Fragility analysis of degraded structures considering soil-structure interaction

Victor Randy Medina[1], Younes Aoues[1], Didier Lemosse[1]

[1]*Normandie Univ, INSA Rouen Normandie, Laboratoire de Mécanique de Normandie (LMN)*
victor.medina_mordan@insa-rouen.fr, younes.aoues@insa-rouen.fr, didier.lemosse@insa-rouen.fr

ABSTRACT

The fragility curve plays an important role in estimating the structural vulnerability under an earthquake disaster. The zone of the most interest is the fragility curve where failure rarely occurs. Due to the lognormal hypothesis, the classical approach is limited by a considerable quantity of epistemic uncertainty. A second approach, the nonparametric one overcomes this problem. However, it requires Monte Carlo Simulations to estimate the probability of exceedance of the limit state, which can be computationally intensive, to estimate the interest zone of the fragility curve. To overcome this drawback, this work aims to reduce the number of nonlinear response evaluations of the pushover analysis, to estimate the fragility curve by using surrogate modeling updated by adding new samples that best represent the system's response, also known as Active Learning Approach. This paper proposes a methodology for calculating failure probabilities of the seismic fragility curve with a considerable reduction of the computational cost.

Keywords fragility curve, active learning, soil-structure interaction, Kriging, degradation.

I. INTRODUCTION

Undoubtedly, earthquakes are among the natural phenomena that mostly affect structures, where severe economic and human losses can be caused, especially in large cities [1]. To assure the safety of the occupants, it is very important to understand the behavior of structures under earthquake effects. The fragility curve is a measure of the probability of a structure reaching a certain level of damage for a given seismic intensity. The classical fragility curve approach is limited by its high epistemic uncertainty, due to its dependency on the log-normal assumption, especially when the amount of data is limited [2]. A nonparametric approach based on Monte Carlo simulations can be employed, but the large number of required simulations and complexity of nonlinear evaluations make it impractical. A new methodology is proposed to overcome these drawbacks, based on a surrogate model and active learning approach. Today, the combination of Monte Carlo simulations and surrogate modeling with active learning approaches are the most powerful methods to perform the reliability analysis of complex structures [3].

The use of surrogate modeling and an active learning approach to estimate the seismic fragility curve represents an original method that can be substantial progress in earthquake engineering. This approach has the potential to improve the assessment of a structure's vulnerability to earthquake damage by reducing the computational cost and improving the representation of the structural response. Engineers could benefit significantly from this development because it would enable them to better understand the risks posed by earthquakes and develop more effective strategies for risk mitigation. Moreover, this study's proposed approach has broader applications in other areas of engineering where an accurate representation of nonlinear response is critical but computational cost is a concern.

II. FRAGILITY CURVE

A fragility curve is a useful tool for evaluating the vulnerability of a system to external hazards such as earthquakes, and it plays a critical role in engineering, insurance, and risk assessment. It represents the relationship between the hazard intensity and the resulting damage to a system. Generally, shows that as the intensity increases, the probability of damage or failure also increases.

There are two main types of fragility curves: parametric and nonparametric. *Parametric fragility curves* assume a specific functional form for the relationship between hazard intensity and probability of damage or failure, typically described by a known mathematical function. While they are easy to interpret and provide a simple representation between hazard and probability of damage, they may not be appropriate for systems with complex nonlinear relationships or limited data.

Nonparametric fragility curves, on the other hand, are based on data-driven approaches and do not assume a specific functional shape for the relationship between hazard intensity and probability of damage or failure. They can capture complex and nonlinear relationships and can handle heterogeneous data. However, constructing nonparametric fragility curves may be more computationally intensive and require a larger amount of data to accurately capture the relationship.

Both types of fragility curves have their advantages and limitations, and choosing which type to use depends on the specific characteristics of the system being evaluated. In general, a structural fragility curve is a powerful tool for estimating the potential damage caused by earthquakes, allowing engineers, policymakers, and risk assessors to better understand the risk posed by external hazards and develop effective strategies to mitigate them, as well as design timely maintenance and repair plans to avoid loss of structural capacity in the event of stronger earthquakes.

III. STRUCTURAL ANALYSIS

Nonlinear static analysis

In seismic engineering assessment, for economic and convenience reasons, structures must be designed considering plastic deformations. For this reason, a nonlinear analysis is necessary, although in the literature the result of the dynamic analysis is shown as the reference response, it also turns out to be an analysis with high computational cost. For this reason, this study bases its structural response on a static nonlinear analysis that shows good agreement with the dynamic response in structures where the first mode of vibration is predominant. This method allows for efficient capture of the plastic response of the structure considering the plastic hinges.

For this study, a two-story structure was used with 4.7 m on the first floor and 3.7 m on the second floor, with 9.1 m between columns, type I steel beam structure is evaluated. Considering a bilinear material model with Young's modulus of 200 GPa and yield strength of 250 MPa and hardening's coefficient of 1% taking as design parameter the relative displacement at the reference node, located at the center of mass of the upper level, and the total height of the structure.

The finite element model is evaluated by using ANSYS software, with BEAM188 type elements, respecting the strong-column weak-beam design. Both the dead and live loads are considered for the modal analysis and the fundamental period determination of the structure.

The fundamental period is used to determine the design spectral acceleration according to the European standard Eurocode 8. With it, in addition to the seismic mass (ratio of the fixed and variable load according to EC8) and the normalized modal displacement, the equivalent lateral force is calculated to perform the nonlinear static analysis. This high-step size-dependent analysis requires the application of Newton's and Arc-Length's method of response search to ensure convergence and reliable results.

Degradation model

Corrosion is one of the most observed degradation phenomena in the literature for steel structures. In steel is defined as the deterioration of the material due to the environment over time. If structure deterioration is measured as mass loss, then the amount of mass per unit of time that a structure loses due to the environment is known as the corrosion rate. The mass loss usually occurs at the surface of the structure and at a uniform rate, called uniform corrosion, where structural members gradually lose thickness at a uniform rate, corrosion rate can be estimated as the following power function [4]:

$$C = At^B \tag{1}$$

Here we have: C = average depth of corrosion (μm); t = time in years; A = corrosion rate at first year represents the initial rate of the corrosion; and B = represents the long-term corrosion. Table 1 shows the average values, according to different types of environments for carbon steel and weathering steel.

TABLE 1 Average values for corrosion parameters A and B for carbon and weathering steel [5]

Environment	Carbon steel		Weathering steel	
	A	B	A	B
Rural	34.0	0.65	33.3	0.50
Urban	80.2	0.59	50.7	0.57
Marine	70.6	0.79	40.2	0.56

Corrosion is a complex phenomenon that varies widely and depends on the environment. It occurs when the surface of a structure is exposed to the elements and results in the formation of oxide, which reduces the thickness of the structural member. The thickness reduction is an estimate based on the assumption of average uniform corrosion, rather than an actual measurement of the structural member. Despite this limitation, the approximation is commonly used in the literature to study the effects of degradation on structures and civil constructions [6-7].

Soil-structure iteration

Winkler's simplified model is commonly used to analyze soil-structure interaction. The model represents the interaction by using a beam supported on a series of independent but closely spaced springs. The behavior of these springs can be modeled as linear, elastic-plastic, or multi-linear hysteresis.

Linear springs are the simplest model and remain linear regardless of the load. Elastic-plastic springs, on the other hand, relative strength required to produce a unitary deformation change after the yield point. Multi-linear hysteresis models improve the representation of soil-structure interaction after the elastic limit is reached [8]. For this paper, perfect elastic-plastic behavior is assumed to model the springs of the Winkler model. This assumption simplifies the analysis while still providing accurate results.

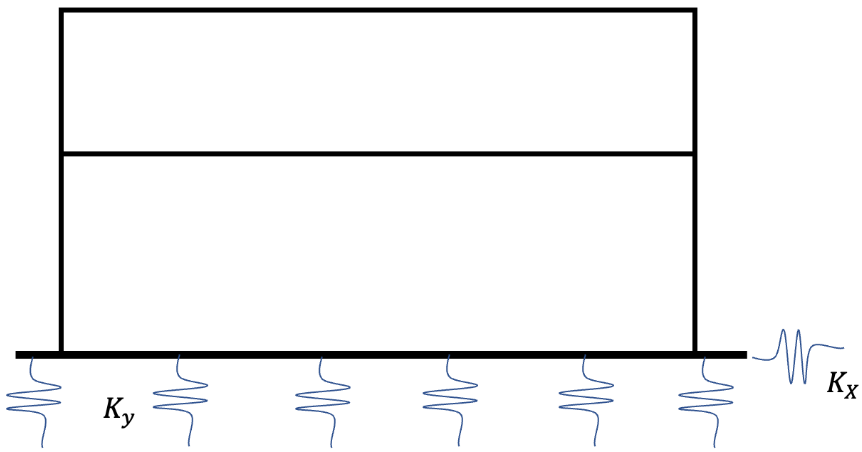

FIGURE 1. Soil-Structure Interaction Winkler Spring Model

Malekizadeh et al. [9] suggested that a constant stiffness in all vertical springs can be assumed if the existence of hinges in the columns is considered because these consider the participation of rotation in the footing. Gazetas et al. [8] proposes expressions for the stiffness value of the vertical and horizontal springs of the Winkler model. These expressions are used in the framework of this work to represent the soil-structure iteration.

Vertical stiffness:

$$K_y = \frac{GL}{(1 - \nu)}[\,0.73 + 1.54\,(B/L)^{0.75}] \tag{2}$$

Horizontal stiffness:

$$K_x = \frac{GL}{(2 - \nu)}[\,2 + 2.5(B/L)^{0.85}] \tag{3}$$

Where G is the shear modulus, L is the length of the footing, B is the width, and ν is the Poisson's ratio of the foundation material. According to the literature, the depreciation of the soil-structure interaction can lead to an underestimation of the total displacement of the structure in the seismic analysis.

TABLE 2 Average values for soil-structure interaction Winkler model

Parameter	Value
G0	50 MPa
L	10.2
B	0.3

IV. RELIABILITY ANALYSIS

Active Learning

Active learning is a machine learning tool that focuses on the learning process by actively selecting samples to be used for training the model. The goal of active learning is carefully selecting the samples so that the machine learning algorithm can learn as much as possible with a minimum amount of data. Active learning is especially useful in situations where the data process is time-consuming [10].

Surrogate Model

A surrogate model is a simplified or approximate model that is used to represent the behavior of a more complex system. The purpose of a surrogate model is to provide a faster and more efficient way of predicting a system response, while still capturing the important characteristics of the system's behavior. There are several types of surrogate models, including polynomial models, response surface models, neural networks, and Kriging models.

The choice of surrogate model depends on the specific characteristics of the system being modeled, including the type of input-output relationship, the presence of nonlinearities or discontinuities, and the number and quality of available data.

Surrogate models are often used in combination with optimization and uncertainty analysis methods, such as design optimization, sensitivity analysis, and probabilistic analysis. The surrogate model provides a fast and efficient way of evaluating the objective function or the system's response, while the optimization and uncertainty analysis methods provide a way of finding the optimal inputs and quantifying the uncertainty in the system's outputs.

Uncertainties Parameters

For the scope of this study, uncertainty parameters associated with geometry and material are considered. Young's modulus, yield strength, and live loads are considered uncertainty parameters. Soil shear modulus and corrosion degradation curve constants are also considered uncertainty parameters. The table summarizes the uncertain parameters, their mean values, and their respective distributions.

TABLE 3 Random variables with their probability distribution

Parameter	Mean	COV (%)	Distribution
Young’s modulus (E)	200GPa	10	Lognormal
Yield strength (Fy)	250MPa	10	Lognormal
Hardening Coeff (b)	1%	10	Normal
Live load (Q)	25 ton	10	Normal
First-year corrosion (A)	70.6 μm	66	Lognormal
Long-term corrosion (B)	0.79	2	Lognormal
Soil-Shear modulus (G0)	50 MPa	10	Lognormal

The effect of 20 years of corrosion is evaluated, assuming the structure is located in a marine environment. In Type D soil according to the Eurocode classification and the seismic intensity is imposed in terms of peak ground acceleration.

V. RESULTS AND DISCUSSIONS

The capacity curve describes the maximum load that a structure can withstand. Therefore, changes in this curve represent a change in the total capacity of a structure to resist an external hazard, such as an earthquake. Figure 2 illustrates the reduction of the structural capacity when soil-structure interaction is considered. It is also possible to observe that with a lower force, it is possible to reach a given limit state. Neglecting the influence of soil on the maximum displacement given a ground motion intensity may lead to a possible overestimation of the actual capacity.

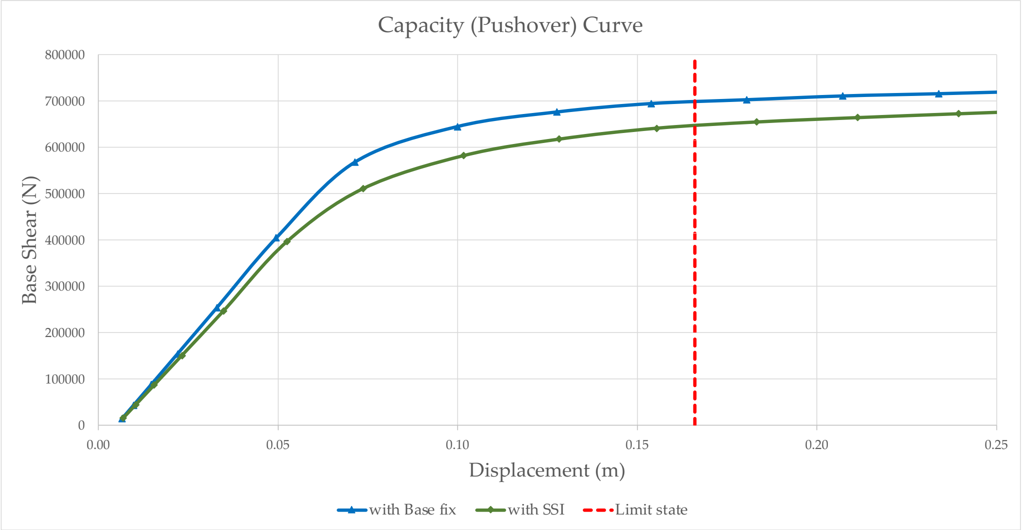

FIGURE 2. Base fix vs Soil-Structure Interaction model capacity curve

Like the previous case, figure 3 displays variations in the pushover curve, when a degradation model is applied due to corrosion that increases exponentially over the years according to the power degradation model.

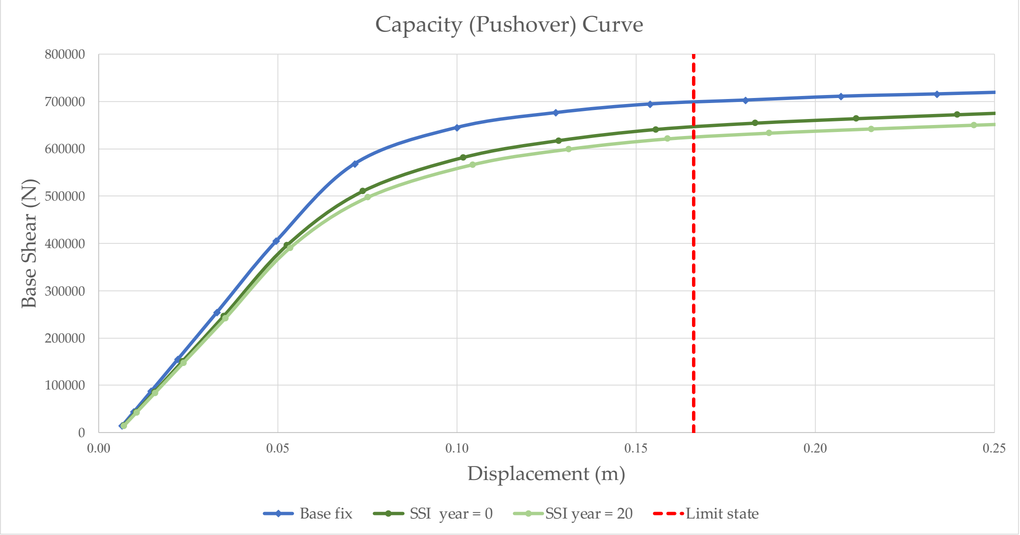

FIGURE 3. Base fix vs SSI with uniform corrosion model capacity curve

To test the effectiveness of Active Learning based Monte Carlo simulations, a fragility study with a simple configuration is made. In the first case, there was no degradation, and the structure was fixed to the base. Both methods were evaluated to compare their results. Figure 4 displays the correspondence between the two methods, with estimates of the probability of failure. The Confidence Interval (CI) is shown in dot lines and is imperceptible for Active Learning but considerably larger for Monte Carlo simulations. The uncertainties associated with material, capacity, and load are quantified by the Modulus of Elasticity, yield strength, hardening coefficient, and live loads.

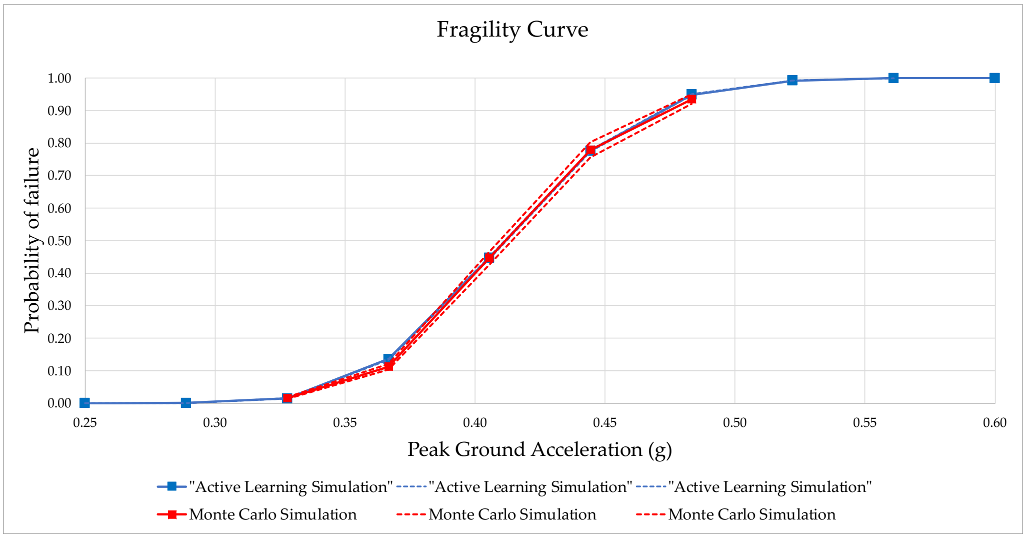

FIGURE 4. Monte Carlo vs Active Learning Fragility Curve

Figure 5 shows the difference lies in the required time to obtain each discrete point on the fragility curve. With the Active Learning method, the necessary time is much lower than in Monte Carlo.

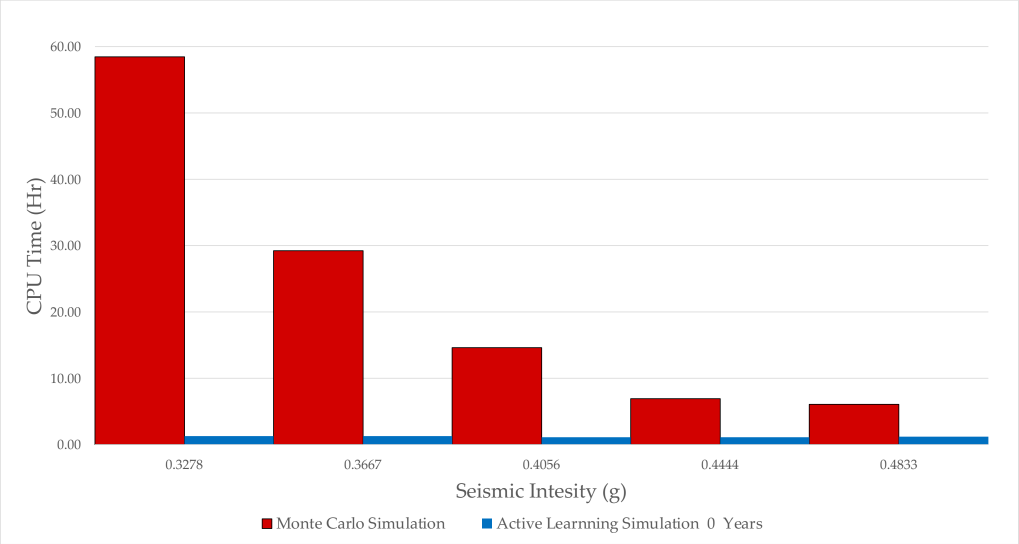

FIGURE 5. Monte Carlo vs Active Learning CPU Time

The Active Learning method demonstrates its robustness by measuring the estimation's coefficient of Variation (CoV). Referring to Figure 4, it is evident that the confidence interval is larger in the Monte Carlo simulations, while it is imperceptible in Active Learning-based Monte Carlo simulations. Figure 6 displays the comparison in the coefficient of variation (CoV), resulting in much smaller values for the Active Learning method.

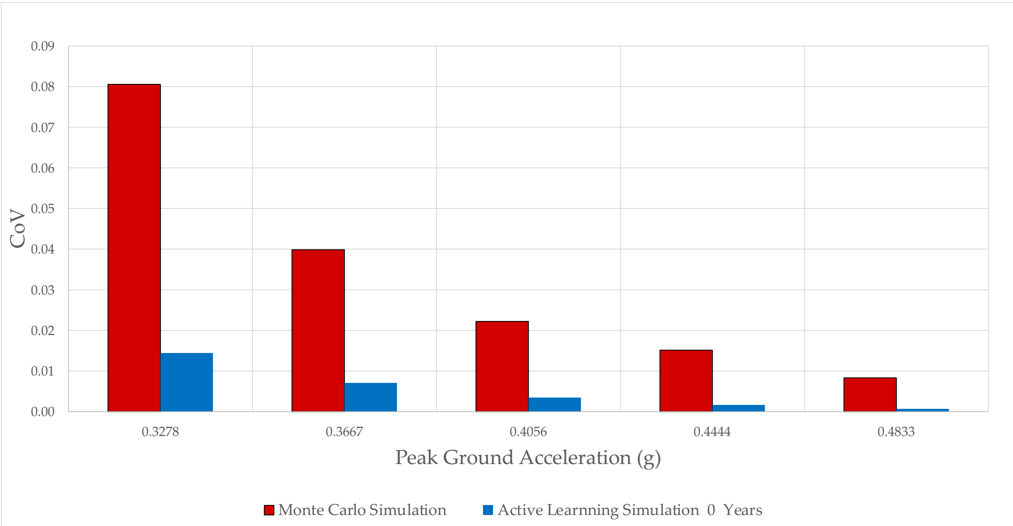

FIGURE 6. Monte Carlo vs Active Learning Coefficient of Variation

It should be noted with a simple analysis, where factors such as degradation and soil-structure interaction are not considered. In the case of an acceleration of 0.3278g, Monte Carlo Simulation takes more than two days (60 hours) and 10 000 simulations to achieve a probability of failure of 1.45% and a relatively high coefficient of variation of 8%.

Changes in probabilistic fragility analysis are observed when the soil-structure interaction is considered, as well as a degradation model in nonlinear response. No implementation of these considerations in seismic studies may result in an unrealistic analysis that deviates from reality. Figure 7 shows the degradation in the structural fragility between the cases of fixed-base, SSI with no corrosion, and 20 years of corrosion, increasing the probability of failure for a given seismic acceleration.

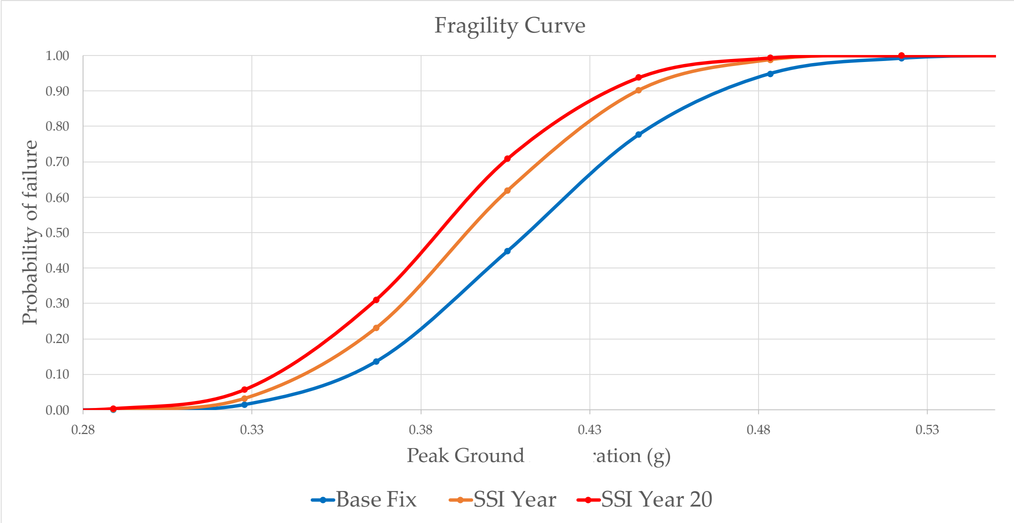

FIGURE 7. Fragility variation in different scenarios

When considering soil-structure interaction and degradation in seismic fragility analysis, the required time to access the failure probability increases by an average of 60%, making Monte Carlo simulations impractical. The computation time comparison in the following Figure 8 is based on the use of Active Learning.

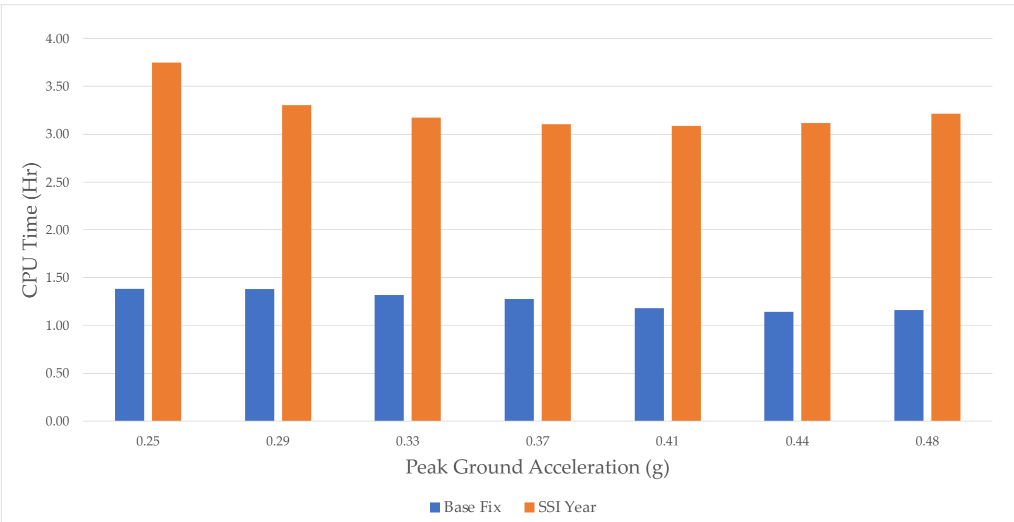

FIGURE 8. The computation time of the discrete points on the fragility curve with ALS

VI. CONCLUSIONS

Based on the results shown above, it is possible to reach the following conclusions:

1. Soil-structure iteration can affect the seismic response of the structure, so it is important to consider it in the seismic analysis.

2. The degradation model due to corrosion can cause important variations in the pushover curve, which should be considered in seismic vulnerability studies.
3. Active Learning-based Monte Carlo simulations are a more efficient methodology than crude Monte Carlo simulations in estimating the probability of failure and reducing the coefficient of variation in the fragility curve.
4. Considering the degradation and soil-structure interaction in the seismic fragility analysis requires more time to estimate the probability of failure, making Monte Carlo simulations impractical.
5. Significant changes in probabilistic fragility are observed when a degradation model is considered. Neglecting these considerations in the seismic vulnerability studies may lead to underestimating the damage.

VII. REFERENCES

[1] M. Kassem, F. M. Nazri and E. N. Fargasi, "The seismic vulnerability assessment methodologies: A state of the art review," *Ain Shams Engineering Journal,* pp. 849-864, 2020.

[2] B. Sudret et C. Mai, «Calcul des courbes de fragilité sismique par approches non-paramétriques,» 2013.

[3] M. Moustapha, S. Marelli and B. Sudret, "Active learning for structural reliability: Survey, general framework and benchamark," *Structural Safety,* pp. 804-832, 2022.

[4] M. Secer and E. T. , "Corrosion Damage analysis of steel frames considering lateral torsional buckling," *Procedia Engineering,* vol. 171, pp. 1234-1241, 2017.

[5] J. R. Kayser and A. S. Nowak, "Reliability of Corroded Steel Girder Bridges," *Structural Safety ,* vol. 6, no. 1, pp. 53-63, 1989.

[6] Y. Bai, K. Younghoon, Y. Hui Bin, S. Xiao Feng and J. Hua, "Reassessment of the jacket structure due to uniform corrosion damage," *Ships and Offshore Structures,* vol. 11, no. 1, pp. 105-112, 2016.

[7] D. E. Choe, P. Gardoni, D. Rosowsky and T. Huakaas, "Probabilistic capacity models and seismic fragility estimates for RC columns subject to corrosion," *Reliability Engineering and System Safety,* vol. 93, no. 3, pp. 383-393, 2008.

[8] G. Gazetas, "Formulas and charts for impedances of surface and embedded foundations," *Journal of Geotechnical Engineering,* vol. 117, no. 9, pp. 1363-1381, 1991.

[9] M. Malekizadeh, N. Fanaie and A. A. Pirasteh, "Vertical component effects of earthquake and soil-structure interaction on steel gabled frames," *Journal of Constructional Steel Research,* vol. 196, no. 1346, 2022.

[10] B. Echard, N. Gayton and M. Lemaire, "AK-MCS: an active learning reliability method combining Kriging and Monte Carlo simulation," *Structural Safety,* vol. 33, no. 2, pp. 145-154, 2011.

[11] T. Zhao, Y. Zheng and W. Zhe, "Improving computational efficiency of machine learning modeling of nonlinear processes using sensitivity analysis and active learning," *Digital Chemical Engineering,* vol. 3, 2022.