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A sequential fragility framework using machine learning for prestressed concrete containment vessel in nuclear power plant

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1. Introduction

A reactor containment building is the last line of defense in nuclear power plants to prevent radioactive materials from being released into the environment [1]. Thus, it is essential to evaluate the safety of the containment building. As probabilistic safety assessment has been introduced in nuclear power plants, many investigations have examined the internal pressure capacity of nuclear containment buildings subjected to internal pressure during accidents. Because of the need to explicitly consider and quantify all sources of uncertainty, the probabilistic safety assessment requires an extensive amount of finite element analysis. Therefore, this study proposes a sequential fragility framework using machine learning to efficiently estimate fragility curves with minimizing FE analysis.

2. Validation and verification of 1:4 scaled PCCV FE model

To investigate the performance of a Prestressed Concrete Containment Vessel (PCCV) under internal pressure, Sandia National Laboratories conducted an experiment [1]. In this study, a Finite Element (FE) model of the PCCV developed and validated from the experimental testing are used [2]. The FE model used shell elements to represent the liner, solid elements for the concrete structures, and truss elements to simulate the rebar and tendons (Fig. 1). Importantly, the global hoop strain at the free-field of the PCCV during the experiment closely matched the results predicted by the FE model, demonstrating the model validation as shown Fig. 1.

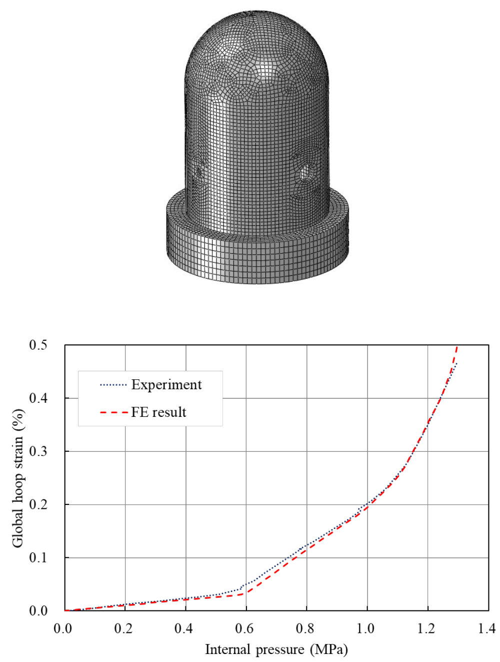

Fig. 1. FE model of PCCV and model validation.

3. Machine learning based sequential fragility framework

The proposed framework is shown in Fig. 2. It includes 13 steps:

1) Extracting of a Monte Carlo population (S) of input variables. From the population of input variables, 1 input dataset is sequentially extracted to train and test the machine learning model until the convergence rate is satisfied. A large enough number of samples is required because the appropriate number of finite element analyses for the fragility analysis is vague at this step. In this study, 1000 samples are generated for each input variable to obtain the benchmark.

2) Extracting initial input datasets (ni, i = 1) from the population (S) and running finite element analysis with the initial input datasets through the validated finite element model of the PCCV. The analytical results

obtained from the initial input datasets are collected and used to train and test the machine learning models for the next stage. In this study, the ratio of training and testing datasets is assumed to be 7:3; thus, the 10 input datasets are initially extracted from the population (S), and output data (global hoop strain) obtained from finite element analyses are collected. Finally, the initial datasets (Ni, i = 1) for the training and testing is generated for the next stage.

3) Training and testing the machine learning model on the initial datasets (Ni, i = 1). To optimize model performance and prevent overfitting/underfitting, we will employ the average correlation coefficient (R^2) between training and testing results as an evaluation metric.

4) Determining the most accurate model for the next step.

5) Generating a Monte Carlo population of input variables for a fragility analysis to predict the response of the PCCV and estimate a fragility curve using the machine learning model chosen in the 4th step. In this step, we'll generate a Monte Carlo population of 1000 input datasets that reflects the uncertainties. This population (input datasets) will join into the machine learning model chosen earlier.

6) Predicting of global hoop strain for the liner at defined internal pressure levels using the machine learning model with the 1000 input datasets.

7) Calculating the probability of a failure at the defined internal pressure levels. A limit state, derived from the experimental testing, are used: ultimate limit state (0.4% global hoop strain). The calculated probabilities are stored for comparison in future iterations.

8) Performing finite element analysis with new one input dataset extracted from the population (S) and generating new datasets (Ni+1, i = 1)

9) Training and testing the machine models with the new datasets (Ni+1, i = 1)

10) Determining the most accurate model for the next step like the 4th step

11) Repeating the 6th and 7th steps.

12) Calculating Convergence Index (*CI*) between previous and present the probability of a failure at the defined internal pressure levels, where *CI* represents the gradient between the previous and the present fragility curves;

(1) $$CI = 1 - \frac{\sum_{j=1}^{n_{IM}}(p_j - p_j')^2}{\sum_{j=1}^{n_{IM}}(p_j - \overline{p}_j)^2}$$

where, n_{IM} is the total number of the defined internal pressure levels. p_j is the previous fragility curve, $\overline{p}_j$ is the average value of the previous fragility curve at the previous , and p_j' is the present fragility curve. In this study, the value of *CI* is used for stopping this framework and it assumes 0.99995 of *CI* as a threshold;

(2) CI > 0.99995, five times in a row

8th to 12th steps are repeated until the criterion is satisfied.

13) Finally, estimating a final fragility curve with present probability data at each internal pressure levels using Maximum Likelihood Estimation.

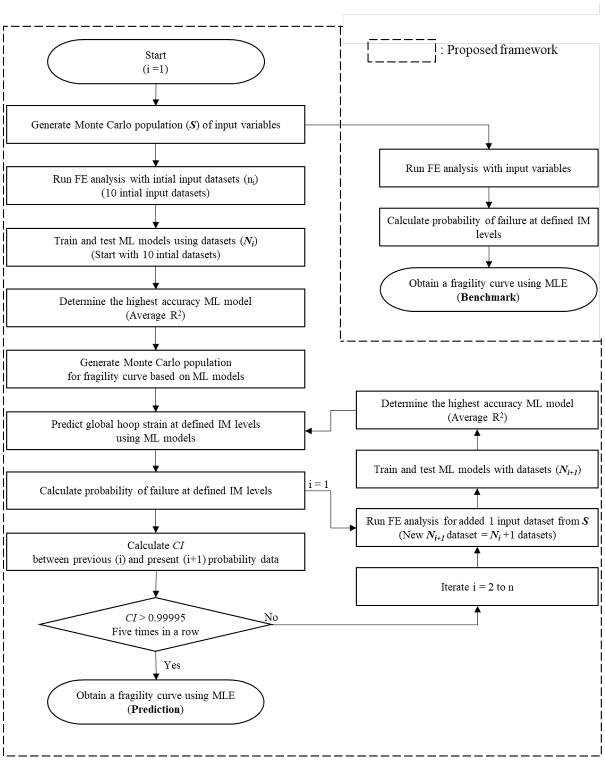

Fig. 2. Proposed sequential fragility framework using machine learning

4. Result

In this study, nine uncertainties in material are considered: compressive strength of concrete, yield stress of rebar, Young's modulus of rebar, yield stress of tendon, Young's modulus of tendon, yield stress of liner, Young's modulus of liner, Horizontal tendon stress, and Vertical tendon stress [1, 3]. In addition, four different machine learning models are employed: linear regression, support vector machine, neural network, and Gaussian process regression. Among them, Gaussian process regression emerged as the most effective model for prediction as shown in Fig. 3. As discussed earlier, the framework terminates when the *CI* exceeds 0.99995 for five consecutive iterations. As a result, only 34 datasets are satisfied with this criterion, resulting in the estimation of fragility curve based using only this limited data within this framework. Fig. 4 shows parameters of fragility curves according to # of datasets. After incorporating 28 datasets, the parameters of the fragility curves are converged into a specific value. Fig. 5 compares benchmark with fragility curves using the proposed framework and FE analysis. The framework provides an accurate fragility curve with only 34 datasets compared to the benchmark. On the other hand, the fragility curve obtained from only 34 FE analyses is significant different from the benchmark.

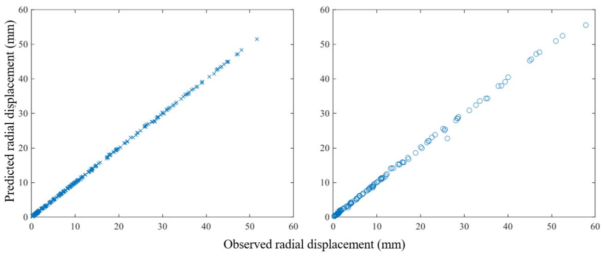

Fig. 3. Comparison between observed and predicted results (training and testing)

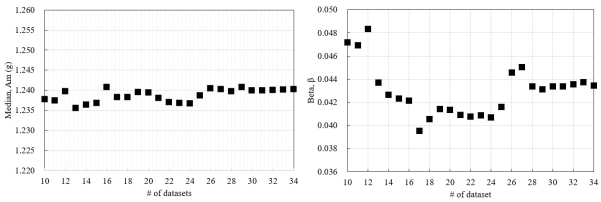

Fig. 4. Variation of Mean (Am), and standard deviation (β) of fragility curve according to # of datasets

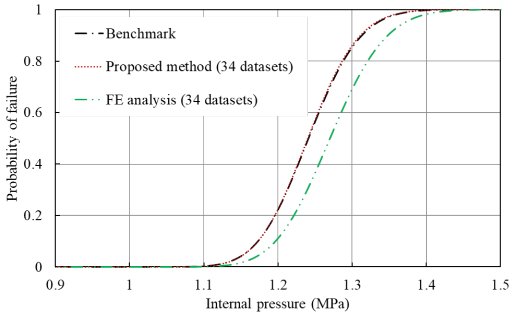

Fig. 5. Comparison of benchmark with fragility curves using the proposed framework and FE analysis

5. Conclusion

This study proposes a sequential fragility framework using machine learning to efficiently estimate fragility curves with minimizing FE analysis. Within this framework, the appropriate number of the FE analysis are actively determined. As a result, the framework provides an accurate fragility curve with only 34 datasets compared to the benchmark. On the other hand, the fragility curve obtained from the same number of FE analyses is significant different from the fragility curve calculated within the framework.

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