall containment building and the associated systems and components (Reactor Pressure Vessel; Steam Generators, etc.) was presented in NARSIS deliverable D2.4 (Lo Frano et al., 2022).

The containment of this reactor system consists of an outer and an inner containment (Figure 5). The outer containment shell is a reinforced concrete structure with large wall thickness. It protects the inner containment from the direct effects of external hazards. A steel liner ensures the leak-tightness function on the inner surface of the containment, which is anchored in the inner containment wall by *L*-profiles ("continuous anchors") and by headed studs. The inner containment structure consists of the base slab, cylindrical, and dome parts. The base slab is connected to the cylindrical portion by the gusset area in which the wall thickness increases considerably. Materials can be assumed elastic or damageable (e.g., for the concrete structure).

The FE model was developed using the MSC Marc® software[2]. It contains volume, shell, and beam elements. The total number of finite elements is 133,000, and the number of DOFs is 600,000 approximately.

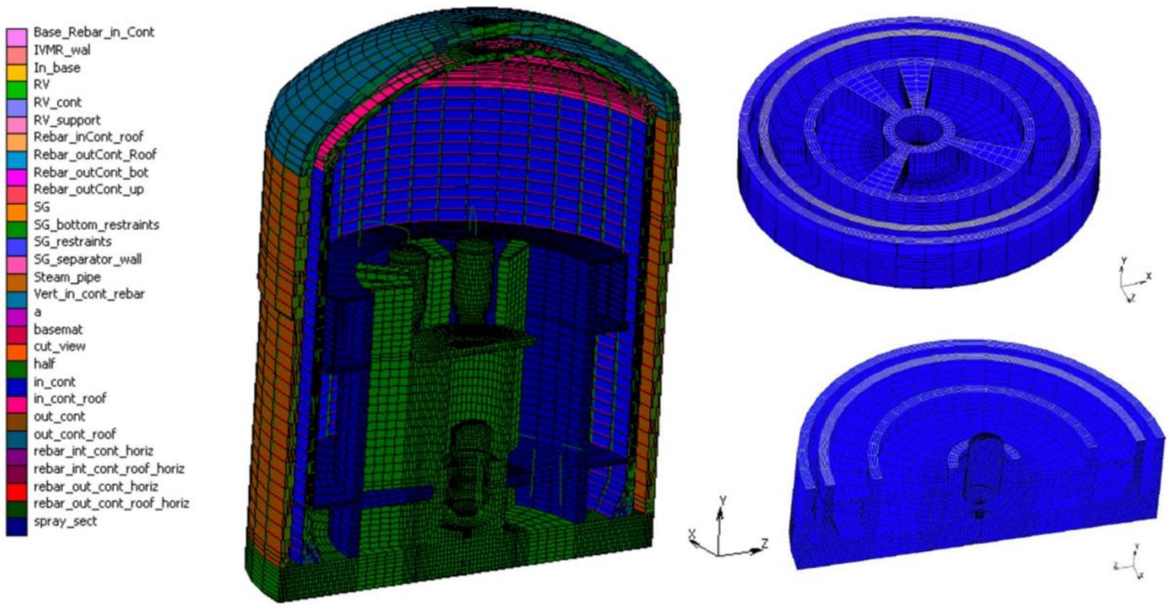

Figure 5 – NARSIS-NPP – Overview of the geometrical model and FE model of a simplified Gen III Nuclear Power Plant containment building and associated systems.

[2] *Marc (https://www.mscsoftware.com/product/marc) is a general-purpose, nonlinear finite element analysis solver to simulate structural responses under static, dynamic and multi-physics loading scenarios.*

5.2 Non-intrusive model reduction methods – Metamodels for seismic risk assessment

5.2.1 SVM-based methodology – Representative example

A non-linear single DOF system was considered for the illustrative application of the SVM-based method (Figure 6). Despite its extreme simplicity, such a model may reflect the essential features of the non-linear responses of some structures (Wang & Feau, 2020). Moreover, in a probabilistic context requiring MC simulations, it is possible to have reference results with a reasonable numerical cost (33,000 MC simulations were conducted in this example). Figure provides the fragility functions expressing the probability of failure as a function of the PGA.

Computations were performed using an in-house-developed code in the MATLAB® environment. As already mentioned, no FE structural models were used to build the metamodel. Instead, the system's equation of motion was solved using a simple finite difference scheme. Consequently, the computational cost of the model building and training was extremely low.

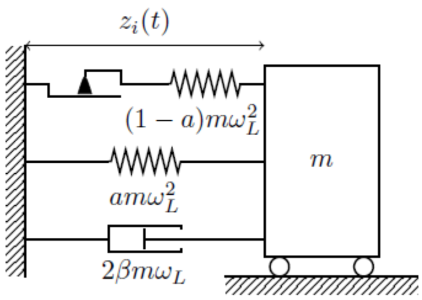

Figure 6 – SVM-based metamodel – Rheological hysteretic model of the non-linear oscillator.

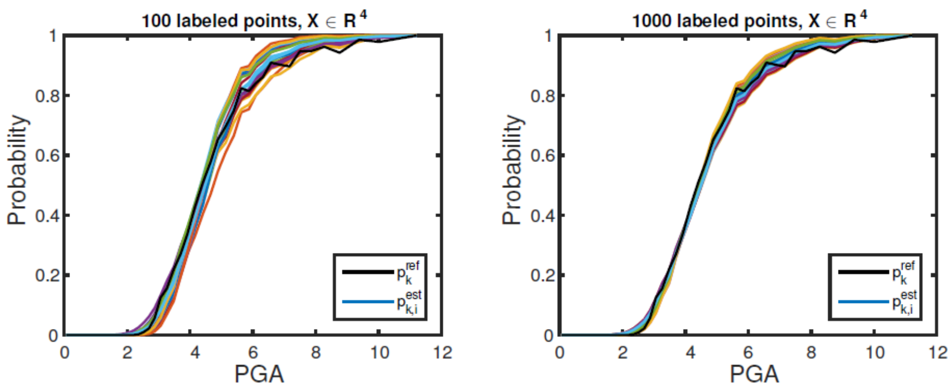

Figure 7 – SVM-based metamodel – Reference & estimated fragility curves vs. PGA.

5.2.2 ANN-based methodology – Representative example

A larger-scale test case was considered to illustrate the application of the ANN-based metamodel. The reliability of a hypothetical electrical cabinet located on the 5th floor of the Unit 7 reactor building of the Japanese Kashiwazaki-Kariwa (K-K) NPP[3] was analyzed (Figure 8 - left).

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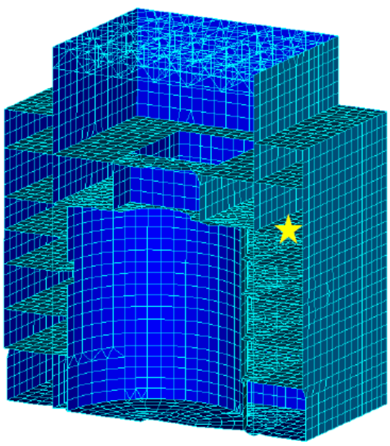
[3] In 2007, the Japanese Kashiwazaki-Kariwa (K-K) NPP was affected by the Niigataken-Chuetsu-Oki Earthquake (NCOE) with a magnitude Mw = 6:6 and an epicenter distance of 16 km.

The structural FE model consists of 92,000 DOFs with 10,700 nodes and 15,600 elements, including bar, beam, and different shell elements. All materials were assumed to behave according to a linear elastic constitutive model. The NPP model is embedded in the soil. Structural analyses were performed with the FEM software Code_Aster®[4], while the soil part (for SSI analyses) was solved using the boundary element method (BEM)[5].

Anchorage failure of the electrical cabinet was considered. The capacity was given by the floor spectral acceleration of the anchorage point around 4Hz (the assumed natural frequency of the cabinet). The maximum value of the floor spectral accelerations (SA) in both horizontal directions, integrated over a frequency interval around 4Hz to account for the uncertainty, was defined as the DM.

The ANN metamodel was constructed and trained based on 100 FE simulations. Figure 8 (right) represents the SA registered at the equipment location as a function of the PGA. Based on these results, the Average Spectral Acceleration (ASA) was identified as the most relevant IM to the considered DM. The ANN was trained then. The metamodel was finally used to carry-out fast-running simulations and build fragility curves (Figure 9).



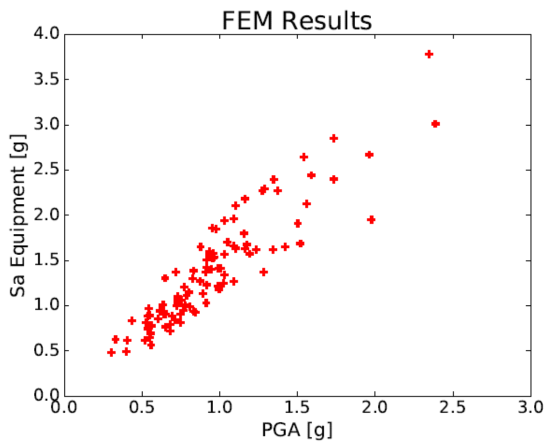


Figure 8 – ANN-based metamodel – Location of the electrical cabinet in the K-K model, indicated by the star symbol. Spectral acceleration at the equipment level as a function of the PGA.

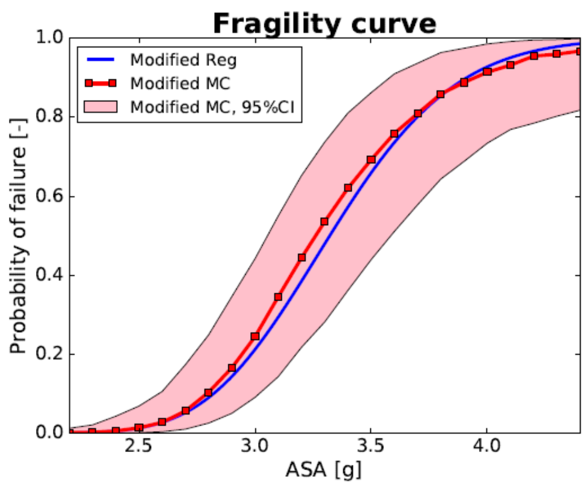


Figure 9 – ANN-based metamodel – Fragility curve computed for the electrical cabinet in the K-K model.

[4] *Code_Aster® (https://www.code-aster.org/) is a general purpose and open-source FE solver developed by the EDF group.*
[5] *MISS (http://www.mssmat.ecp.fr/miss), a BEM software in earthquake engineering was used.*

Based on the soil impedances computed by BEM, one single FEM simulation takes 1.87 hours on an Intel Xeon E5-2600V2 CPU of 2.7GHz. This makes it almost unaffordable to run many FEM simulations for performing a pointwise MC fragility analysis. However, once the ANN metamodel is established (319.29 hours of computation), the CPU time needed to conduct MC fragility analyses is less than half an hour.

5.2.3 Applicability to the NARSIS-NPP safety assessment

Thanks to their non-intrusive nature, the proposed SVM- and ANN-based metamodelling strategies can be applied to the NARSIS-NPP without significant developments.

Concerning the SVN-based formulation, one has to replace the simple DOF oscillator's response with the NARSIS-NPP's response to building the metamodel. The active learning algorithm will determine (at each stage) the seismic signal to be used to perform the dynamic simulation and build the metamodel. Similarly, one can simply replace the K-K model with the NARSIS-NPP model for the ANN-based metamodel.

In both cases, complex dynamic simulations need to be repetitively run to build and train metamodels. This task could enormously benefit from parallel and high-performance computing (HPC) methodologies to lower the CPU time associated with the solving process.

5.3 Intrusive model reduction methods – A novel LATIN-PGD methodology for seismic analyses

5.3.1 Representative example

Rodriguez-Iturra (2021) tested the LATIN-PGD methodology on simple numerical models involving quasi-brittle (concrete) and elasto-viscoplastic (steel) materials.

As an example, Figure depicts the results obtained for a simply supported concrete beam (6m length) submitted to a dynamic motion of its supports. For simplicity, a simple isotropic continuum damage mechanics model was used to represent the material behaviour, but similar results can be obtained with an elasto-viscoplastic formulation. The FE mesh comprises 4,535 linear tetrahedral elements. 1000 Lagrange polynomials of order 2 in time were used for integration on 20 seconds.

Simulations were performed using an in-house FE solver written in the MATLAB® environment.

The classical step-by-step integration method (Newmark-like time integration method combined with a Newton-Raphson algorithm for non-linear solving) and the LATIN/PGD methodology provided results that are in excellent agreement (Figure 10).

The LATIN-PGD formulation ensured better computational performances. In this simple example, the CPU time was already in favour of the LATIN/PGD method (about 30%). However, it is in the computation of parametric solutions that one can fully benefit from the method's performance. For instance, to perform the parametric study of Figure 11, the computational gain was more than 700% in favour of the LATIN/PGD approach compared to classical step-by-step resolution (see D4.3 for details).

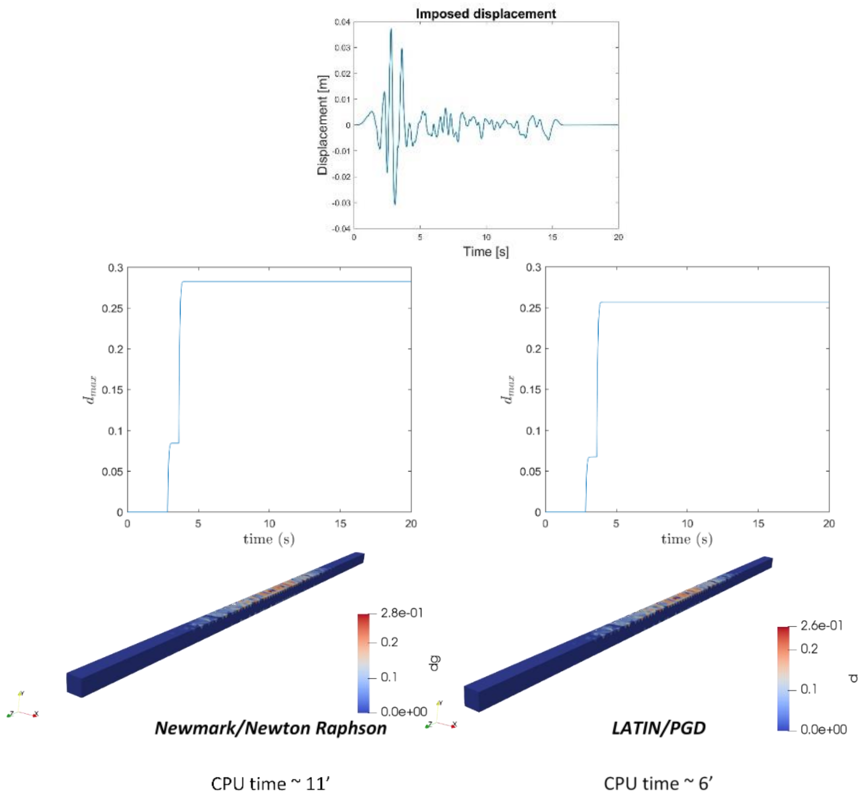


Figure 10 – LATIN-PGD approach – Comparison between the classical step-by-step and LATIN/PGD resolution in non-linear dynamics. Seismic signal considered in computations, time evolution of the damage variable at the same integration points, damage field in the beam.

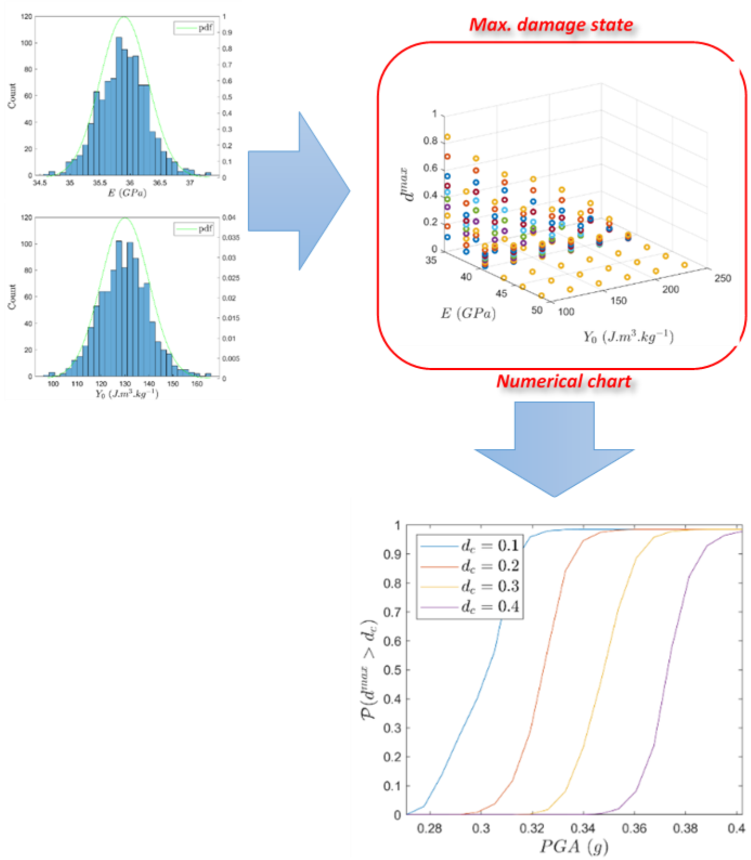


Figure 11 – LATIN-PGD approach – Example of the use of a parameterized solution (top left) to derive a numerical chart (top right), which is then used to produce fragility curves (bottom right).

5.3.2 Applicability to the NARSIS-NPP safety assessment

The LATIN-PGD methodology reduces the computational time compared to classical incremental solvers when solving non-linear problems. This reduction is directly proportional to the number of DOFs considered for spatial and temporal domains.

As mentioned before, simple structural models containing linear solid (hexahedral, tetrahedral) finite elements were simulated. The numerical simulation of a typical reactor building requires considering solid elements, but also plates, shells, and beam elements. More generally, complex kinematics (e.g., multilayer elements) and material behaviours can be needed to represent the different structures, components, and their interactions. Other sources of nonlinearities may also be involved, e.g., the frictional contact between components.

The LATIN-PGD method can be considered an excellent candidate to increase the efficiency of non-linear simulations for the safety analysis of such structures. However, some additional developments are necessary to apply the method to simulate the response of the NARSIS-NPP. From a practical point of view, two approaches are possible:

1. Implementing the LATIN/PGD method within the MSC Marc® code. Given the complexity of the solver, this would imply very intrusive modifications to the solver.
2. Exporting the NPP model from the MSC Marc ® code to the MATLAB® platform for conducting computations. This would require implementing all the numerical ingredients (i.e., elements, kinematics, constitutive models) needed for this purpose.

6 Conclusions

High-fidelity seismic mechanics FE simulations can be highly demanding from a computational viewpoint. Model reduction techniques allow obtaining accurate and computationally less expensive models of the considered structures, systems, and components. In NARSIS, two families of model reduction techniques were developed for seismic risk assessment: metamodelling techniques on one side (Wang et al., 2018; Sainct et al., 2020) and numerical solvers including model reduction on the other one (Rodriguez-Iturra, 2021).

In the cited references, these methodologies have been applied to different test cases (with varying levels of complexity) and proved to reduce computational costs associated with probabilistic analyses (e.g., for computing fragility curves).

This report shorty discussed the applicability of such modelling techniques to the safety assessment of the NPP model developed in the NARSIS project (Brunèliere et al., 2018; Lo Frano et al., 2022), the so-called NARSIS-NPP.

It was shown that the application could be pretty straightforward in the case of the SVN- and ANN-based metamodels. Thanks to their non-intrusive nature, one can use the NARSIS-NPP model to build and train metamodels in both cases. The sole limitations could come from the CPU time needed for performing the mechanical simulations, depending on the performance of the FEM software used.

The application of the LATIN-PGD strategy is less straightforward. In that case, some additional numerical developments are still needed. This work is in progress in the framework of a new PhD thesis in collaboration between the CEA and Ecole Normale Supèrieure Paris-Saclay. Once these developments are performed, one could also imagine combining the different model reduction strategies, using a LATIN-PGD-based FE solver to efficiently compute the structural responses for constructing ANN- and SVM-based metamodels.

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