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MACHINE LEARNING APPLICATIONS IN EARTHQUAKE ENGINEERING: LITERATURE REVIEW AND CASE STUDIES

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Abstract

A survey of the existing literature is conducted in this paper to systematically present the progress and challenges of implementing ML in the earthquake engineering domain. The state-of-the-art review indicates to what extent ML has been applied in four topical areas of earthquake engineering, including seismic hazard analysis, system identification and damage detection, seismic fragility assessment, and structural control for earthquake mitigation. Moreover, two case studies have been presented in more depth to exemplify the capabilities of ML techniques in tackling two problems in earthquake engineering, which are difficult to solve using traditional approaches. Finally, research challenges and the associated future research needs are discussed. In general, ML has emerged as a promising tool to solve various challenging problems in earthquake engineering, while significant opportunities still exist to accelerate their applications. Researchers working on the cross-field of ML and earthquake engineering are encouraged to embrace the next generation of data sharing and sensor technologies, implement more advanced ML techniques, and develop physics-guided ML models.

Keywords: machine learning; hazard analysis; system identification; seismic fragility; structural control

1. Introduction

Machine learning (ML) is a field of study that gives computers the ability to learn without being explicitly programmed [1]. Two primary classes of ML algorithms are supervised learning and unsupervised learning. In supervised learning, prior knowledge of the labeled dataset is used to recognize a pattern or make general predictions. Conversely, unsupervised learning aims to infer the natural structure present with a set of data points without relying on label characteristics.

ML and other advanced soft computing tools have shown great promise in solving challenging problems in civil engineering, where several review works exist in the literature [2–9]. Some of these review studies have touched on a few of the ML applications in earthquake engineering. However, a comprehensive review is lacking in this area. As a result, it remains unclear to what degree ML has permeated the earthquake engineering domain, enabling and advancing research or supporting decision makers to mitigate seismic effects on civil structures. To this end, prominent academic databases, including Web of Science, Engineering Village, and Wiley Online Library, are used to search the publications that have titles or keywords consisting of ML algorithms in an earthquake engineering context. As shown in Fig. 1, the search results indicate that nearly two hundred relevant publications are now available, with a clear exponential growth in publications that intersect these two fields.

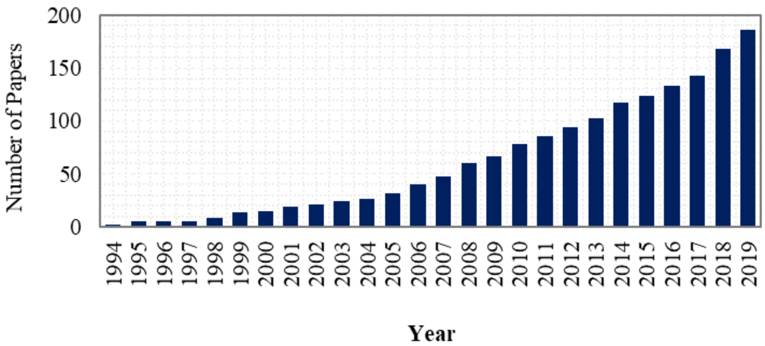


Fig. 1 – Accumulated number of research publications on the use of ML algorithms in earthquake engineering

This paper reviews the literature by subdividing earthquake engineering domain into four topic areas: (1) seismic hazard analysis; (2) system identification and damage detection; (3) seismic fragility assessment; and (4) structural control for earthquake mitigation. ML techniques and their four areas of applications are investigated in detail in order to understand the current state of the field, disclose the most popular ML methods, elucidate connections across various studies, and pave the path to promote broader and more fundamental ML advances in solving related research issues in earthquake engineering. Moreover, two case studies are discussed in depth to exemplify that ML techniques have the capability to tackle complex problems that are challenging to solve using traditional methods. Finally, a discussion of existing challenges and future opportunities concludes the paper in anticipation of the future growth of ML applications in the earthquake engineering domain.

2. Seismic Hazard Analysis

Seismic hazard analysis consists of the studies that predict the level of ground shaking and its associated uncertainty at a given site or location. In addition, the use of ML tools to evaluate soil liquefaction potential and predict the liquefaction-induced lateral spread displacement is considered within this area.

2.1 Ground motion prediction and generation

As opposed to conventional empirical methods that rely on predefined mathematical structures to derive ground motion prediction equations (GMPEs), ML methods can eliminate such constrains and develop parametric or non-parametric models to predict different intensity measures of ground motions. As shown in Fig. 2, ML studies in predicting GMPEs benefited from the availability of the strong motion databases in Taiwan, Turkey, Iran, Europe, western United States (i.e., the NGA and NGA-West2 database), and central America for induced earthquakes. Time-domain intensity measures, such as peak ground acceleration (PGA), peak ground velocity (PGV), and peak ground displacement (PGD), and frequency-domain measures such as pseudo-spectral acceleration (PSA), were predicted as functions of three to five significant predictors, including moment magnitude of the earthquake, source-to-site distance, the average shear-wave velocity of the site, faulting mechanism, and focal depth. The ML tools utilized in GMPEs include the artificial neural network (ANN), genetic programming (GP), multi-expression programming (MEP), support vector regression (SVR), as well as other methods listed in Fig. 2 [10,11]. In particular, the newly compiled NGA-West2 strong motion database [12], consisting of 21,336 recordings from 599 shallow crustal earthquakes, has significantly advanced the ML research in GMPEs.

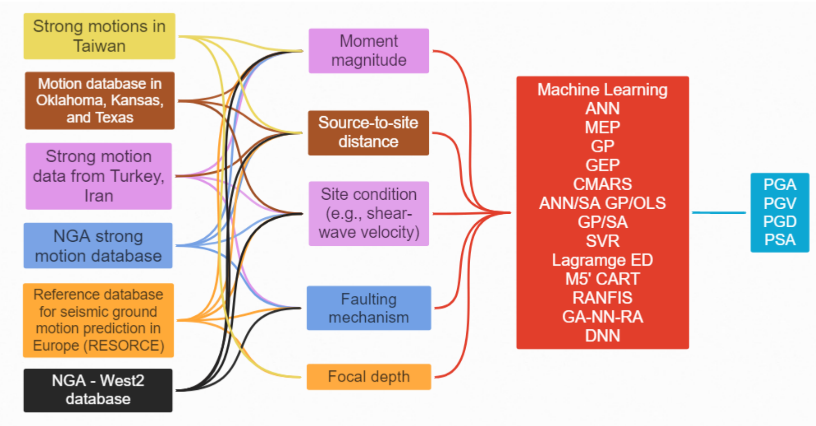


Fig. 2 – ML framework developed for predicting ground motion attenuation equations

2.2 Soil liquefaction potential and liquefaction-induced lateral spread

Two areas of ML applications in soil liquefaction research include (1) the triggering of soil liquefaction and (2) the prediction of liquefaction-induced lateral spread. First, as shown in Fig. 3, ML techniques outperform empirical studies in more objectively capturing the nonlinear and multi-dimensional relationship between the critical inputs and the triggering of soil liquefaction. Based on Cone Penetration Test (CPT) and Standard Penetration Test (SPT) databases, various ML methods have been explored to identify the boundary that separates liquefaction and non-liquefaction. These methods include support vector machine (SVM), ANN, a combination of kernel Fisher discriminant analysis (KFDA) with SVM, a combination of ANN and response surface model (RSM), random forest (RF), stochastic gradient boosting (SGB), generalized linear model (GLM), and evolutionary polynomial regression (EPR) (e.g., [13,14]).

Moreover, liquefaction-induced lateral spreads involve a large number of influential factors, including earthquake magnitude, fault-to-site distance, and local soil profile information such as the slope of the ground and the fine content and particle sizes of liquefiable sediments. Prediction of lateral displacement under soil liquefaction has been improved by developing different ML tools, which include multilinear regression (MLR), ANN, a hybrid neuro-fuzzy procedure, SVR, multivariate adaptive regression splines (MARS), RF, GP and evolutionary computing (EC), and multilayer perceptrons (MLPs) and the adaptive neuro-fuzzy inference system (ANFIS) (e.g., [15,16]).

The data quality of the case history datasets significantly affects the effectiveness of using ML models to predict the lateral spread displacement. In particular, history datasets contain considerable subjective information, which inevitably prevents an explicit mapping between the inputs and the lateral displacement outputs. As a consequence, most of the lateral spread regression models have a prediction accuracy within 200%; namely, the predicted displacements vary from 50% to 200% of the observed values.

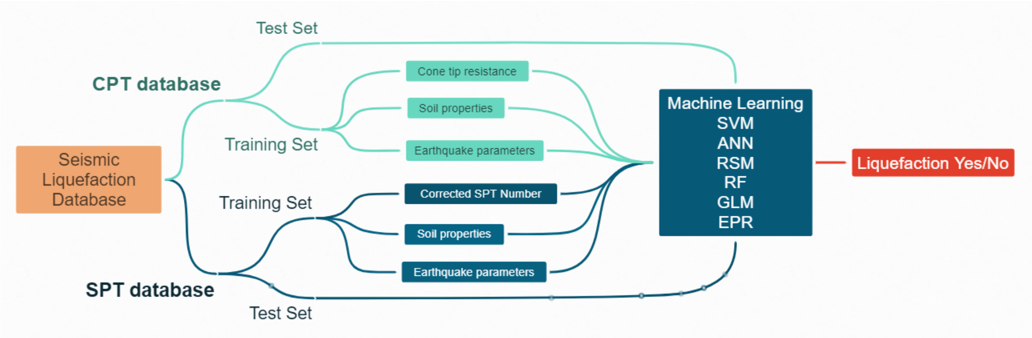


Fig. 3 – Overall framework for the evaluation of soil liquefaction potential using ML methods

3. System Identification and Damage Detection

The topic area of system identification comprises a collection of studies that utilize ML to emulate a structural system and predict its deterministic seismic response; and damage detection is broadly defined as the use of ML models to recognize, classify, and assess seismic damage to civil structures.

3.1 System identification

Based on data resources, ML applications in system identification can be classified into two subareas. First, laboratory tests on reinforced concrete (RC) structures have provided one source of data that enables ML methods to identify their failure modes, strength, capacities, and constitutive behaviors [17,18]. The adopted ML models include, but are not limited to, logistic regression (LR), least absolute shrinkage and selection operator (LASSO), discriminant analysis, K-nearest neighbors, naïve Bayes classification, SVM, decision tree (DT), RF, extreme learning machine (ELM), and multi-output least-squares support vector machine (MLS-SVMR). Hybrid methods that couple ANN with wavelet analysis and fuzzy logic have also been examined to simulate the seismic behavior of building frames [19]. The second group of studies in system identification deals with the datasets from numerical simulations. To this end, ML methods, particularly ANNs, have been verified to be effective in replacing finite element modeling of civil structures [20]. Moreover, ANNs have been combined with other soft computing algorithms to minimize the prediction error, increase the training speed, and improve the generalization capability [21].

3.2 Damage detection

Data resource is also used as the main trait to subdivide the relevant studies herein. First, ML models have been developed to predict structural damage based on post-earthquake linguistic or photographic records, satellite imageries, and digital maps [22–25]. For instance, the damaged RC column images collected after the 2010 Haiti earthquake have been used by German et al. [23] to develop a procedure that automatically detects spalled regions on the column surface and measures the properties of the spalling. Also, a large part of the existing literature uses simulated and test data to detect the seismic damage of building structures. As an example shown in Fig. 4, ANN has been employed to infer the damage conditions for a variety of structures (e.g., [26,27]). ML has also been utilized to link the seismic damage patterns of buildings to the residual structural capacity indices [28]. The proposed framework integrates seismic demand analysis, component damage simulation, and residual collapse capacity estimation on both intact and damaged structures. The applied ML algorithms involve DT and RF for safety classification, and LASSO and SVM for capacity index prediction.

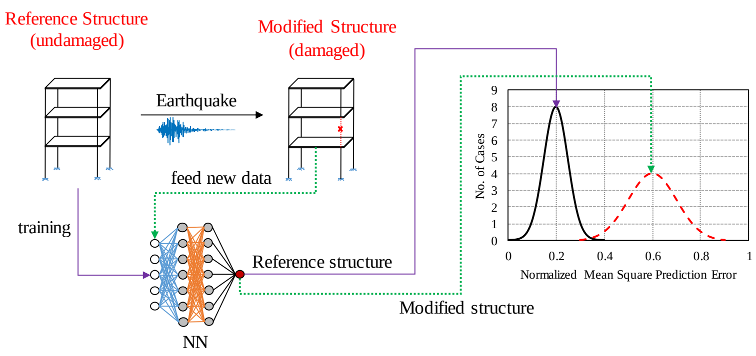


Fig. 4 – Scheme of using ANNs in earthquake-induced damage detection

4. Seismic Fragility Assessment

Fragility models are one of the critical components in performance-based earthquake engineering (PBEE) frameworks. Recent work supporting fragility and risk modeling of regional portfolios of structures consider PSDMs with multiple predictors that reflect the variation across a portfolio and consequently multidimensional fragility models [29,30]. First, the high dimensional nonlinear relationship between the predictors and the engineering demand parameters (EDPs) of concern can be efficiently quantified through ML methods. In this regard, multi-predictor PSDMs have been prevalently derived using RSMs, stepwise regression and other regularization algorithms [31]. Other than RSMs, multi-predictor PSDMs have been developed using ANN, bootstrapped ANN, SVM, kriging metamodeling, GLM, MARS, K-nearest neighbor, naïve Bayes classifier, high dimensional model representation, and RF (e.g., [32]). Once the PSDMs are obtained, Monte Carlo simulations can be used to convolve the PSDMs with the capacity models to develop multidimensional fragility functions. Such fragility models typically have no explicit mathematical expression and cannot be easily reproduced. To address this issue, researchers have used an alternative approach to compare the demand versus capacity and generate binary survival-failure samples, from which additional models are trained (often adopting the LR model) to develop a parameterized fragility model. Relevant studies in this area have developed LR-based fragility models for highway bridges [33], single-degree-of-freedom structures on liquefiable sand deposit [36], rigid blocks installed with safety devices [37], and RC shear walls [38].

Research advances can be further pursued on this portfolio of work to leverage the full capability and efficiency of available ML methods. For example, despite that one structure may have multiple EDPs of interest, most of the existing work develop separate PSDM for each EDP. To this end, multivariate PSDMs that incorporate all EDPs in a single model can not only save multiple rounds of model calibration but also capture the correlation among different EDPs in the same structure, resulting in more realistic demand models [34]. Also, alternative ML methods should be explored to avoid using too many correlated predictors in one PSDM. Recent studies have shown promise in developing sparse PSDMs that consist of a small subset of uncorrelated predictors for better accuracy and generalization capability [35]. Moreover, parameterized fragility models have been primarily developed through LR, while it remains unclear whether there exist other models that can provide significant advantages over existing LR models.

5. Structural Control for Earthquake Mitigation

Based on the control mechanism, ML applications in structural control can be further classified as those in active control and semi-active control.

5.1 Active control using ANN

Considerable studies have explored the soundness of engaging ANN in designing active control schemes to alleviate the seismic impacts on buildings, e.g., [39]. As shown in Fig. 5, the neural-controller (i.e., the actuator controlled by the neural network instead of an ad hoc control algorithm) is trained with the aid of the emulator neural network, which not only learns the structural behavior but also incorporates the effects of the actuator dynamics and sampling period [40]. After the neural-controller is well trained, it can generate appropriate signals to the actuator based on the feedback signal from the sensors.

The neuro-controller concept was further developed in several studies that enhance the efficiency and robustness of the active control scheme [41]. Improvements have been made in the following areas: (1) the use of a cost function to train the ANN [42]; (2) the use of a sensitivity evaluation algorithm to replace the emulator neural network for saving the training time [43]; (3) the development of a counter propagation network (CPN) to realize unsupervised learning [44]; (4) the use of lattice forms in the training pattern to save the calculation efforts and accelerate the training process [45]; (5) the utilization of an extended minimal resource allocation network to accomplish real-time on-line adaptation of the ANNs. Recently, a fuzzy wavelet neuro-emulator model was developed [46] that can predict the nonlinear structural response in future time steps only from the immediate past structural response and actuator dynamics.

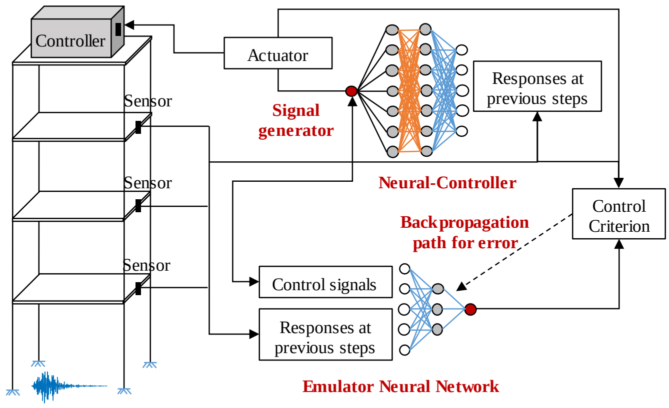


Fig. 5 – Schematics of the training of the neuro-controller with the aid of emulator neural network [40]

5.2 Semi-active control using ANN

Semi-active control devices have the capability of adapting to the changes in earthquake loading conditions, similar to the fully active systems, yet without requiring access to large power supplies. In this regard, interest in the use of ANN has grown remarkably, particularly for structures that are designed with magnetorheological (MR) dampers (e.g., as shown in Fig. 6). Contributions include: (1) an ANN model to represent the nonlinear differential equations and simulate the dynamic behavior of the MR damper [47]; (2) an inverse optimal ANN model to predict the required voltage given the desired force of the MR damper [48]; (3) the use of ANN to replicate the damper's dynamics and induce the MR damper in controlling the seismic shaking of non-isolated and isolated structures [49].

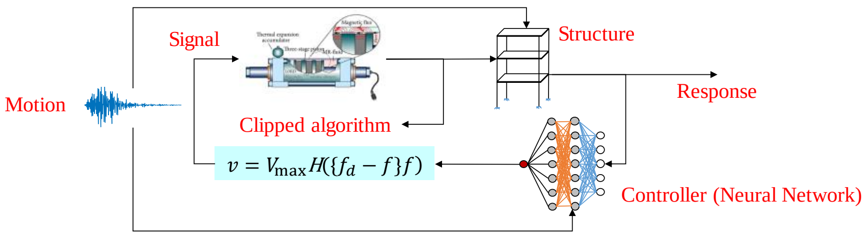


Fig. 6 – Schematics of the semi-active neuro-control system using MR damper [50] (MR damper schematics adopted from Yang et al. [51])

6. Case Studies

This section presents two case studies to illustrate in depth how ML can be involved in advancing research in earthquake engineering. Both studies fall into the category of seismic fragility assessment. The selected cases belong to two previous works from the authors, where more technical details can be found in [31] and [29].

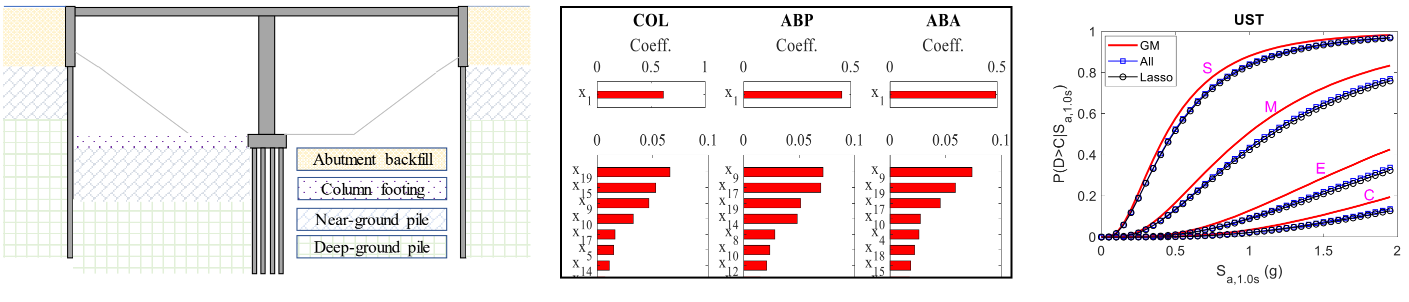
6.1 Sensitivity of bridge performance to soil-structure interaction (SSI) modeling

SSI effects are expected to yield a significant alteration on the seismic performance of bridges and structures. The typical layout of highway bridges requires consideration of multiple sources of SSI effects during their seismic analysis. In particular, the effect of SSI modeling on the seismic performance of highway bridges turns out to be a multi-parametric problem, involving various sources of uncertainty in soil properties and ground motions.

The relative impact of various uncertain SSI parameters on the seismic performance assessment of a typical highway bridge in California was presented in a recent study by the authors [31]. Seismic responses of a well-instrumented bridge-soil system are analyzed through the development of a rigorous p-y modeling approach. Changes are made on the overcrossing to benchmark it against typical designs of similar 2-span highway bridges in California (Fig. 7(a)). A probabilistic framework is set up to account for the various sources of uncertainty in the modeling of soils. The sensitivity study presented utilizes stepwise and LASSO regressions to identify which SSI modeling parameters significantly affect the seismic response of a number of different components in the diaphragm and seat abutment bridges, respectively (Fig. 7(b)). The findings of the sensitivity study are extended to evaluate the influence of uncertainty treatment in SSI modeling on the fragility estimates of the specimen bridges. The relative importance of inherent uncertainty with respect to ground motion and various SSI modeling parameters is evaluated by comparing three sets of fragility curves developed under increasing levels of uncertainty treatment (Fig. 7(c)).

The use of ML techniques (stepwise and LASSO regressions) in this case study indicates that structural components such as columns and deck are less sensitive to the SSI parameters, while bridge foundations and abutment components are much more influenced by the uncertain parameters for near-ground soils. In particular, a much stronger interaction is recognized between center bents and end abutments for the diaphragm abutment bridge. In particular, uncertainty in SSI modeling parameters plays a significant role on the damage estimates and fragility curves of bridge foundations and abutment components, such as shear keys, bearings and span unseating (Fig. 7(c)). Fragility curves developed considering only those important parameters identified in the LASSO regression are identical to those developed with all parameters treated as variables.

The application of ML techniques in this study offers an attractive way to determine the proper level of modeling fidelity and uncertainty treatment in SSI modeling. The findings can help analysts and bridge owners to allocate their computational resources, refine the most significant SSI modeling parameters, and develop reliable fragility curves for classes of highway bridges.



(a) (b) (c)

Fig. 7 – ML applications in assessing the sensitivity of bridge performance to SSI: (a) soil uncertainty considered in different zones for numerical analysis; (b) coefficient magnitude ranking of SSI parameters using LASSO regression; (c) fragility curves of bridge components considering three levels of SSI modeling

6.2 Probabilistic seismic assessment of vertical concrete dry casks

Continuing and efficient operation of nuclear power plants requires a safe method for the storage of spent nuclear fuel (SNF) produced at the nuclear power plants. In the United States as well as many other countries, spent fuel pools and independent spent fuel storage installations (ISFSIs) are used for short-term and interim storage of SNF, respectively. Vertical concrete dry casks are one of common structures used at ISFSIs for the midterm storage. The dry casks are vertical cylinders that typically receive the SNF in a steel canister, storing it to cool down by flow of air through the structure and to shield the radioactive radiations by layer(s) of concrete (and steel). Since the dry casks are freestanding structures that are not anchored to their foundation, they are vulnerable to lateral forces such as earthquakes. Large seismically-induced motions may result in collision incidents, potentially leading to release of radioactive materials from the dry casks. To enable estimation of the probability of such large motions for various dry cask configurations subjected to different seismicity levels, a probabilistic study is performed.

Simulation-based methods such as Monte-Carlo simulations often require running a large number of models. In this study, however, the results from fewer models are used to develop ML models for the maximum horizontal displacement and maximum rocking angle of the vertical concrete dry casks in seismic events (Fig. 8): (1) A finite element model of the seismic response of a scaled cask was developed and validated against an experimental study [29]; (2) In an experimental design, different configurations of the concrete dry casks were paired with selected ground motion records, resulting in 480 finite element models of seismic response of the concrete dry casks [29]; (3) Four different ML models, namely RSM, MARS, regression tree (RT), and SVR, are trained on the datasets provided by running the finite element models, and PSDMs are developed for the key responses of the vertical concrete dry casks in seismic events. The results of the training process are presented in Table 1, indicating that while the tested ML models produce high R^2 values on the training sets, some of them, such as MARS and RT, tend to over-fit the test samples. Considering the performance of the RSMs and other features such as transparency and transferability, the PSDMs obtained via the RSM are adopted for further analysis, in which the probability of large seismically-induced motions at different locations in the United States is estimated for various dry cask configurations. The results show that the probability of large seismically-induced motions is within the acceptable range in the nuclear industry, however, the estimated probabilities are one order of magnitude larger on the West Coast [29]. Moreover, the probability of observing large seismically-induced rocking motions on the West Coast approaches the acceptable rate in the industry [29], providing insight about the more probable cause of failure and effective mitigation actions, such as adjusting the friction at the casks' base or the distance between adjacent casks to reduce the probability of subsequent impacts.

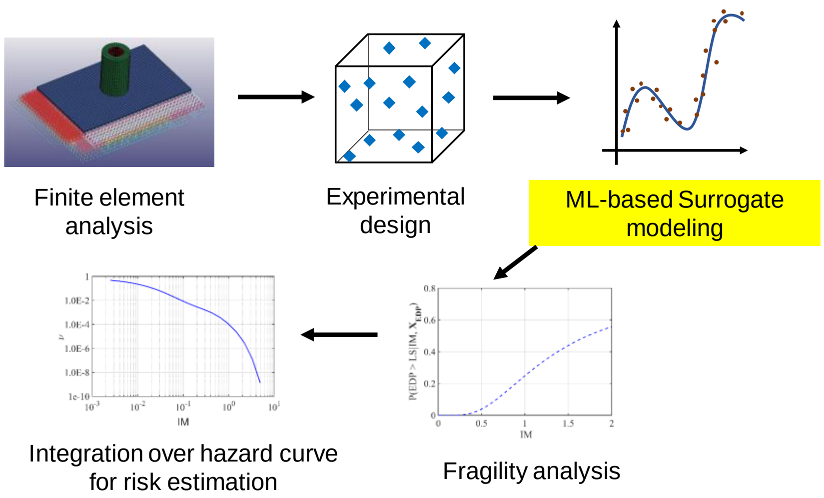


Fig. 8 – Probabilistic seismic assessment of vertical concrete dry casks using ML-based approach

Table 1 – Comparison of the ML models tested for PSDM development for the concrete dry casks

Response	**Maximum horizontal displacement**				**Maximum rocking angle**			
ML model	**RSM**	**MARS**	**RT**	**SVR**	**RSM**	**MARS**	**RT**	**SVR**
R^2 on training set	0.94	0.98	0.95	0.95	0.88	0.95	0.91	0.91
R^2 on test set	0.93	0.95	0.93	0.95	0.87	0.90	0.88	0.90

7. Discussions and Conclusions

This paper reviewed ML applications in four topic areas in earthquake engineering, which include seismic hazard analysis, system identification and damage detection, seismic fragility assessment, and structural control for earthquake mitigation. Datasets collected from laboratory and field tests, previous earthquake events, and numerical simulations have enabled researchers to practice a collection of advanced ML tools. Moreover, two case studies, which belong to the previous works of the authors, are presented in more detail to exemplify the capabilities of ML techniques in advancing the existing earthquake engineering research. In general, the cross field of ML and earthquake engineering is a new but increasingly dynamic area for high impact research, where a vast breadth and depth of topics can be investigated. For the purpose of further promoting ML applications in earthquake engineering, the potential challenges and associated research needs are discussed herein.

7.1 Data quantity and quality

To be effective, ML requires large amounts of high-quality data. In certain areas that require high-fidelity computational analyses or large-scale field tests, high-quality data points are often limited to hundreds or fewer. As is expected, ML in these areas is facing a strong challenge. Note that such data quantity issues cannot be easily tackled by switching or developing a more advanced ML model. Also, low data quality often leads to inferior ML models in earthquake engineering. To address this data issue, research efforts are suggested in the following directions. First, more transparent, accessible, and high-quality data are needed to be compiled in a computer-readable form, making a widely accepted platform required to store and share such data. Moreover, the time spent running ML is generally much less in comparison with the time to gather data, integrate it, clean it, and pre-process it. In this regard, it is vital that in earthquake engineering, there exists a community-driven cyberinfrastructure embraced by the community that allows researchers to share and analyze data more effectively, integrate diverse datasets, and practice and develop ML tools. One such cyberinfrastructure platform is the DesignSafe (https://www.designsafe-ci.org/) [52] that supports natural hazards engineering research, through which various recently generated datasets have been uploaded and shared, e.g., [53]. Also, since experimental laboratory or field derived databases are limited and initiating new large-scale campaigns can be time-consuming and cost-prohibitive, researchers should be encouraged to provide more simulation-based data, especially for those that have high quality, are physics-driven, and are well-validated against existing test results. Moreover, researchers conducting ML in earthquake engineering are expected to increasingly deal with new sources of data generated from other cutting-edge technologies, such as wireless sensing, computer vision, internet of things (IoT), smart cities, geographic information system (GIS), and quantum computing, etc. Once earthquakes occur, these technologies can provide new forms of data on a completely different scale.

7.2 Implementation and development of ML methods

Given potential rapid data growth due to above-mentioned technologies, ML is expected to provide a tremendous opportunity to systematically advance the research and practice in earthquake engineering. However, the next generation of spatiotemporal data, which tend to be large-scale, high-dimensional, nonlinear, non-stationary, and heterogeneous, are expected to challenge the capabilities of existing ML methods often adopting in the earthquake engineering domain. To this end, more advanced ML techniques, such as active learning, reinforcement learning, and deep learning, are needed to (1) characterize the higherorder correlation and dependencies within the data; (2) perform efficient and reliable imputation and prediction for decision making; and (3) develop scalable learning models for large-scale and time-dependent problems. Moreover, there exists an emerging trend for a paradigm shift that requires earthquake engineering researchers to consider how to best balance the use of physics-based approaches, which are transparent, interpretable, and somewhat predictable, with the use of data-driven ML models that are not unique and sometimes hardly interpretable. Distinct from physics-based approaches, ML algorithms produce models that are entirely data-driven and cannot alone explain the physical cause-effect mechanisms between variables. To be specific, although spurious relationships can be learned for a complex problem that look deceptively accurate on training and test sets, the model may perform much worse outside the available labeled data. A rational path forward lies in the increasing incorporation of physical knowledge into ML-based earthquake engineering studies. Theory-guided ML can be developed through a variety of approaches. Opportunities exist to accelerate work along this path. First, domain experts can take the lead in converting raw data into a new feature space that reflects better the scientific nature of the underlying problem. Second, an ensemble of different ML algorithms, or similar algorithms with different values for their internal parameters, should be examined to create a more robust overall model. Third, physical understanding of a problem can be increasingly used to design and learn ML models.

In summary, despite the growing number of studies every year, the implementation of ML in earthquake engineering is still in its early stage when compared with other disciplines. However, supported by the next generation of diverse data sharing and sensor technologies, ML has a great promise to revolutionize the profession of earthquake engineering. Furthermore, the earthquake engineering community has the opportunity to probe unexplored ML algorithms in various contexts, or inspire new ones driven by our application needs, while opening dialogue on best practices to integrate physics-based and data-driven methods to solve grand challenges in earthquake engineering.

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