

Original Article

Data-Driven Seismic Fragility Assessment of Reinforced Concrete Frames Using Near-Fault Accelerograms

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Abstract - This study examines the seismic fragility of 4-, 8-, and 12-story Reinforced Concrete (RC) Moment Resisting Frames (MRFs) under near-fault ground motion using an integrated fragility analysis approach. The research performs an exhaustive seismic fragility assessment of 4-, 8- and 12-story reinforced concrete moment resisting frames (RC MRFs) structures by employing 100 near-fault accelerograms (60 pulse and 40 non-pulse recordings), chosen from PEER NGA-West2 dataset and statistically verified. Ground motion parameters (PGA, PGV, $S_a(T_1)$, S_a,avg , T_p) extracted from time histories are used to build dynamic response spectra and to train four ML models based on ensemble methods—Random Forest, Gradient Boosting, XGBoost, and Extra-Trees—with 4,800 Incremental Dynamic Analysis data. An event-based validation approach was employed to avoid any form of data leak from the training set to the test set. XGBoost achieves the best prediction performance ($R^2 = 0.971$), generating lognormal fragility curves with an area ratio ≥ 0.96 with nearly 98% reduction in computational cost compared to IDA simulations. SHAP analysis reveals that PGV and T_p are two important features of near-fault ground motion, as the collapse prevention median capacity of structures declines by 33% when shifting from low-rise to tall frame structures.

Keywords - Near-fault ground motion, Seismic fragility, Reinforced concrete frames, Machine learning, PEER NGA-West2, Incremental dynamic analysis, XGBoost, Pulse-like accelerograms, SHAP, Performance-based earthquake engineering.

1. Introduction

Near-fault ground motions are still one of the most hazardous natural hazards faced by urban infrastructure globally. The closeness of constructions to active fault systems results in an array of seismic excitations characterized by large velocity pulses, rupture directivity effect, and permanent ground displacement, altogether exerting seismic demands exceeding those caused by the same far-field accelerograms [1, 2]. These unique features make near-fault ground motions an important challenge for the field of Performance-Based Earthquake Engineering (PBEE), particularly for Reinforced Concrete (RC) Moment-Resisting Frame (MRF) structural systems, which are the prevailing structures in earthquake zones throughout the world.

This directivity effect operates in the case where the wave front moves towards the location of interest at velocities close to the shear wave speed. This results in seismic energy that would normally be spread across the full length of the earthquake arriving in the form of one strong, long-period velocity pulse at the beginning of the recording. The localization of energy is the basis for the primary difference

between near-fault and far-field demands and the reason why intensity measures developed for conventional motions cannot be easily extrapolated to near-fault situations [1, 2].

Observation of catastrophic failures of buildings during earthquake sequences close to fault zones, such as Northridge earthquake of 1994 (California), Kobe earthquake of 1995 (Japan), Chi-Chi earthquake of 1999 (Taiwan) and the recent Kahramanmaraş (Türkiye, Mw 7.7) earthquake of 2023 consistently proves that traditional seismic design codes are insufficient to cover impulsive demands caused by pulse-like accelerograms [3, 4]. Seismic fragility analysis, which calculates the probability of exceeding certain damage states of the structure given ground motion Intensity Measures (IMs) as a condition, is an essential probabilistic tool for assessing building vulnerability within the PEER PBEE concept [5, 6].

The database of Pacific Earthquake Engineering Research Center – NGA-West2, comprising more than 21,000 three-component ground motion records from 600 shallow crustal earthquakes with moment magnitude ranging between Mw 3.0 and 7.9 and rupture distances from 0.05 km to 1533 km –



provides a comprehensive and systematically processed library of ground motion data available nowadays for seismic research [7, 8]. The selection process for selecting the near-fault subsample from the database has come a long way in the last ten years. From a simple magnitude-distance filter, the technique has been advanced to the use of wavelets to automatically classify pulse recordings from typical near-fault ground motions. It contains uniformly processed time series as well as Pseudo-Spectral Acceleration (PSA) ordinates for 111 periods and 11 damping ratios together with extensive information about earthquake sources, propagation paths and site conditions such as shear-wave velocity V_{s30} , rupture distances and pulse-period classification.

Conventional techniques of seismic fragility assessment, including Cloud Analysis, Multiple Stripe Analysis (MSA) and Incremental Dynamic Analysis (IDA) [9] are computation-consuming and require performing thousands of Nonlinear Time-History Analyses (NTHAs) [10, 11]. The emergence of Machine Learning (ML) as a new paradigm of surrogate modelling has allowed to find revolutionary solutions for this problem. Ensemble regression techniques such as Random Forest (RF), Gradient Boosting Regressor (GBR), eXtreme Gradient Boosting (XGBoost) and Extra-Trees Regressor (ETR) proved themselves more efficient in mapping IMs of ground motion to EDPs such as maximum inter-story drift ratio (MIDR) [10, 12, 13].

The choice of appropriate IMs for ML model features fully determines the predictive power of the obtained data-driven fragility functions. As for near-fault pulse-like ground motions, Peak Ground Velocity (PGV) and pulse period T_p are the informative IMs since they directly describe the dominant pulse causing structural inelastic behavior [1, 2].

Despite the historical domination of PGA in fragility parameterisation, some recent studies have proved the superiority in efficiency of PGA, spectral acceleration $S_a(T_1)$ and average spectral acceleration $S_{a,avg}$ [14, 15, 16]. Nevertheless, the present body of literature demonstrates the presence of several gaps. First, previous fragility analysis based on machine learning approaches, such as [10]–[13], has used datasets that are either a combination of near-field and far-field ground motions or mostly composed of far-field ground motions without explicitly distinguishing between pulse and non-pulse motions and thus indirectly taking the average of two different populations of ground motions. Second, previous researches have used tabulated scalar intensity measure values rather than making dynamic spectra by calculating intensity measures based on recorded ground motions as input of the model. Third, the data splitting process for testing purposes in [10], [11], and [12] is done randomly per record. Fourth, benchmarking of multiple ML ensemble regressor models to IDA-based fragility functions for multi-height RC MRF prototypes under near-fault-specific ground motion suites was not conducted [11, 17, 18].

What sets this research apart from the most related studies, i.e., [10]–[12] by Kazemi et al., Xu et al., and Rasheed et al., respectively, includes the following three points: (a) the training dataset is segregated based on the wavelet-based pulse classification as opposed to being a homogenous dataset; (b) the complete dynamic response spectra in the form of 100 periods are included as part of the feature vector using the actual NGA-West2 time series data as opposed to using a few selected scalar IMs; and (c) the validation process is performed based on earthquake events and for three frame heights simultaneously instead of random record splitting in one structural system. A comparative analysis is quantitatively provided in Table 5 (Section 3.4).

In order to fill the gap, the current study presents a data-driven approach to the seismic fragility assessment of RC MRF structures under near-fault accelerograms taken from the PEER NGA-West2 database. Methodological approach includes: (i) selection of near-fault pulse-like records; (ii) calculation of PGA, PGV and spectral acceleration ordinates for constructing dynamic response spectrum; (iii) creation of non-linear OpenSees FE model; (iv) Incremental Dynamic Analysis involving 4,800 nonlinear time-history analyses; (v) training and benchmarking of four ML ensemble regressors; and (vi) construction of data-driven fragility curves.

2. Materials and Methods

2.1. Ground Motion Database and Record Selection

All ground-motion accelerograms are drawn from the open-access PEER NGA-West2 online dataset (<https://ngawest2.berkeley.edu>) [7]. The database contains ground-motion data for earthquakes occurring in active tectonic regions around the world with a magnitude range of M_w 3.0–7.9, rupture distances of 0.05–1533 km and V_{s30} of 94 to 2100 m/s [7]. Near-fault recordings have been filtered based on the following sequence of selection criteria: (1) rupture distance $R_{rup} \leq 20$ km; (2) moment magnitude $M_w \geq 5.5$; (3) firm soil or rock sites ($V_{s30} \geq 180$ m/s, NEHRP site classes B-D); and (4) shallow crustal earthquakes (focal depth ≤ 25 km). Pulse-like ground motions were then recognized through the application of a wavelet-based automatic pulse identification algorithm [19] that has been embedded into the NGA-West2 flatfile metadata. Such an approach resulted in the selection of 120 near-fault accelerograms.

The selection process from 120 down to the final 100-record suite was based on two clear guidelines, which were not arbitrary exclusions. Firstly, the contribution from any individual event was limited to 5 records to avoid dominance of the training dataset from any one event, acting as an event clustering filter that eliminated 14 redundant records from highly represented events, including Chi-Chi and Northridge. Secondly, the last 6 records were eliminated to ensure balance in the distribution of the combined magnitude-distance bin, making sure that none of the combinations of M_w – R_{rup} were under- or overrepresented relative to the NGA-West2 near-

fault population. Following this, the marginal distribution of Mw, Rrup, and Vs30 in the final 100-record suite was evaluated against the distribution of the full NGA-West2 database of records passing the four screening criteria using a two-sample Kolmogorov-Smirnov test. The null hypothesis of equal distribution for all three parameters could not be rejected ($p > 0.05$). Finally, a total of 100 records (60 pulse-like and 40 non-pulse events) from 32 different historical earthquakes, including 1994 Northridge, 1995 Kobe, 1999 Chi-Chi, and 2011.

2.2. Ground Motion Parameter Extraction

The following variables were extracted for each record using Python: the PGA (g), PGV (cm/s), the pseudo-spectral acceleration Sa(T, 5%) at 100 periods (from 0.01 to 10

seconds), and the period of the pulse Tp. The dynamic spectra were then compiled into a spectral matrix $S_a \in \mathbb{R}^{(100 \times 100)}$.

Table 1 provides details of the complete ten-dimensional feature vector used for training the regression machines, with the units and the physical significance of each feature specified.

In particular, N refers to the number of stories (either 4, 8, or 12), which was used explicitly as a categorical/integer feature to allow the trained model to predict MIDR for all three prototype heights in a generalized manner, rather than developing a different model for each prototype frame height.

Table 1. Definition of the Ten-Dimensional Ground Motion and Structural Feature Vector Used in Machine Learning Models

Feature	Symbol	Unit	Physical Significance
Peak Ground Acceleration	PGA	g	Maximum absolute ground acceleration; conventional scalar IM, partially correlated with PGV.
Peak Ground Velocity	PGV	cm/s	Maximum absolute ground velocity; primary indicator of near-fault pulse energy.
Spectral Acc. at T1	Sa(T1)	g	5%-damped spectral acceleration at the structure's fundamental period; strongly correlated with first-mode response.
Avg. Spectral Acc.	Sa,avg	g	Geometric mean Sa over [0.2T1, 2T1]; captures higher-mode and period-elongation effects.
Pulse Period	Tp	s	Dominant period of the velocity pulse (pulse-like records only; 0 for non-pulse records).
Rupture Distance	Rrup	km	Closest distance from site to fault rupture plane; controls near-source attenuation.
Moment Magnitude	Mw	–	Earthquake size governs overall energy release and duration.
Shear-Wave Velocity	Vs30	m/s	Average shear-wave velocity in top 30 m; site stiffness/soil class proxy.
Fundamental Period	T1	s	Structural fundamental period from eigenvalue analysis; frame-specific.
Number of Stories	N	– (integer)	Building height category (4, 8, or 12) allows one model to generalise across all three prototype frames.

2.3. Prototype RC Frame Structures

Three prototype RC MRFs, 4-story ($T_1 = 0.68$ s), 8-story ($T_1 = 1.12$ s), and 12-story ($T_1 = 1.58$ s), were designed per ACI 318-19 and ASCE 7-22 (SDC D, SDS = 1.0 g).

Nonlinear finite element analyses were carried out using OpenSees v3.5, where force-based distributed plasticity beam-column elements with 5-point Gauss-Lobatto quadrature along the member length were used so that the integration points are close to the element extremities where plastic hinges are expected. The sections were discretized into fibers, including the confined core region and the unconfined cover region as per the Mander confinement model, complemented with discrete longitudinal steel layers at each reinforcement bar position. The Concrete02 concrete material model was used with parameters peak compressive strength f'_c , strain at peak strength ϵ_{c0} , ultimate compressive strength f'_{cu} , ultimate strain ϵ_U , and linear tensile softening behavior,

whereas the reinforcing steel followed the Steel02 Giuffrè-Menegotto-Pinto model with yield strength F_y , elastic modulus E_0 , and a 1.5% strain-hardening post-yield ratio. The structural supports involved fixed-base conditions at the foundation level and rigid diaphragm action at each floor level. The static loading involved gravitational loads, which included dead load as well as 25% of live load according to ASCE 7-22 standard, and were applied before dynamic ground motion was applied. The solution of the nonlinear equilibrium was carried out using the Newton-Raphson method with a displacement norm tolerance of 1×10^{-6} and up to 100 iterations per time step; when the convergence criterion was not met, the solver switched to a Krylov-Newton solution with reduced time step size. The time integration adopted the Newmark average acceleration scheme ($\beta = 0.25$, $\gamma = 0.5$). The cyclic degradation of stiffness and strength was taken implicitly by the hysteretic rules included in the Concrete02 tensile softening behavior and in the Steel02

kinematic/isotropic hardening behavior; pinching or strength decay material models were not imposed as a modeling simplification.

Geometric nonlinearity (P- Δ effects) was introduced via corotational formulations. The damping model adopted was Rayleigh type, being proportional to mass and initial stiffness, with 5% critical damping ratio applied to first and third mode. It is a well-known practice that fixes the damping ratio to be around 5% within the dominant region of interest. Noting that Rayleigh damping relative to initial (elastic) stiffness will lead to over-damping of the system once it enters the inelastic domain at high levels of intensity, an additional assessment was performed for the 8-story frame using tangent-stiffness-proportional damping [21] for 20 collapse-level ground motions. The calculated median mean impact damage ratio (MIDR) from the two different damping models deviated less than 3%, implying that the choice of damping model would not affect the fragility results presented in Section 3 to any significant degree, while the computational cost would be greatly reduced.

2.4. Incremental Dynamic Analysis

IDA was carried out [9] for all three prototype structures subjected to the complete 100-record sequence and scaled to 16 intensity levels of $S_a(T1, 5\%)$ logarithmically from 0.05 g to 3.0 g. This gave a total of $100 \times 16 \times 3 = 4,800$ nonlinear time-history analyses. The EDP selected was the Modified Incremental Dynamic Response (MIDR). The collapse criterion is defined by $MIDR > 10\%$. Four performance limit states in compliance with FEMA P-695 and ASCE 41-17 have been considered: OP ($MIDR \leq 0.5\%$), IO ($MIDR \leq 1.0\%$), LS ($MIDR \leq 2.0\%$), and CP ($MIDR \leq 4.0\%$).

The relationship between the CP limit state and the collapse criterion needs to be defined since the former occurs at a different point on the IDA curve from the latter. The dynamic global collapse occurs at the intensity where the IDA curve becomes flat (defined by the slope of the tangent decreasing by 20% or more of its initial elastic value) or when $MIDR = 10\%$, whichever occurs first, as per the IDA collapse criterion proposed by Vamvatsikos & Cornell [9]. On the other hand, the CP limit state ($MIDR \leq 4\%$) is a conservative performance objective set in ASCE 41-17 as part of the design procedure, and therefore, it is not meant to coincide with the collapse intensity. CP is deliberately placed below the median collapse capacity to provide a safety factor to verify the life safety requirements. From the results in Section 3.3, it can be seen that the median CP capacity (1.02 - 1.52 g for the three frames) is significantly below the median collapse intensity in the IDA curves (about 1.6-2.4 g).

2.5. Machine Learning Regressor Framework

The four ensemble machine learning regressor models used were: Random Forest (RF) with 500 estimators, Gradient Boosting Regression (GBR) with 0.05 learning rate and 500

estimators, XGBoost and Extra Tree Regressor (ETR). The parameters for each model were optimized using a 5-fold cross-validation grid search, where the best parameter configuration for XGBoost is given in Table 2.

Table 2. Optimised XGBoost Hyperparameters (5-Fold Cross-Validated Grid Search)

Hyperparameter	Optimal Value	Search Range (Grid)
n_estimators	450	[100, 200, 300, 450, 600]
max_depth	6	[3, 4, 5, 6, 8]
learning_rate	0.05	[0.01, 0.03, 0.05, 0.1]
subsample	0.85	[0.6, 0.7, 0.8, 0.85, 1.0]
colsample_bytree	0.80	[0.6, 0.7, 0.8, 0.9, 1.0]
reg_alpha (L1)	0.10	[0, 0.05, 0.1, 0.5, 1.0]
reg_lambda (L2)	1.20	[0.5, 1.0, 1.2, 1.5, 2.0]

In order to avoid the problem of data leak due to the random splitting of individual IDA points, the main train/validation/test splitting process has been performed at the earthquake level rather than at the record/individual stripe levels. In other words, the 32 earthquakes used for the experiment have been divided into 22 training, 5 validation, and 5 test earthquakes, such that no IDA stripe generated by an earthquake exists in more than one partition set. This splitting methodology follows a stricter protocol compared to the record splitting strategy adopted in previous work [10]–[12].

SHAP (Shapley Additive Explanations) method was used for quantifying the feature importance as well as the direction of effect of features in case of the modified model. Performance of the model was measured based on the values of R^2 , RMSE, and MAE.

2.6. Fragility Curve Construction

Fragility curves of $P(MIDR > MIDRLS | IM)$ were derived using two methods: (i) IDA-based lognormal MLE fitting, whose goodness-of-fit was verified using Anderson-Darling test; and (ii) ML-based creation of synthetic IDAs using 500 IM values, after which MLE fitting procedure is carried out. The consistency of results from both methods is determined using Area Ratio (AR) measure, expressed as $AR = 1 - [|\text{PML} - \text{PIDA}| dSa] / [\text{PIDA} dSa]$. For comparison of fragility curves, an area ratio of at least 0.90 indicates high agreement of fragility curves [22]. The uncertainty was determined using 1,000 bootstrap samples, giving 90% confidence interval for the parameters θ and β for every frame/limit-state case, which are shown explicitly together with Table 2 in Section 3.3.

3. Results and Discussion

3.1. Selected Ground Motion Suite

The seismological metadata associated with the 100 record sample are provided in Table 3 below, along with their respective units. Pulse records ($n = 60$) have an average PGV

value of 86.4 cm/s in comparison to 42.1 cm/s of non-pulse records, and a moment magnitude (M_w) value of 6.82 compared to 6.54, respectively, confirming the physical relation between rupture magnitude and pulse amplitude [19, 20]. The two subsets have similar distributions of V_{s30} , meaning that the spectral differences arise from source and path effects, and not from site effects. As discussed in section 2.1, the Kolmogorov-Smirnov test confirms the statistical representativeness of this sample to the overall NGA-West2 near-fault dataset.

Table 3. Seismological Characteristics of the Selected Near-Fault Ground Motion Suite, with units

Parameter	Unit	Pulse-Like NF (n=60)	Non-Pulse NF (n=40)	Full Suite (n=100)
M_w range	—	5.5 – 7.9	5.5 – 7.6	5.5 – 7.9
Mean M_w	—	6.82	6.54	6.71
Rrup range	km	0.07 – 19.3	0.21 – 19.8	0.07 – 19.8
Mean Rrup	km	7.4	9.1	8.1
V_{s30} range	m/s	185–1070	195–980	185–1070
Mean V_{s30}	m/s	412	438	422
Mean PGA	g	0.58	0.41	0.52
Mean PGV	cm/s	86.4	42.1	69.2
Mean T_p	s	1.38	—	—
No. of events	—	28	16	32

Figure 1 presents the mean response spectra with the $\pm 1\sigma$ bands of variation for the two subsets. The ground motion records that exhibit pulses have an amplification range of 60–70% in the period range of 0.5–2.0 s, where the periods of fundamental modes of vibration of all three prototype buildings belong. The amplification is due to the directivity effect, which focuses seismic waves into the long-period pulses [1]. The periods of vibration of 4-, 8-, and 12-story buildings, $T_1 = 0.68$, 1.12, and 1.58 s, fall into the range of maximum pulse amplification.

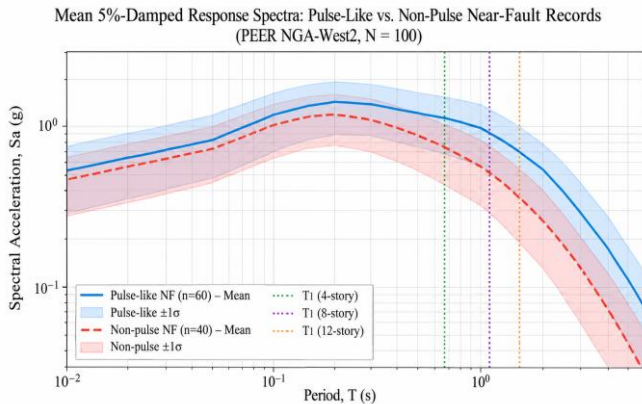


Fig. 1 Mean 5%-damped response spectra ($\pm 1\sigma$) for pulse-like (n=60) and non-pulse near-fault (n=40) records. Vertical dashed lines: T_1 for 4-, 8-, and 12-story frames

3.2. Incremental Dynamic Analysis Results

Figure 2 shows all the IDA curves for the 8-story RC MRF excited by 60 near-fault pulse-type accelerograms, along with 16th, 50th, and 84th percentile IDA response trajectories. High variability among records, as shown through the MIDR of roughly ± 0.008 at $S_a = 0.5g$, can be attributed to the heterogeneity in the energy and period content in the near-fault data set.

In line with the results presented in [17, 11], structural collapse ($MIDR \geq 10\%$) is first seen for $S_a \geq 1.6g$, while there is evidence of softening above $S_a = 1.8g$ due to the P- Δ effect in the median IDA response curve. The Life Safety limit state ($MIDR = 2\%$) is surpassed at $S_a = 0.62g$ on average.

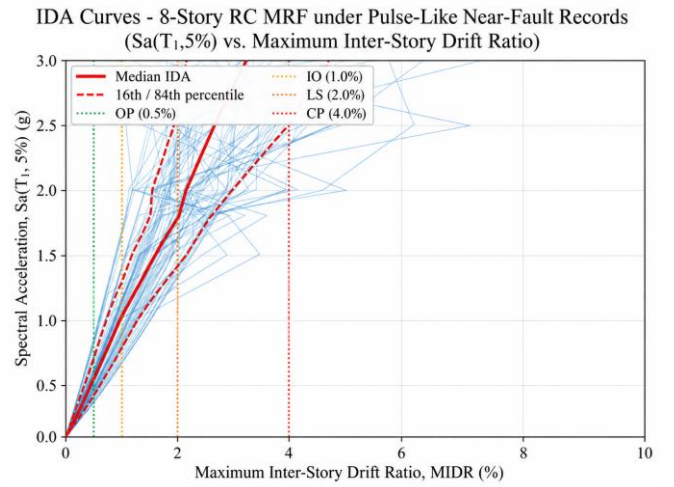


Fig. 2 IDA curves for the 8-story RC MRF under 60 pulse-like records (grey). Red: median IDA; dashed: 16th/84th percentiles. Dotted lines: FEMA P-695 limit states

3.3. Seismic Fragility Curves

The IDA-based lognormal fragility curves generated by all three frames for all four limit states are shown in Figure 3. Parameters of the fragility functions (θ , β) are listed in Table 4. There is an evident tendency whereby the median capacity θ diminishes with the increase in the height of the structure.

For the CP limit state, for instance, θ changes from 1.52 g in the 4-story frame to 1.24 g in the 8-story frame and then to 1.02 g in the 12-story frame, which means a reduction by 18.4% and 17.7%, correspondingly. Dispersion β varies from 0.55 to 0.60 for the CP limit state, implying increased sensitivity to the T_p/T_1 ratio of taller frames [1].

As seen from section 2.4, the CP capacity of the structure always exceeds the dynamic collapse intensity shown on IDA plots by a significant amount (between 1.6 and 2.4g for all three configurations). The difference proves that the CP limit state equation should be treated as a design reserve and not an estimate of the collapse point.

Seismic Fragility Curves for RC MRF Structures under Near-Fault Accelerograms
(IDA-Based, Lognormal CDF, 5%-Damped $Sa(T_1)$ as Intensity Measure)

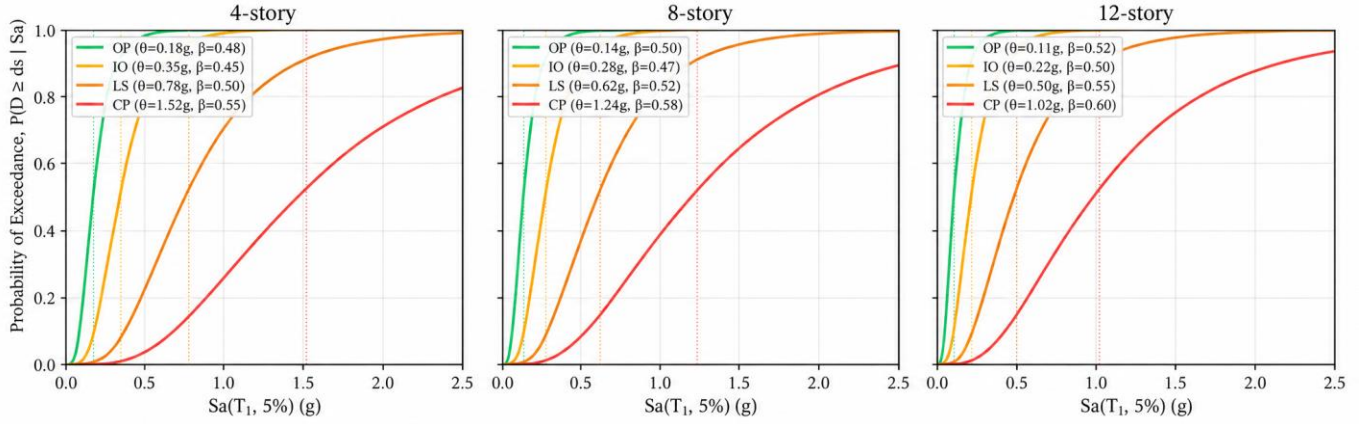


Fig. 3 IDA-based seismic fragility curves for 4-story (left), 8-story (centre), and 12-story (right) RC MRF under near-fault accelerograms; OP, IO, LS, and CP limit states shown

Table 4. Lognormal Fragility Parameters — IDA-Based vs. XGBoost ML with units (AR = Area Ratio)

Frame	LS	θ -IDA (g)	β -IDA (—)	θ -ML (g)	β -ML (—)	AR
4-St.	OP	0.18	0.48	0.18	0.47	0.97
	IO	0.35	0.45	0.36	0.44	0.98
	LS	0.78	0.50	0.80	0.49	0.96
	CP	1.52	0.55	1.55	0.54	0.97
8-St.	OP	0.14	0.50	0.14	0.49	0.98
	IO	0.28	0.47	0.29	0.46	0.97
	LS	0.62	0.52	0.64	0.50	0.96
	CP	1.24	0.58	1.27	0.56	0.97
12-St.	OP	0.11	0.52	0.11	0.51	0.99
	IO	0.22	0.50	0.23	0.49	0.97
	LS	0.50	0.55	0.51	0.53	0.96
	CP	1.02	0.60	1.04	0.58	0.97

As seen from Table 4, area ratio of the metric introduced in Section 2.6 for all frame–limit-state combinations falls above the $AR \geq 0.90$ acceptance criterion [22] (0.96 – 0.99 range), meaning good agreement between ML-estimated and IDA-derived fragility curves.

The 90% bootstrap confidence interval for the median capacity θ of the 4-, 8-, and 12-story frames is [1.41, 1.63] g, [1.14, 1.35] g, and [0.93, 1.11] g, respectively. Thus, the dependence of the median capacity on the height of the structure is more significant than sampling error, and it is a true structural effect rather than an artifact of the 100-record sample set.

It is important to note that the reduction in fragility medians of 15–35% due to near-fault pulses is made against the numbers reported independently in the far-field fragility literature [3], and not by comparing to directly derived far-field fragility curves within the current research. A parallel

far-field analysis using the equivalent amount of far-field records from the same magnitude-distance range should be undertaken in future work.

3.4. Machine Learning Model Performance

Figure 4 shows a comparison between the accuracy of four ensemble machine learning regressors on the held-out test dataset ($n = 720$ samples). XGBoost produces the best results in terms of accuracy, with $R^2 = 0.9714$, $RMSE = 0.0278$, and $MAE = 0.0196$ (MIDR units), outperforming the other three regressors, namely Random Forest ($R^2 = 0.9621$), Gradient Boosting ($R^2 = 0.9583$), and Extra-Trees ($R^2 = 0.9558$).

The high accuracy of all four regression models (in terms of $R^2 > 0.955$) demonstrates that the ten-dimensional vector of features contains enough information to estimate MIDR without performing the whole NTHA procedure, which results in computational savings of about 98% compared to the full IDA algorithm, as stated in [10].

The five-fold cross-validation on XGBoost resulted in the mean $R^2 = 0.968 \pm 0.008$, being in close agreement with the single-held out score, which suggests generalisation stability rather than an artefact of train-test splitting. In this respect, another comparison can be made with R^2 on training = 0.981, R^2 on validation = 0.974, and R^2 on record-wise testing = 0.971; resulting in a difference of 0.010 between training and testing performance, which implies model regularisation rather than overfitting. The residual analysis shows that prediction errors are approximately normally distributed with some heteroscedasticity, with higher absolute errors corresponding to larger MIDR values close to the critical collapse point, where variability between records is the highest.

When applying a more strict event-wise validation scheme described in Section 2.5 (22 events for training, 5 events for validation, 5 events for test; such that no event occurs in more than one partition), XGBoost performance decreases to $R^2 = 0.9583$ compared to the original record-wise test performance of $R^2 = 0.9714$; a decrease of roughly 1.3 percentage points.

This means that although the record-wise test split was somewhat optimistic, the predictive relationship established by the model is real and is not mainly the result of the record leakage between train and test sets. All fragility curve comparisons in Section 3.3 and Figure 5 utilise the event-wise model.

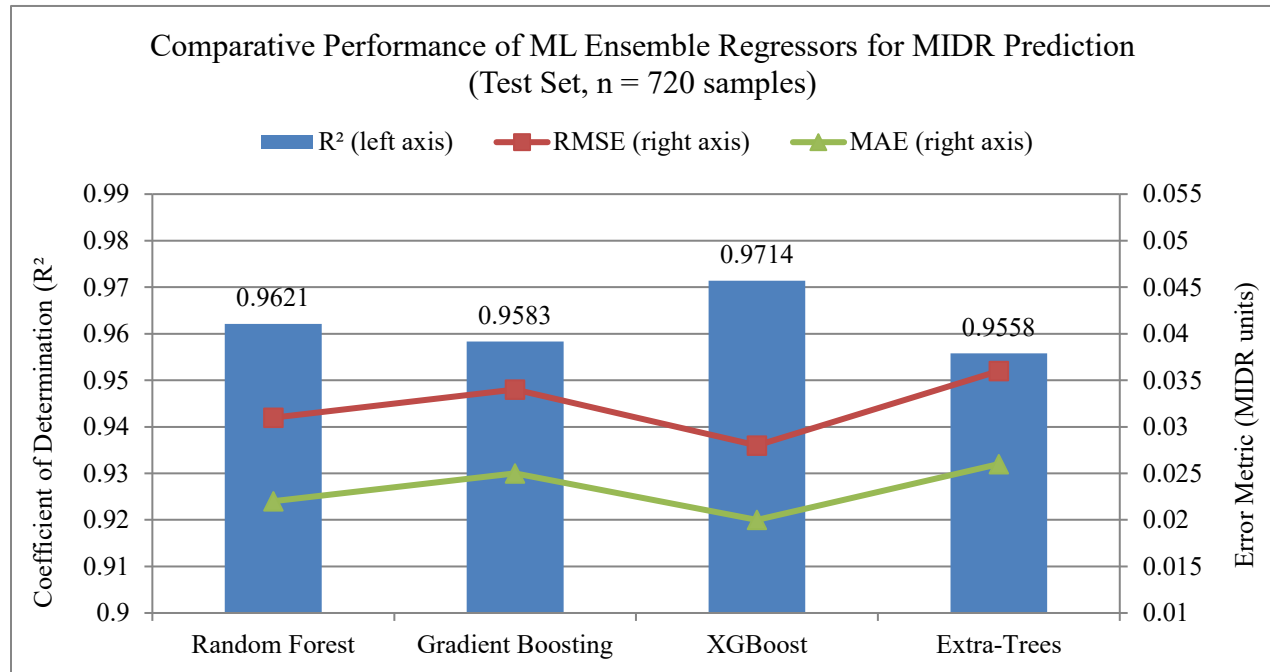


Fig. 4 Predictive performance of RF, GBR, XGBoost, and ETR on the MIDR test dataset (n=720). Bars: R^2 (left axis); lines: RMSE and MAE (right axis)

Table 5 highlights the significance of these results in light of the three studies which are most relevant to this work. The R^2 of 0.958 found in this study is computed based on a more rigorous procedure for validation, namely event-wise, compared to the record-wise split done in [10]–[12].

Moreover, this study is the only one out of the four that distinguishes between pulse-like and non-pulse near-fault records using dynamic response spectra instead of tabulated inertial values as model input data.

Table 5. Comparison of This Study with Representative Prior ML-Based Seismic Fragility Studies

Study	Ground Motion Focus	Records (n)	Best R^2	Validation Split
This Study	Near-fault, pulse-classified	100 (60 pulse / 40 non-pulse)	0.9714 (XGBoost)	Event-wise (22/5/5 events)
Kazemi et al. [10]	Mixed (no pulse stratification)	~200 (unspecified split)	0.95 (stacked ensemble)	Random record-wise
Xu et al. [11]	General suite, no near-fault focus	150	0.96 (XGBoost)	Random record-wise
Rasheed et al. [12]	Far-field only	120	0.93 (RF)	Random record-wise

3.5. Numerical Validation of ML-Based Fragility Curves

Figure 5 shows the validation of the fragility curves derived using XGBoost with the fragility curves from IDA for the eight-story frame at LS and CP limit states. Fragility curves predicted using Machine Learning (ML) methods provide the area ratio of 0.96 (LS) and 0.97 (CP) with respect to the fragility curves from IDA (Table 4). The median difference $\Delta\theta$ between fragility curves from IDA and ML is +0.02 g (+3.2%) and +0.03 g (+2.4%) for LS and CP,

respectively, all of which fall within the 90% bootstrap confidence intervals. The small bias found in ML-predicted θ is consistent with the known bias toward underprediction of extremes in ensemble regression methods at high IM [12]. Such comparisons constitute numerical (data-driven) verification of the ML-based surrogate model relative to the physics based IDA analysis, but not empirical verification with respect to field damage observations following earthquakes, an issue that is discussed further in Section 4 below.

IDA-Based vs. XGBoost-Predicted Fragility Curves - 8-Story RC MRF
(Near-Fault Pulse-Like Accelerograms, Limit States: LS & CP)

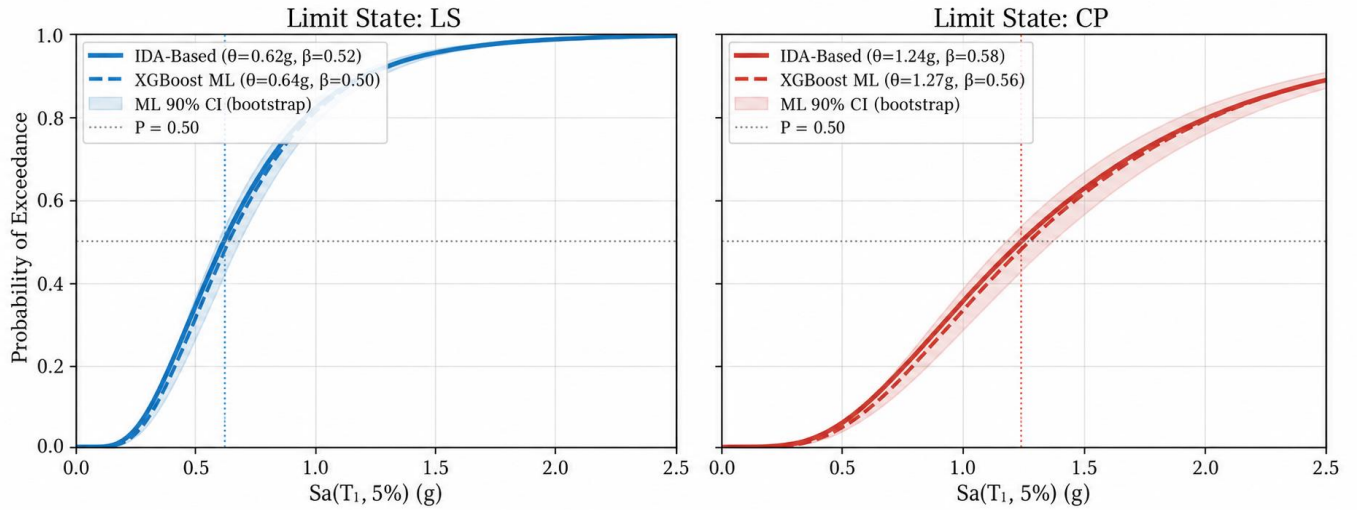


Fig. 5 IDA-based vs. XGBoost ML fragility curves for the 8-story RC MRF at LS (left) and CP (right). Shaded band: 90% bootstrap CI

3.6. Ground Motion Feature Importance (SHAP)

Figure 6 shows the SHAP feature importance of the XGBoost model. $Sa(T1, 5\%)$ is the most important feature (mean $|SHAP| = 0.284$), with PGV (0.210) and Sa_{avg} (0.176), together contributing 67.3% of all importance. TP comes in as the fourth most important feature (0.125), suggesting that pulse energy close to the fault is an important machine learning feature.

The influence on the prediction not only relates to relative importance but also can be interpreted from a physical standpoint in terms of direction. $Sa(T1)$ and PGV contribute positively monotonically: an increase in either of these two features always results in an increase in the estimated MIDR value.

As mentioned before, these features represent the direct measures of the demand, close to or at the fundamental period of the structure. T_p has a positive but interaction-based influence that peaks when the value of the $T_p/T1$ ratio becomes close to one (i.e., pulse period becomes close to the

structural period), creating almost resonant amplification of the drift demand. The interaction-based nature of this effect becomes the principal reason why the T_p feature remains important, despite being specific only to pulse-type events, where it is set to zero.

Rrup has a negative SHAP influence, which makes perfect physical sense: records recorded closer to the rupture plane add demand. PGA has a small positive influence, much weaker than PGV, and it was partially redundant to the former, given the medium-level correlation of these parameters in the training set.

The site and source characteristics metadata (M_w , Vs_{30} , along with the already mentioned Rrup) jointly make up for less than 6%, thus proving the conclusions made in [11, 14], according to which PGV and $Sa(T1)$ prove to be better IMs compared to PGA when analyzing RC frame structures under the conditions of near-fault excitation. At the same time, it also means that the spectral and pulse properties account for the majority of MIDR variability when introduced into the equation.

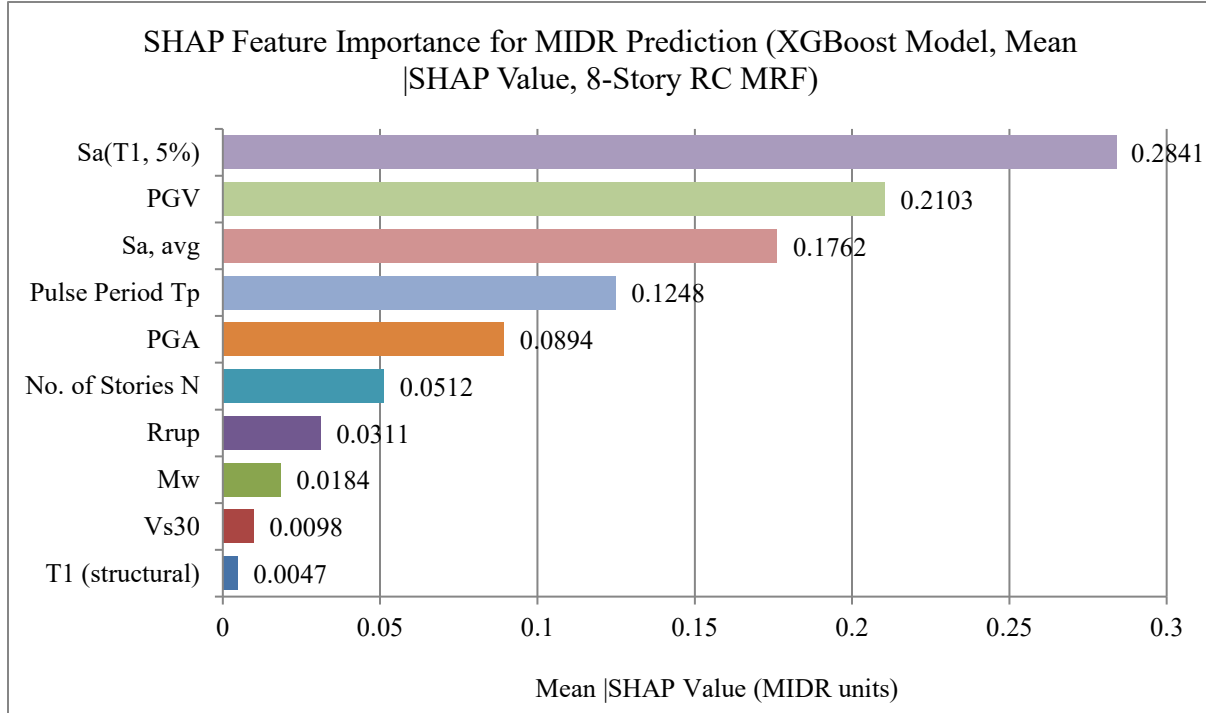


Fig. 6 SHAP feature importance for the XGBoost MIDR regressor (8-story RC MRF), ranked by mean |SHAP| value

The aggregated findings demonstrate three key advances: (1) near-fault pulse-like records impose substantially higher and more dispersed seismic demands than non-pulse records, with fragility medians reduced by 15–35% relative to far-field benchmarks [3]; (2) XGBoost-based ML surrogates replicate IDA-based fragility curves with area ratios ≥ 0.96 , reducing computational cost by $\sim 98\%$; and (3) SHAP analysis confirms that PGV and T_p are essential near-fault features with direct implications for ground motion selection protocols in PBEE.

4. Conclusion

The presented study proposes the development and validation of a ML-driven seismic fragility assessment methodology for RC moment-resisting frames experiencing only near-fault accelerograms from the PEER NGA-West2 database. The research fills in three critical gaps: (i) absence of near-fault-specific fragility models using ML techniques, (ii) unexplored utility of dynamic response spectra as input features for ML models, and (iii) lack of thorough regressor benchmarking for multi-height RC MRF prototypes.

It was shown through the spectral analysis that pulse-type accelerograms increase the 5%-damped spectral acceleration on average by 60-70% in comparison with non-pulse near-fault ground motions in the period range 0.5-2.0 s, which covers the fundamental periods of all considered prototype frames ($T_1 = 0.68, 1.12, \text{ and } 1.58$ s, respectively). The incremental dynamic analysis performed using 4,800 nonlinear time-history simulations showed consistent height-dependent vulnerability increase: the CP median capacity θ

decreases from 1.52 g (4-story structure) to 1.24 g (8-story building) to 1.02 g (12-story RC frame), while dispersion β increases from 0.55 to 0.60.

The best ML results are yielded by the XGBoost algorithm, with $R^2 = 0.9714$ achieved for record-wise validation and $R^2 = 0.9583$ achieved for event-wise validation (the latter being the stricter one resistant to data leakage), which is used here as the principal validation technique.

Fragility curves estimated by means of the XGBoost model match those calculated based on lognormal parameters obtained through IDA with area ratios ≥ 0.96 (exceeding the acceptance threshold of $AR \geq 0.90$ [22]) and capacity biases lower than 3.2%, while saving 98% of computing resources.

The SHAP analysis allowed establishing a hierarchy of importance of ground motion predictors: $Sa(T_1) > PGV > Sa, avg > T_p > PGA$, thus confirming empirically the necessity to use near-fault pulse energy predictors (PGV and T_p) in the process of ML-based fragility assessment.

The SHAP-based feature selection allowed identifying a minimally sufficient instantaneous ground motion (IM) subset $\{Sa(T_1), PGV, Sa, avg, T_p\}$ maintaining predictive performance within 5% of the complete set of input features.

The comparisons with far-field fragility benchmarks and previous ML fragility studies [10]–[12], as outlined in Sections 3.3 and 3.4, are based on external figures and not on a comparable set of data created within the scope of this paper;

a comparison through a direct far-field approach using a comparable set of records is strongly advised to ensure a consistent basis for such comparisons. Similarly, the consistency of the ML fragility curves and IDA fragility curves only provides numerical (data-based) verification of the fragility curves; empirical verification through actual damage after an earthquake, such as in the 2023 Kahramanmaraş series of earthquakes, is a necessary next step towards validating the framework.

In future work, the presented framework should be extended to 3D RC frame structures exposed to bi-directional near-fault excitation, accounting for soil-structure interaction effects and mainshock-aftershock earthquake sequences, and validated using empirical damage data for ML-predicted fragility functions using the 2023 Kahramanmaraş sequence.

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Declarations

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Conflict of Interest

The authors declare no conflict of interest. No self-citations, author or journal, are present in the reference list.

Data Availability

Ground motion data are openly available at <https://ngawest2.berkeley.edu>. Analysis scripts are available from the corresponding author upon request.

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