

Article

Mechanically Informed Feature-Enhanced Surrogate Modeling for Seismic Response Prediction and Fragility Assessment of Multi-Ribbed Composite Slab Structures Under Near-Fault Pulse-like Ground Motions

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Abstract

Near-fault pulse-like ground motions produce coupled intensity, duration, and period-matching effects, making nonlinear seismic assessment of multi-ribbed composite slab structures (MCSS) computationally expensive and difficult to generalize. To address this problem, a 4000-case OpenSees nonlinear time-history analysis (NLTHA) database is generated from Wenchuan ground motions through Latin hypercube sampling, and a mechanically informed feature-enhanced deep neural network (MIFE-DNN, previously denoted as PE-DNN in the first submission) is trained using equivalent stiffness, equivalent yield strength, mass proxy, demand-capacity ratios, period-matching ratio, normalized duration, and energy-capacity proxy; a validation-weighted stacked surrogate is further constructed from multi-seed MIFE-DNN and residual learners. On the independent test set, the mean R^2 increases from 0.9645 for the ordinary deep neural network (DNN) and 0.9686 for the single MIFE-DNN to 0.9782 for the stacked mechanically informed surrogate, while the maximum inter-story drift-ratio R^2 reaches 0.9541. Additional checks include 16 active-learning OpenSees enrichment cases, 12 analyses under two external near-fault records, 3 out-of-domain parameter cases, 100 cross-story tests, SHAP-based interpretation, and multi-EDP fragility post-processing. These checks show that the surrogate is reliable for interpolation and screening within the calibrated equivalent-model domain, but direct OpenSees recalculation is required for boundary, out-of-domain, and cross-configuration use. Parameter-importance, SHAP, and fragility analyses identify peak ground acceleration (PGA), pulse index, period matching, rib height, rib spacing, and damping ratio as dominant factors, indicating that mechanically informed feature-enhanced surrogate modeling provides an interpretable and efficient tool for MCSS response prediction and conditional fragility assessment within the sampled structural and ground-motion domain.



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Keywords: near-fault pulse-like ground motion; multi-ribbed composite slab structure (MCSS); nonlinear time-history analysis (NLTHA); OpenSees; mechanically informed feature-enhanced deep neural network (MIFE-DNN); parameterized conditional fragility; surrogate model

1. Introduction

Near-fault ground motions often contain velocity pulses. Their destructive potential is governed not only by peak ground acceleration (PGA), but also by peak ground velocity, duration, pulse period, and the relationship between the pulse period and the fundamental period of the structure. Wang and Leung [1] used spectrally equivalent pulse-like and non-pulse-like ground-motion records to quantify intensity-measure amplification factors for site-specific probabilistic seismic hazard analysis, showing that pulse characteristics can change demand-relevant intensity measures even when spectra are controlled. At the structural-system level, floor and slab deformability can also alter the distribution of seismic demand. Ruggieri et al. [2] evaluated floor deformability in existing reinforced-concrete buildings and showed that diaphragm deformability can affect structural response and seismic fragility. Therefore, structural assessment under near-fault excitation should consider both amplitude-related intensity measures and the structural mechanisms that redistribute demand.

The selection and representation of earthquake input can change structural risk assessment results. Kim et al. [3] used a comparative nonlinear-response framework to evaluate recorded and spectrum-compatible synthetic ground motions and showed that the input-motion source can affect structural damage assessment. Ji and Kim [4] used recorded moderate-earthquake motions to generate input ground motions for seismic risk assessment and highlighted the need to preserve realistic record characteristics during motion selection. Chen [5] used generalized ordinal-regression models to fit seismic fragility relationships and showed that the statistical form of the fragility model affects damage-state probability estimates. These studies indicate that near-fault response prediction should keep the recorded-motion source, intensity-measure definition, and fragility-model assumption explicit. The main database in this study uses corrected near-fault east-west records from the 51MZQ and 51SFB stations of the 2008 Wenchuan Ms 8.0 earthquake. The supplementary verification further processes the east–west, north–south, and vertical components from the two stations. The records are only truncated, baseline-corrected, scaled by PGA, and parameterized by duration; they are not treated as artificial synthetic waves.

The nonlinear time-history analyses are performed using OpenSees 3.8.0. OpenSeesPy provides a Python 3.11 interface for the OpenSees finite-element framework and facilitates batch modeling and post-processing [6]. Previous experimental and computational studies on MCSS wall panels indicate that ribs, infill blocks, and exterior frames can jointly form multiple seismic-resistance reserves [7]. More generally, the literature on slab participation, wall-panel systems, and surrogate-based seismic performance assessment shows that floor and slab mechanisms can substantially modify stiffness distribution, force transfer, and damage concentration; these effects must therefore be stated explicitly when a simplified global model is used. These studies provide the basis for the equivalent global model and the batch OpenSees nonlinear time-history analyses used in this work.

The current state of the art in machine-learning-assisted seismic assessment can be organized into three complementary lines. The first uses data-driven surrogates to replace repeated nonlinear time-history analyses for specific structural systems. Recent studies have demonstrated this strategy for damped structures [8], elevated steel tanks [9], steel diagrid systems [10], composite plate shear wall–concrete-filled systems [11], and high-speed railway bridges [12]. Across these applications, the principal advance is rapid multi-parameter response estimation after an expensive numerical database has been generated. However, the resulting models are generally system-specific, and their credibility depends on the provenance and coverage of the training data, comparison with appropriate baseline algorithms, and explicit separation of interpolation from extrapolation.

The second line introduces physical or mechanical knowledge into machine learning. This line spans loss-based physics-informed models, architecture-level constraints, and feature-level mechanical priors rather than a single formulation. Cicirello [13] emphasized that the form of physical information and its coupling with data-driven learning should be selected according to the dynamical-system problem. Parisi et al. [14] further showed that structural-mechanics information can be embedded through structured priors in graph-based surrogate models. These developments improve interpretability and physical consistency, but they also require precise terminology because a mechanics-informed feature surrogate is not equivalent to a governing-equation residual PINN. Accordingly, the present study adopts a mechanically informed feature-enhanced DNN (MIFE-DNN): equivalent stiffness, equivalent yield strength, mass, demand-capacity, period-matching, duration, and energy descriptors are supplied as explicit inputs, while equilibrium and constitutive residuals are not imposed in the loss function.

The third line extends surrogates from response prediction to probabilistic performance assessment and design decision support. Contemporary approaches include Bayesian fragility estimation [15], Gaussian-process active learning for regional multi-component portfolios [16], machine-learning-based fragility classification for reinforced-concrete components and structures [17,18], surrogate-assisted performance-based optimization [19], and explainable inverse engineering [20]. Together with engineering damage-state formulations such as Hazus [21], these approaches establish a progression from response prediction to fragility estimation and design screening. Their reliability nevertheless depends on consistent engineering-demand parameters, defensible damage thresholds, uncertainty-aware validation, and post-checks when a candidate lies near or outside the calibrated domain.

Despite these advances, the three lines remain weakly connected for multi-ribbed composite slab structures under near-fault pulse-like motions. Within the literature reviewed above, data-driven seismic surrogates have primarily been developed for other structural systems; mechanics-informed studies have focused on general structural-analysis formulations; and fragility or inverse-design studies have not jointly addressed MCSS-specific mechanical descriptors, recorded pulse characteristics, multiple engineering-demand parameters, and validation of applicability boundaries. The resulting gap is therefore not simply a shortage of data, but the absence of an integrated and interpretable assessment chain for this specific structural typology and excitation regime. This study addresses that gap for a ten-story MCSS model by: (1) establishing a 4000-case structural-ground-motion database from real Wenchuan near-fault records using OpenSees nonlinear time-history analysis; (2) embedding mechanically normalized stiffness, strength, mass, demand-capacity, period-matching, duration, and energy descriptors in a MIFE-DNN and benchmarking it against ordinary data-driven and tree-ensemble models; (3) combining permutation importance and SHAP analysis to identify dominant pulse, stiffness, damping, and geometric drivers; and (4) linking active-learning enrichment, external-record checks, multi-EDP fragility analysis, out-of-domain and cross-story tests, and experimental-literature evidence to explicit applicability limits. The conclusions remain limited to the equivalent ten-story MCSS model, the selected near-fault record set, and the parameter ranges tested in this study.

2. Materials and Methods

2.1. Multi-Ribbed Composite Slab Structural System

The configuration of the MCSS is shown in Figure 1. The system consists of composite wall panels and an exterior frame, which are assembled and cast together. As the main load-bearing component, the slab is prefabricated as a reinforced-concrete frame grid composed of rib beams, rib columns, and lightweight blocks. The structural system investigated in

this study is supported by actual experimental work and has also been applied in engineering practice. Representative applications include residential demonstration projects in Tangshan, Xi'an, and Lankao, indicating that the system has moved beyond a purely conceptual or numerical model and has practical construction background.

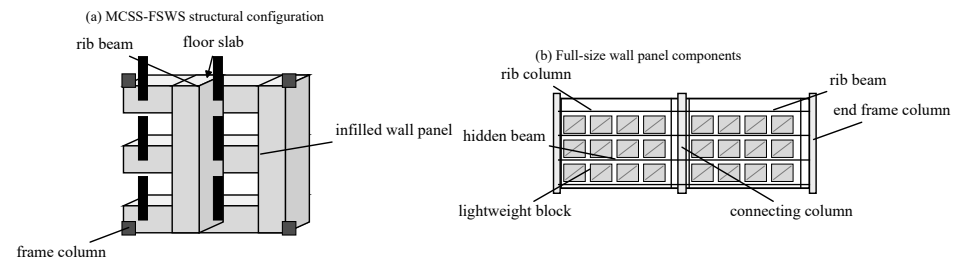


Figure 1. Configuration of the multi-ribbed composite slab structure.

Figure 1 shows the basic components of the MCSS, including the exterior frame, reinforced-concrete rib-beam and rib-column grid, and lightweight infill blocks. This configuration means that seismic resistance is not provided by a single wall panel or frame alone. Instead, the exterior frame, rib grid, and infill blocks progressively resist lateral action, which provides the structural basis for the following equivalent modeling, damping analysis, and multi-level seismic-resistance interpretation.

2.2. Hysteretic Model, Equivalent Simplification, and Database Construction

Based on previous low-cycle reversed loading tests of MCSS wall panels, this study uses the IDARC three-parameter hysteretic model as the basis for the equivalent non-linear model. The stiffness degradation parameter α , strength degradation parameter β , and pinching parameter γ are identified from existing tests. Because the original point-by-point test data were not completely preserved, the previously published hysteretic and skeleton curves were digitized and rechecked to support the applicability of the equivalent model. This treatment is used only to verify the overall force-deformation trend and is not intended to replace new component tests.

The digitized verification also provides a quantitative error range. Using initial stiffness, peak bearing capacity, and single-cycle hysteretic energy area as control indicators, the relative errors between the equivalent model and the existing experimental curves are controlled within approximately 15%. Therefore, the model can be used for global macroscopic response analysis in this study. However, this error level also means that the model is not used for refined prediction of local crack propagation, interface slip, or detailed component damage. The surrogate trained later in this paper is therefore a simulation surrogate of the calibrated equivalent OpenSees model. Its direct training target is the OpenSees nonlinear response, which defines the numerical-response domain evaluated in the present parametric study.

An MCSS wall panel consists of a reinforced-concrete rib grid, an exterior frame, and lightweight masonry blocks. To reduce computational complexity, this study adopts the equivalent flexural stiffness principle for global simplification. Based on Equation (1), the reinforced-concrete frame grid and lightweight block system are simplified into an equivalent homogeneous concrete shear wall, as shown in Figure 2. This simplification is based on three assumptions: (1) good bond performance exists between the MCSS wall panel and lightweight blocks; (2) good deformation compatibility exists between the MCSS wall panel and the surrounding frame; and (3) the in-plane stiffness of floor slabs and roof slabs is not explicitly modeled. This assumption is acceptable for the global shear-type response investigated here, but it may underestimate local slab-wall interaction, diaphragm

flexibility, connection damage, and local stress redistribution. These effects are therefore treated as applicability limits rather than as responses predicted by the surrogate model.

$$b_{eq} = \frac{EA + E_q A_q}{Eh} \quad (1)$$

where E is the elastic modulus of concrete; E_q is the elastic modulus of the lightweight blocks; A is the horizontal projected area of the frame grid; A_q is the horizontal projected area of the infill blocks; b_{eq} is the equivalent wall thickness; and h is the wall length.

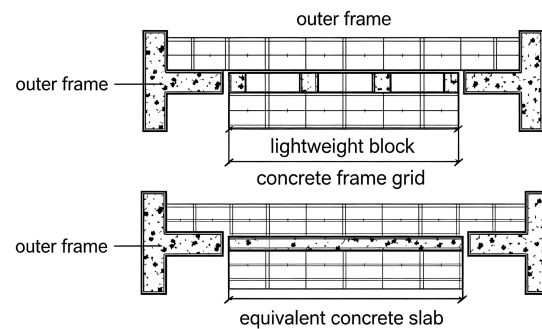


Figure 2. Equivalent modeling scheme for the multi-ribbed composite slab.

Figure 2 gives the simplification route from the real composite component to the equivalent wall model. The equivalent treatment retains the global flexural stiffness and lateral deformation characteristics of the composite slab while reducing the modeling complexity of nonlinear time-history analysis. It therefore provides a unified mechanical basis for the subsequent IDARC/OpenSees parameterized computation and machine-learning database construction. The price of this simplification is that surrogate accuracy is conditional on the equivalent-model assumptions, the calibrated hysteretic parameters, and the selected response outputs. For this reason, all validation metrics in the Results section are reported as agreement with withheld or newly recalculated OpenSees NLTHA samples. This is the appropriate validation target for a simulation surrogate intended to replace repeated nonlinear numerical simulations within a defined model domain.

The revision further strengthens numerical validation by adding 24 newly recalculated OpenSees interpolation cases. These cases were selected from 1024 LHS candidates inside the 5–95% quantile envelope of the original 4000-case database and were balanced across the QP_EW and BJ_EW records. All 24 analyses converged and are reported in Supplementary Data S6. After these cases were added to the numerical database, the augmented 4024-case database was used for an additional 85–15% retraining check with mechanics-informed input features. The resulting mean multi-output R^2 is 0.9699, which confirms that the surrogate workflow remains stable after OpenSees enrichment. The near-fault bidirectional shake-table tests on waffle-flat plate structures by Benavent-Climent et al. [22], the shaking-table and numerical study of a ten-story frame-supported multi-ribbed composite wall structure [23], and the low-reversed cyclic tests of frame-supported multi-ribbed composite walls by Jia et al. [24] are retained only to support the interpretation of stiffness degradation, residual deformation, and wall-panel damage mapping. The main accuracy validation remains OpenSees-based, which is consistent with the goal of building an efficient replacement for repeated nonlinear numerical simulations.

On this basis, a strong-motion structural-response database for machine learning is constructed. The ground motions are near-fault strong-motion records from the 2008 Wenchuan Ms 8.0 earthquake. Corrected east–west acceleration time histories from the 51MZQ (Qingping) and 51SFB (Bajiao) stations of the China Strong Motion Networks

Center are selected as the basic inputs. The time step of both records is 0.005 s, and their original peak accelerations are approximately 824 gal and 556 gal, respectively. To maintain physical realism, each sample is reanalyzed through a full OpenSees 3.8.0 nonlinear time-history analysis. All response indicators are extracted from finite-element output files rather than generated by surrogate-model interpolation.

Latin hypercube sampling (LHS) is used to generate 4000 input samples so that the database is not limited to a small number of fixed PGA cases. The sample size was selected as a practical compromise between coverage of the 12-dimensional input space and the computational cost of full nonlinear time-history analysis. In preliminary convergence checks, smaller trial sets produced visibly less stable validation errors and parameter-importance rankings, whereas the 4000-case database provided 2800 training cases, 600 validation cases, and 600 strictly withheld test cases while keeping all records traceable to direct OpenSees calculations. The sampling space includes 12 dimensions covering structural parameters, material parameters, damping, site class, and ground-motion parameters, as summarized in Table 1. Continuous variables follow uniform distributions within engineering ranges, and site class and record type follow discrete uniform sampling. For each sample, the program extracts the strong-motion segment of the QP or BJ record, scales it to the target PGA, and inputs it into the OpenSees equivalent nonlinear shear model for time integration. Although the database is extensive in terms of structural and intensity sampling, the seismic-source variability is limited because it originates from two Wenchuan near-fault stations. A broader near-fault suite would be required to quantify record-to-record variability across different fault mechanisms, rupture directivity conditions, site spectra, and pulse periods.

Table 1. Twelve input parameters and sampling ranges of the LHS database.

Parameter	Lower Bound	Upper Bound	Distribution	Category
Rib spacing s_r (m)	1.20	2.40	Uniform	Structural
Rib height h_r (m)	0.18	0.42	Uniform	Structural
Slab thickness t_s (m)	0.08	0.18	Uniform	Structural
Concrete strength f_c (MPa)	30	50	Uniform	Material
Column section area A_c (m ²)	0.16	0.36	Uniform	Structural
Damping ratio ξ	0.035	0.120	Uniform	Dynamic
Site class c_s	I	III	Discrete uniform	Site
PGA (g)	0.120	0.480	Uniform	Ground motion
Duration D (s)	20.0	80.0	Uniform	Ground motion
Pulse period T_p (s)	0.62	0.70	Discrete	Ground motion
Pulse index I_p	0.78	0.85	Discrete	Ground motion
Record type	QP	BJ	Discrete uniform	Ground motion

The final database contains 4000 unique cases, including 2000 cases for the Qingping east–west record and 2000 cases for the Bajiao east–west record. All OpenSees analyses return a status of 0, with no convergence failure. The statistical results show that the sample PGA covers 0.120–0.480 g, the duration covers 20.01–79.99 s, the median maximum inter-story drift ratio is 0.00557, and the 95th percentile is 0.01325. The database preserves the engineering background of real near-fault records and provides reproducible high-fidelity computational samples for surrogate-model training.

Each case outputs inter-story drift ratio, floor displacement, floor velocity, floor acceleration, base shear, and a hysteretic energy-demand proxy. The inter-story drift ratio is calculated by dividing the relative displacement between adjacent stories by the story height. The cumulative energy-demand proxy is obtained by stepwise integration of the restoring-force-displacement hysteresis-loop area. Base shear is taken as the sum of restoring forces of the lateral-resisting elements at the bottom story. These responses are obtained from OpenSees post-processing. LHS is used only to generate input parameter combinations and does not participate in response interpolation.

Batch OpenSees calculations automatically generate models, materials, ground-motion inputs, and output files through Tcl scripts. Each case establishes a ten-story equivalent shear model. Story mass, story height, and boundary conditions are consistent with the benchmark structure shown in Figure 3. Nonlinear elements use degrading hysteretic material to describe global lateral restoring force. Rayleigh damping is controlled by the first and third modes, and the damping ratio is defined by each LHS sample. Time integration uses the Newmark average-acceleration method with $\gamma = 0.50$ and $\beta = 0.25$. Nonlinear solution uses the Newton-LineSearch algorithm, with a convergence tolerance of 1.0×10^{-6} and a maximum of 50 iterations per step. When the ground-motion time step is 0.005 s, the analysis time step is kept identical to the record time step.

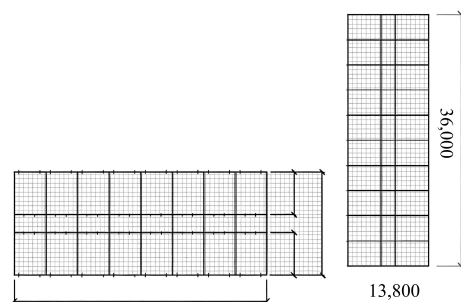


Figure 3. Plan layout and analytical model of the multi-ribbed composite slab structure.

Figure 3 defines the plan layout, number of stories, and analytical boundary conditions of the ten-story structure. This model follows the equivalent-component assumptions above and serves as the common benchmark for the subsequent PGA variation, damping variation, duration effect, surrogate-model training, and inverse design analyses.

2.3. Ground-Motion Selection and Processing

The ground-motion input is organized as wave selection, truncation and scaling, and parameterized processing. This procedure combines the near-fault characteristics of real records with the continuous input space required for machine learning. In the main OpenSees database, the corrected east–west acceleration time histories from the 51MZQ and 51SFB stations of the 2008 Wenchuan Ms 8.0 earthquake are denoted as the QP and BJ waves. Both records come from the same earthquake event, which reduces the interference of source-mechanism differences. For the four-wall-panel damage verification, the east–west, north–south, and vertical column-format records from the two stations are further processed. The east–west and north–south components are used as horizontal inputs for the ten-story equivalent structure, whereas the vertical components are used only to check ground-motion intensity measures.

For each record, the program truncates the strong-motion segment around the acceleration peak and places the peak at approximately 30% of the truncated window. Duration is sampled by LHS within 20–80 s. The acceleration time history is then linearly scaled to the target PGA and written as an OpenSees Path time series. This process changes only the intensity and duration window and does not change the pulse shape of the original record. Each input wave is characterized by PGA, duration D , predominant period T_p , and pulse index I_p . According to the record characteristics, the QP wave uses $T_p = 0.62$ s and $I_p = 0.85$, and the BJ wave uses $T_p = 0.70$ s and $I_p = 0.78$. The later parameterized conditional fragility analysis also introduces T_p/T_1 , where T_1 is the first period of the OpenSees benchmark model.

To test whether the conclusions depend only on the two Wenchuan records, two additional near-fault records from the 2024 Noto Peninsula earthquake are processed as

external ground motions. They are denoted as ISK001_EW and ISK002_EW. These records are not added to the 4000-case training database; instead, the two Wenchuan records and the two external records are used to build a separated 12-case four-record auxiliary OpenSees response-variability database at PGA levels of 0.24, 0.36, and 0.48 g. Table 2 summarizes the processed record metrics. This separation avoids contaminating the original training/test split while providing a direct numerical check of record-to-record variability.

Table 2. Processed metrics of baseline and external near-fault records used for response-variability checking.

Record	Original PGA (g)	PGV (m/s)	5–95% Duration (s)	Pulse Proxy
QP_EW	0.818	0.746	32.23	1.122
BJ_EW	0.645	0.524	41.17	0.992
ISK001_EW	1.457	1.781	43.08	2.584
ISK002_EW	0.474	0.726	28.77	2.763

2.4. Structural Analysis Model

The site conditions, loads, plan layout, and other parameters of the MCSS are determined according to a ten-story corridor-type office building. According to GB 50011-2010, the dynamic analysis adopts seismic fortification intensity 8.0, site class II, and Rayleigh damping. In IDARC 2D, macro-elements are used to represent structural members. The Park model is used to describe the degrading hysteretic behavior of the panels. Based on previously obtained MCSS wall-panel test data, α , β , and γ are taken as 1.80, 0.24, and 0.44, respectively.

2.5. Modernized Processing of Wenchuan Strong-Motion Records and Four-Wall-Panel Damage Mapping

To avoid relying only on previously reported damage-index figures, this study further verifies the results using the east–west, north–south, and vertical column-format records from the 51MZQ and 51SFB stations of the 2008 Wenchuan Ms 8.0 earthquake. The original header files show that the record unit is cm/s^2 and the sampling interval is 0.005 s. The single-column acceleration records are first corrected by subtracting the pre-event mean, removing the linear trend, and applying a 0.05–25 Hz zero-phase Butterworth band-pass filter. Velocity and displacement time histories are then obtained by integration, and PGA, PGV, PGD, Arias intensity, 5–95% significant duration, cumulative absolute velocity, and velocity-dominant period are extracted.

For structural input, the east–west and north–south components are used as horizontal ground motions for the ten-story equivalent shear structure, while the vertical components are used only for ground-motion feature statistics. The ten-story structure uses the benchmark parameters described above, with a fundamental period of 0.85 s, a damping ratio of 5%, and story masses and story heights consistent with the benchmark model. The damage assessment of the four wall panels uses the empirical damage-deformation curves of MLB-1, MLB-2, MLB-3, and MLB-4 from the previous Excel data. The maximum inter-story displacement demand computed from the structural analysis is mapped to each wall-panel damage curve to obtain ductility-related and stiffness-related damage indices. Because the original near-fault record intensity is high, the east–west and north–south horizontal records are also scaled within 0.10–0.80 g to show the continuous development of damage with input intensity.

As shown later in Figures 4–9, this preprocessing step is used as a verification and damage-mapping procedure, not as a separate result thread. It ensures that the near-fault inputs used for surrogate modeling, fragility assessment, and wall-panel damage

interpretation are traceable to corrected records and that the damage interpretation is tied to physical deformation demand rather than to a single global drift threshold.

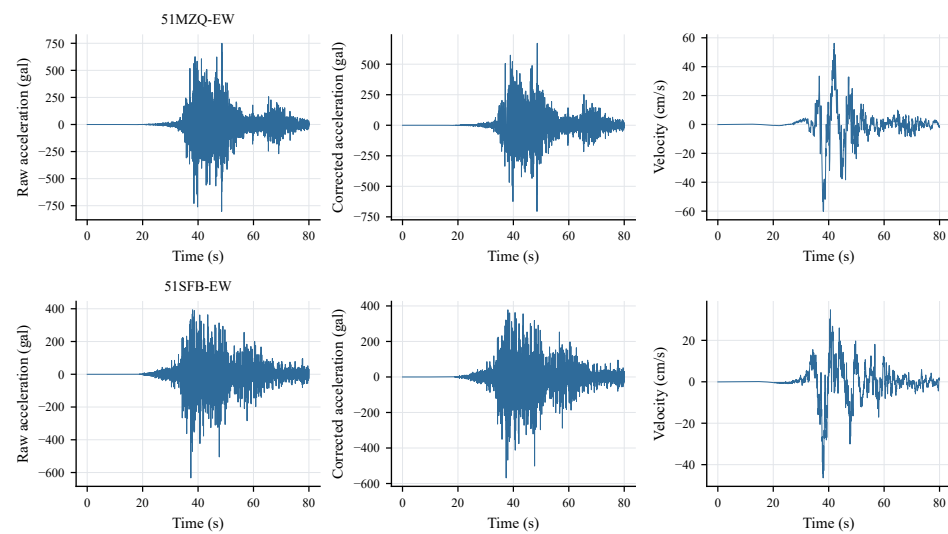


Figure 4. Example of baseline correction and velocity time-history processing for Wenchuan strong-motion records.

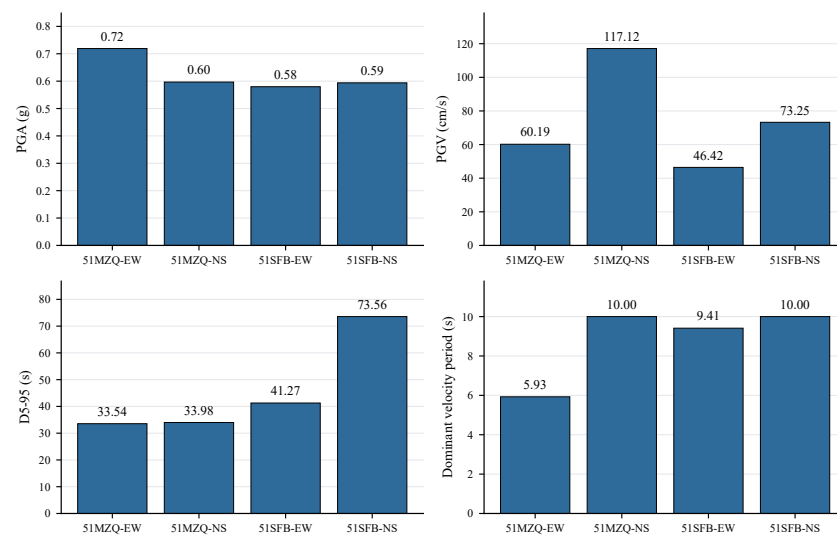


Figure 5. Comparison of intensity measures for Wenchuan horizontal ground motions.

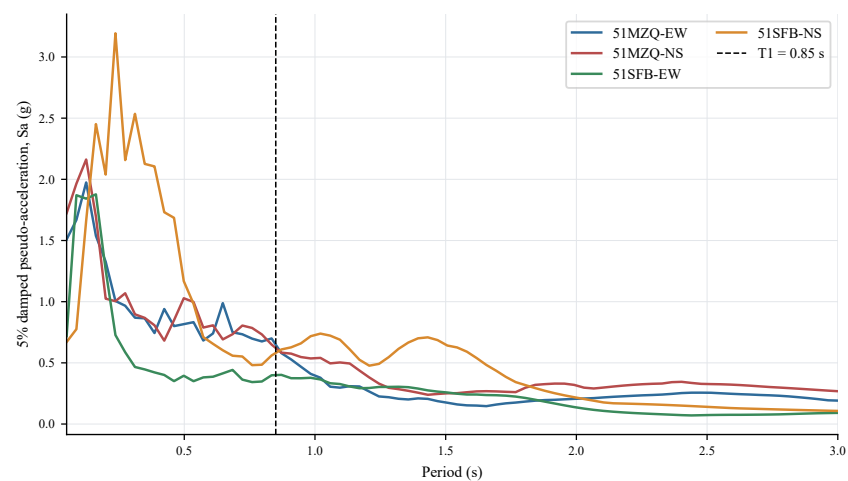


Figure 6. Five-percent-damped response spectra of Wenchuan horizontal ground motions.

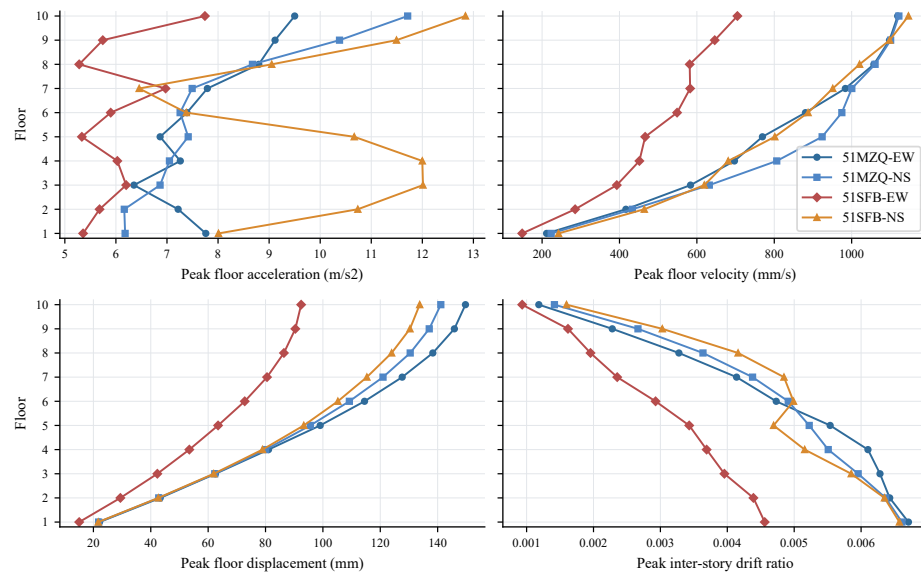


Figure 7. Floor responses of the ten-story structure under Wenchuan horizontal ground-motion input.

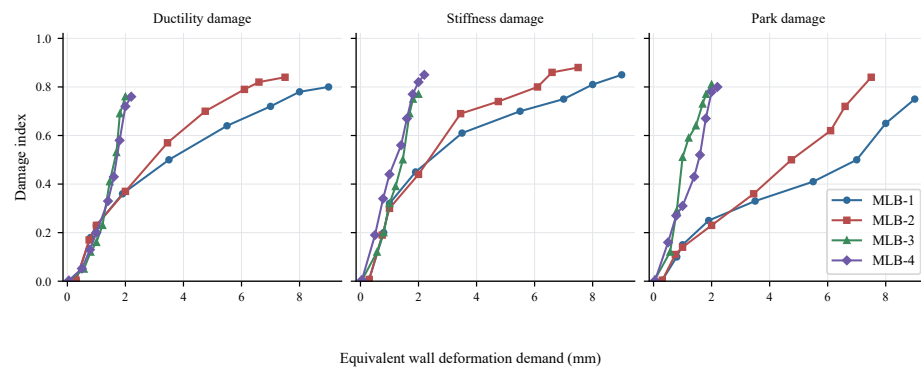


Figure 8. Damage-index curves of four wall panels.

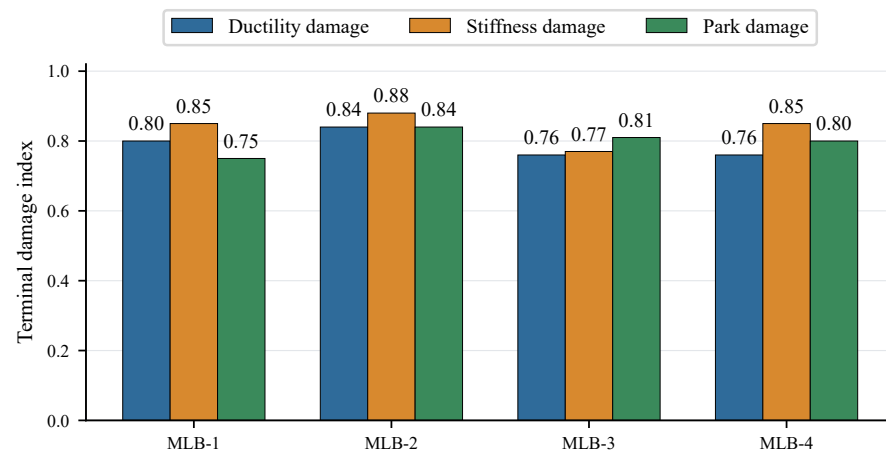


Figure 9. Comparison of terminal damage indices of four wall panels.

2.6. Ground-Motion Processing Verification and Wall-Panel Damage Mapping

As described in the Methods section, the Wenchuan strong-motion processing is used to verify input quality and to connect global structural demand with wall-panel damage mapping. As shown in Figure 4, after modernized processing of the Qingping and Bajiao east–west records, low-frequency baseline drift is removed from the corrected time histories, and the integrated velocity time histories remain stable. This step ensures that subsequent

structural input is controlled by the real pulse and energy-input characteristics of near-fault strong motions rather than by zero-line drift in the raw records.

Figure 5 shows clear differences among the main intensity measures of the four horizontal records. The corrected Qingping east–west component has the largest PGA, whereas the Qingping north–south component has a higher PGV. This indicates that different components represent different amplitude-input and velocity-pulse characteristics and explains why later floor displacement and damage distributions are not governed by PGA alone.

As shown in Figure 6, the 5%-damped pseudo-acceleration response spectra indicate that the first structural period, $T_1 = 0.85$ s, lies within the period range where the near-fault records have concentrated energy. These ground motions can therefore effectively excite the global lateral response of the ten-story structure. The spectral analysis also shows that PGA alone is insufficient to characterize near-fault seismic input.

As shown in Figure 7, all four horizontal records produce clear floor responses in the ten-story structure. The Qingping record is more unfavorable in terms of roof displacement and inter-story drift ratio, while the Bajiao north–south component shows significant velocity amplification. Overall, peak inter-story drift ratio is concentrated in the middle and upper stories, indicating that damage demand under near-fault input is not limited to the bottom stories.

Figure 8 presents ductility damage, stiffness damage, and Park damage-index curves for four wall panels using data capable of describing the damage trend. All three indices increase with displacement demand, but the growth rates differ among wall panels. MLB-1 and MLB-2 gradually approach a damage level of 0.8 at large displacement, whereas MLB-3 and MLB-4 enter the high-damage range earlier, indicating lower damage thresholds.

Figure 9 shows that the terminal damage indices of the four wall panels at the maximum recorded displacement point are different. MLB-2 has high stiffness damage and Park damage, and the Park damage index of MLB-3 reaches 0.81. This result indicates that using only a single ductility index may underestimate the influence of stiffness degradation and energy accumulation.

In summary, the processed Wenchuan records and the redrawn four-wall-panel damage indices supplement the damage-interpretation chain of this study. The Qingping and Bajiao records can trigger clear floor lateral responses, and the empirical wall-panel damage curves further show that different panels may exhibit different damage levels under the same displacement demand. This evidence supports the revised design-method statement above: global inter-story drift is necessary but not sufficient for MCSS design, and wall-panel damage thresholds should be used as post-screening constraints for surrogate-generated candidates.

3. Results

3.1. Prediction Performance of the Mechanically Informed Feature-Enhanced Surrogate Model

The results are organized around three questions: whether the mechanically informed feature-enhanced surrogate improves prediction accuracy, which physical and ground-motion variables control response demand, and how the predicted response translates into parameterized conditional fragility. Fixed-PGA floor-response, damping, duration, inverse-design, and Wenchuan-processing analyses are used as methodological support or discussion evidence rather than as parallel result threads.

The amplitudes of the ground accelerations are adjusted to 350, 400, 450, and 480 gal to first identify response-amplification characteristics of the QP and BJ waves. Three sets of earthquake waves are applied to the structure. The roof acceleration amplification factors are listed in Table 3.

Table 3. Acceleration amplification factors at the roof level.

Earthquake Case	Input PGA (gal)	Maximum Roof Absolute Acceleration (gal)	Amplification Factor
QP	350	883	2.523
QP	400	1005	2.512
QP	450	1103	2.451
QP	480	1153	2.402
BJ	350	1054	3.011
BJ	400	1081	2.703
BJ	450	1212	2.693
BJ	480	1266	2.638

Table 3 shows that, for the same type of input wave, the amplification factor decreases as PGA increases. Under seismic loading, the opening and closing of lightweight blocks are restrained by the concrete frame grid. The multi-ribbed composite slab can therefore continue to carry lateral load effectively, and the lateral resistance stiffness can increase within a certain PGA range. These fixed-parameter results provide mechanical context for surrogate-model construction, but the main prediction, importance, and fragility analyses below are based on the full 4000-case OpenSees database.

To improve the efficiency of parametric studies, a seismic-response surrogate model is trained using 4000 OpenSees nonlinear time-history analysis results. The model inputs include 12 structural and ground-motion parameters and mechanically normalized physical prior features. The outputs include maximum inter-story drift ratio, roof displacement, roof velocity, roof acceleration, base shear, and an energy-demand indicator. The database is divided into training, validation, and test sets with a 70%–15%–15% split, corresponding to 2800, 600, and 600 samples. The training set is used for model fitting, the validation set for hyperparameter selection and stacking-weight estimation, and the test set only for final accuracy evaluation.

The physical features are constructed as follows. The concrete strength correction factor is defined as $\eta_c = f_c/40$. The rib-beam geometric coefficient is $\eta_r = (h_r/0.30)^{1.45}(1.80/s_r)^{1.10}$. The slab-thickness coefficient is $\eta_s = (t_s/0.12)^{0.35}$, the column-section coefficient is $\eta_A = (A_c/0.25)^{0.45}$, and the site correction factor is $\eta_g = 1 - 0.06(c_s - 2)$. The equivalent stiffness proxy is $K_{eq}^* = 1.25 \times 10^8 \eta_r \eta_s \eta_A \eta_c^{0.35} \eta_g$. The equivalent yield-strength proxy is $F_y^* = 2.20 \times 10^6 \eta_r^{0.45} \eta_A \eta_c^{0.55}$. The mass proxy is $M^* = 2.20 \times 10^5 (0.12/t_s)^{-0.15}$. Additional non-dimensional or semi-non-dimensional indices are constructed: strength-demand ratio $\rho_s = F_y^*/(M^*PGA_g)$, PGA-stiffness ratio $\rho_k = M^*PGA_g/K_{eq}^*$, damping-stiffness index $I_\zeta = \zeta \sqrt{K_{eq}^*/M^*}$, period-matching ratio, normalized duration, stiffness-mass frequency, and energy-capacity proxy. These features were selected because they correspond to the main low-order mechanisms controlling the OpenSees output: lateral stiffness, yield resistance, inertial demand, demand-capacity ratio, damping-related energy dissipation, and near-fault pulse-period matching. Variables such as reinforcement detailing, local connection slip, residual drift, and crack-width indicators were not included because they are not directly resolved by the present equivalent shear model or by the 4000-case OpenSees output database. These indicators are fed into the MIFE-DNN and the stacked surrogate together with the 12 original inputs.

DNN training uses a unified preprocessing workflow. Continuous input variables and physical features are standardized by z-score normalization, and output responses are balanced by the standard deviations of the training set. The MIFE-DNN has 18–27 inputs depending on the physical-feature set and 6 outputs. The train/validation/test split is fixed at 70%/15%/15% with random seed 20260708, giving 2800, 600, and 600 samples. Hyperparameter optimization uses a reproducible grid search over hidden-layer size, L2

regularization coefficient α , and initial learning rate η . The tested hidden-layer candidates are (64, 64), (96, 64), and (128, 64); α is selected from 1.0×10^{-5} , 1.0×10^{-4} , and 1.0×10^{-3} ; and η is selected from 1.0×10^{-4} , 5.0×10^{-4} , and 1.0×10^{-3} . Candidate models are trained with validation-loss monitoring and early stopping; in the DeepSHAP checkpoint workflow, the patience value is 35 epochs with restoration of the best validation weights. Candidate models are ranked by validation-set multi-output RMSE after z-score output balancing, and the independent test set is not used during this selection. To reduce sensitivity to neural-network initialization, eight MIFE-DNN predictors with different random seeds are also trained. Their predictions are combined with ExtraTrees, random forest, histogram-gradient boosting, and ridge learners through a positive linear stacking model fitted only on the validation set. The stacking weights are obtained by non-negative least squares and then normalized to sum to one, so the final prediction remains a validation-weighted convex combination of the base learners. Histogram-gradient boosting is included as a reproducible gradient-boosting tree benchmark for the tabular database, analogous in modeling role to commonly used boosted-tree packages. This stacked model is then evaluated once on the independent test set.

To respond to the generalization concern within the current sampled domain, an additional active-learning OpenSees enrichment step is added in the revision. First, ridge regression, random forest, ExtraTrees, and histogram-gradient boosting are trained on the 4000-case database. Second, 384 new LHS candidate points are generated within the same parameter bounds as Table 1. Third, each candidate is scored by a weighted criterion combining normalized multi-model prediction disagreement (70%) and proximity to the LHS boundary (30%). The 16 highest-scoring candidates are then recalculated using OpenSees rather than accepted from surrogate prediction. This procedure is not used to claim universal extrapolation or validation for new structural systems; it is used to identify high-risk boundary samples for direct numerical correction within the present Wenchuan-record and equivalent-MCSS model domain.

As shown in Table 4, the single MIFE-DNN reaches a mean R^2 of 0.9686 and a mean RMSE of 2.673×10^4 on the independent test set, outperforming the ordinary DNN, random forest, and ridge regression. Histogram-gradient boosting reaches a higher mean R^2 of 0.9751, confirming that boosted-tree methods are strong baselines for this tabular dataset. The optimized stacked mechanically informed feature surrogate further increases the independent-test mean R^2 to 0.9782 and reduces the mean RMSE to 2.415×10^4 . The validation-set grid search shows that the hidden-layer configuration (96, 64), $\alpha = 1.0 \times 10^{-4}$, and $\eta = 5.0 \times 10^{-4}$ yields stable MIFE-DNN performance, while positive validation-based stacking captures residual response patterns not fully represented by a single DNN or a single tree-ensemble model.

Table 4. Overall performance comparison of surrogate models on the independent test set under the 70%–15%–15% split.

Model	Mean R^2	Mean RMSE
Stacked mechanically informed feature surrogate	0.9782	2.415×10^4
Histogram-gradient boosting	0.9751	2.943×10^4
MIFE-DNN	0.9686	2.673×10^4
ExtraTrees	0.9649	3.814×10^4
DNN	0.9645	2.776×10^4
RandomForest	0.9161	6.369×10^4
Ridge	0.8123	9.597×10^4

Five-fold cross-validation is further used to examine model stability. Each fold uses 3200 training samples and 800 test samples. The five-fold mean R^2 is 0.9656 with a standard deviation of 0.00114, and the mean R^2 for inter-story drift ratio is 0.9294. These results indicate that model performance is not sensitive to the sample split, although inter-story drift ratio remains the most difficult of the six outputs to predict.

The active-learning enrichment selected 16 additional high-disagreement or near-boundary cases from the 384-candidate pool, as summarized in Table 5. All 16 cases converged in OpenSees with status 0. The selected cases cover PGA values from 0.158 to 0.472 g, duration from 20.76 to 72.22 s, and an equal split between the QP and BJ records. The maximum inter-story drift ratio of the enriched cases ranges from 0.00227 to 0.01498, with two cases exceeding the 1/100 extensive-damage drift threshold. These additional cases show that boundary regions are more difficult for single baseline models, especially for drift-, velocity-, and energy-related responses. Therefore, the revised workflow uses active learning as a numerical enrichment and warning mechanism: high-disagreement candidates should be sent back to OpenSees instead of being accepted only from surrogate predictions.

Table 5. Summary of the active-learning OpenSees enrichment cases added in the revision.

Quantity	Minimum	Median	Maximum
Active-learning score	0.818	0.856	1.000
PGA (g)	0.158	0.425	0.472
Duration (s)	20.76	55.69	72.22
Maximum inter-story drift ratio	0.00227	0.00499	0.01498
Roof displacement (m)	0.0481	0.0977	0.2060
Roof acceleration (m/s^2)	1.945	5.732	8.880
Base shear (N)	3.70×10^5	2.21×10^6	3.38×10^6
Energy-demand proxy	2.93×10^4	4.47×10^5	1.06×10^6

To further test the model-boundary issue raised by the reviewers, three out-of-domain parameter cases and 100 cross-story cases are recalculated with OpenSees. The out-of-domain cases intentionally exceed at least one training bound: rib height is increased to 0.48 m, PGA is increased to 0.60 g, or the pulse-period descriptor is increased beyond the Wenchuan training values. The original ten-story surrogate is then evaluated on these cases only as a diagnostic comparison. The drift relative error ranges from 68.9% to 116.3%, confirming that the model should not be used for extrapolated parameter combinations without OpenSees correction. For cross-story testing, 50 seven-story and 50 thirteen-story equivalent structures are analyzed with the same ground-motion processing. Their mean drift relative errors are 82.0% and 103.6%, respectively, when evaluated by the original ten-story surrogate. These intentionally severe tests support the revised applicability statement: the trained surrogate is a domain-specific screening model, not a transferable predictor for different story numbers or structural configurations.

The left panel of Figure 10 shows that mechanically informed features increase the DNN test mean R^2 from 0.9645 to 0.9686, and the stacked mechanically informed feature surrogate further increases it to 0.9782. This gain is modest but consistent, especially because the ordinary DNN and histogram-gradient boosting baselines already fit the dense OpenSees database well. The middle panel reports the hyperparameter search results, where the smaller two-layer network (96, 64) performs best on the validation set, indicating that a deeper single network does not provide additional benefit for the present sample size. The right panel shows small variation in five-fold cross-validation and supports the prediction stability of the surrogate model within the current LHS parameter envelope.

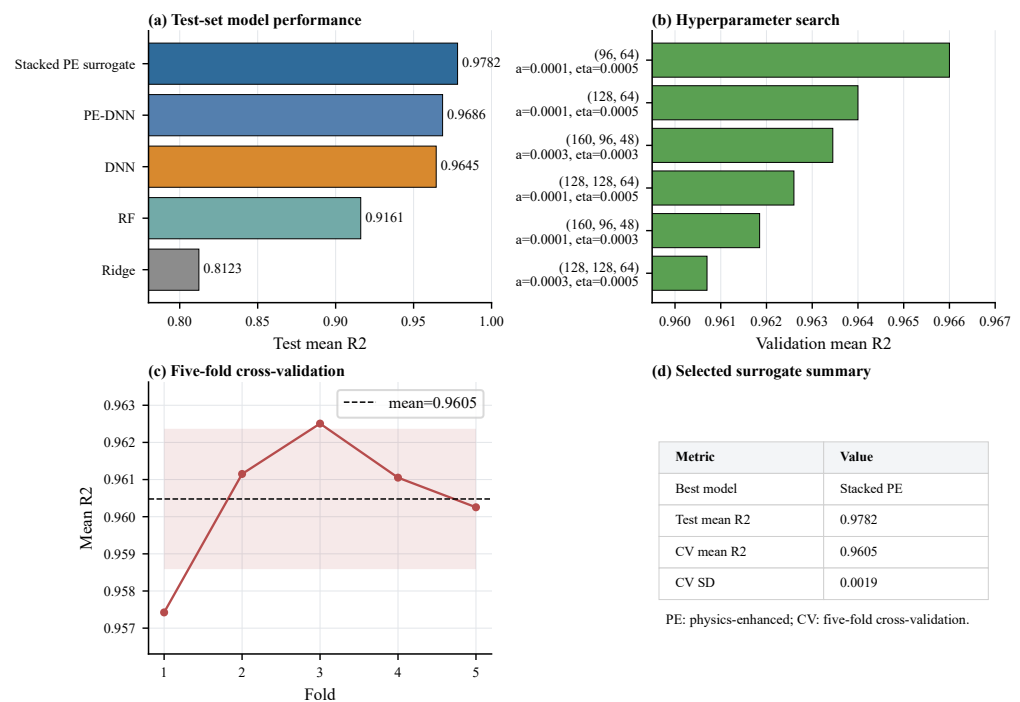


Figure 10. Model performance, hyperparameter search, and five-fold cross-validation. The red line denotes the mean validation trend, and the red shaded band indicates fold-to-fold variability.

Figure 11 further evaluates surrogate-model accuracy from the consistency between predicted values and OpenSees results. Scatter points closer to the diagonal indicate better reproduction of high-fidelity nonlinear time-history analysis. Figure 11, together with Tables 4 and 6, shows that the surrogate model can be used for rapid fragility assessment and inverse optimization rather than only for single-index statistical fitting. The figure should be read as simulation-surrogate validation against withheld OpenSees cases. It demonstrates that the surrogate can efficiently replace repeated OpenSees analyses within the calibrated domain, while additional recalibration is still required for a different finite-element idealization or a new experimental response database.

Tables 4 and 6 and Figures 10 and 11 show that mechanical-feature augmentation improves the prediction of OpenSees samples not used in training. The mean test-set R^2 increases from 0.9645 for the ordinary DNN to 0.9686 for the single MIFE-DNN and to 0.9782 for the stacked mechanically informed feature surrogate. The response-wise comparison shows the largest gain for maximum inter-story drift ratio, which increases from 0.9256 to 0.9541. The proposed method should therefore be interpreted as a mechanically informed feature-enhanced and validation-stacked surrogate model. Its physical consistency comes from the input features representing equivalent stiffness, mass, yield strength, period matching, and strength-demand relations, rather than from hard equation residuals imposed during training.

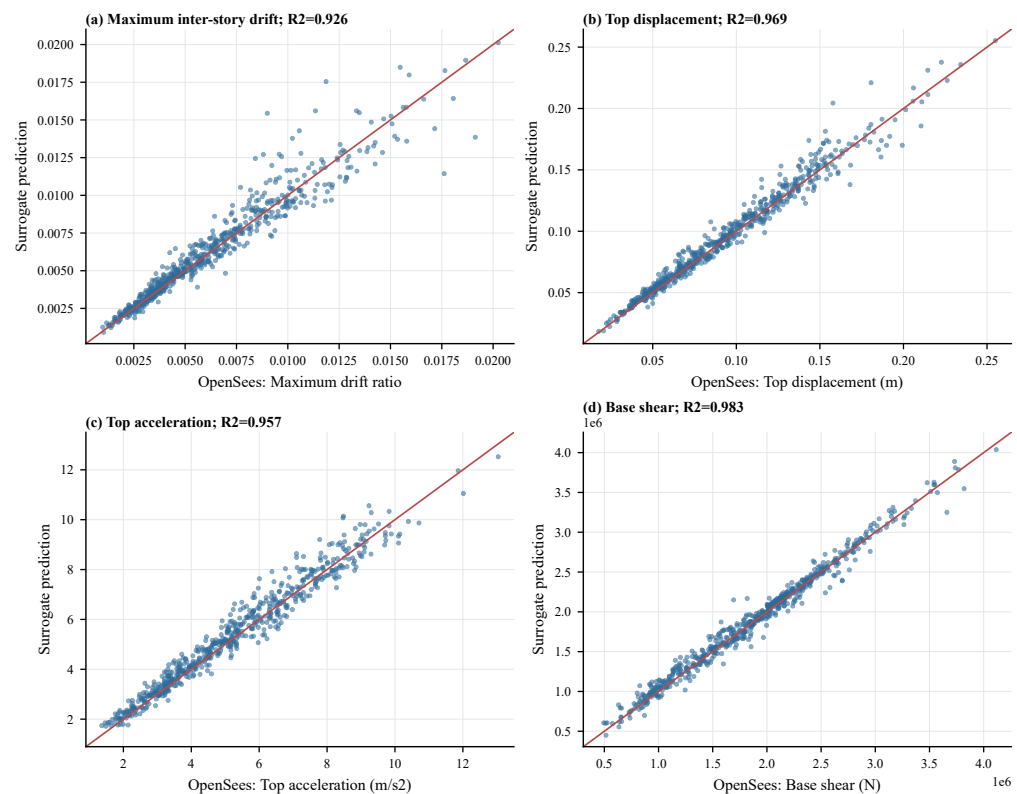


Figure 11. Comparison between mechanically informed feature-enhanced DNN predictions and OpenSees NLTHA results. Blue dots denote individual withheld test samples, and red lines denote the ideal one-to-one prediction reference.

Table 6. Response-wise R^2 comparison between the DNN and mechanically informed feature-enhanced DNN.

Response Metric	DNN	MIFE-DNN Single Model	Stacked Surrogate
Maximum inter-story drift ratio	0.9256	0.9346	0.9541
Roof displacement	0.9641	0.9696	0.9785
Roof velocity	0.9758	0.9786	0.9866
Roof acceleration	0.9560	0.9611	0.9765
Base shear	0.9817	0.9839	0.9873
Energy indicator	0.9839	0.9840	0.9864

3.2. Parameter Importance and Physical Response Drivers

To interpret the prediction basis of the MIFE-DNN, permutation importance is used to rank input variables. The trained model is kept fixed, one input variable is randomly permuted at a time, and the decrease in test-set R^2 is calculated. A larger decrease indicates that the variable is more important for multi-output response prediction. To facilitate comparison among variables, each decrease is divided by the sum of decreases across all variables and plotted as a relative contribution rate in Figure 12.

Figure 12 shows that PGA, rib height, pulse index, damping ratio, and rib spacing are the dominant control factors. To avoid misinterpreting the error increase caused by permutation as a probability contribution, the original permutation importance is normalized by the total importance. The sum of all parameter contributions is therefore 100%. PGA represents input intensity and directly controls inertial force. Pulse index represents the velocity-pulse component of near-fault motion and is linked to displacement demand when the pulse period approaches the first structural period. Rib height and rib spacing affect equivalent lateral stiffness and yield resistance through the rib-grid geometry; in-

creasing rib height generally improves flexural and shear resistance, whereas increasing rib spacing reduces the density of lateral-resisting ribs. Damping ratio affects the dissipation of input energy and therefore reduces velocity, displacement, and drift demands. Lower ranking of some geometric parameters does not mean that they have no engineering significance, but rather that their influence is weaker than ground-motion intensity and key stiffness-related parameters within the present sample space. This ranking is consistent with the parameterized conditional fragility analysis: external intensity and pulse characteristics govern seismic demand, while structural stiffness and strength indicators govern deformation and energy-dissipation capacity.

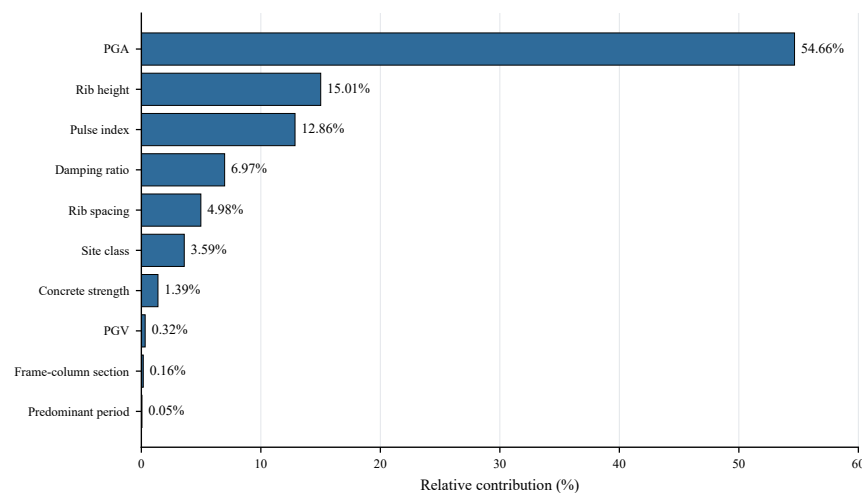


Figure 12. Relative contribution ranking of input parameters in multi-output response prediction.

SHAP analysis is added to provide signed and nonlinear interpretability for drift prediction. To respond directly to the review request, an additional MIFE-DNN drift checkpoint is trained using the same mechanically informed feature set and the 4000-case OpenSees database, and SHAP DeepExplainer is applied to 220 independent test samples with 120 background samples. The checkpoint reaches a drift-response test-set R^2 of 0.9132, a mean absolute error of 0.000672, and a Pearson correlation coefficient of 0.9570. These values are lower than those of the final validation-stacked multi-output surrogate, so the DeepSHAP analysis is used as an interpretability companion for the neural-network feature mechanism rather than as a replacement for the final predictive model. As shown in Figure 13, the largest mean absolute SHAP values for drift are PGA, PGA-stiffness ratio, damping ratio, equivalent stiffness proxy, predominant period, stiffness-mass frequency, equivalent yield-strength proxy, period-matching ratio, and pulse index. The dependence plots in Figure 14 show increasing positive drift contribution with PGA, while larger rib height generally shifts the contribution toward lower drift demand. Figure 15 further shows the coupled influence of PGA with pulse index and rib height with stiffness-mass frequency. Thus, permutation importance and DeepSHAP lead to a consistent engineering interpretation: input intensity and pulse/period compatibility control demand, whereas stiffness, strength, and damping descriptors regulate deformation capacity.

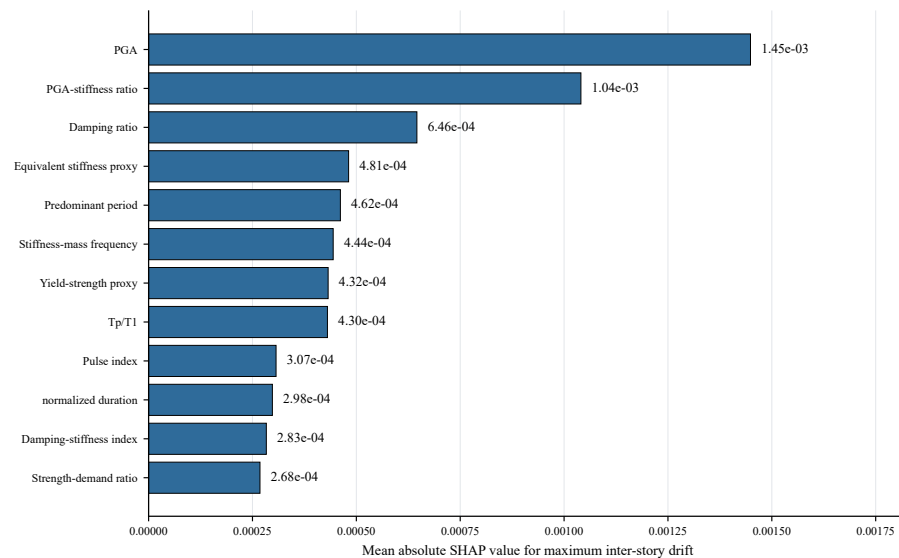


Figure 13. DeepSHAP global importance for maximum inter-story drift prediction using the MIFE-DNN drift checkpoint.

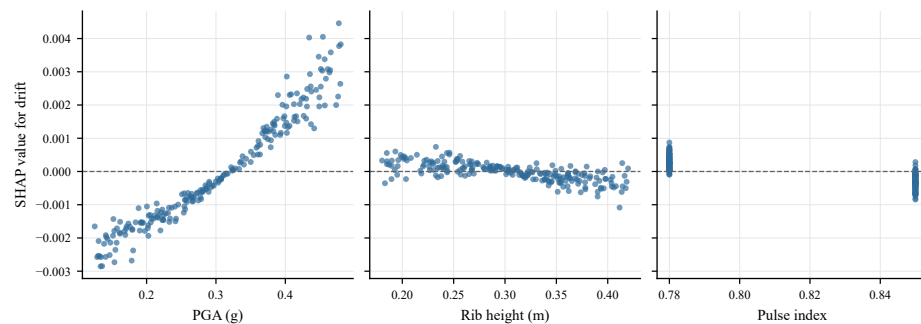


Figure 14. Sample-level DeepSHAP dependence relationships for PGA, rib height, and pulse index. Blue dots denote independent test samples, and dotted lines denote zero-SHAP reference levels.

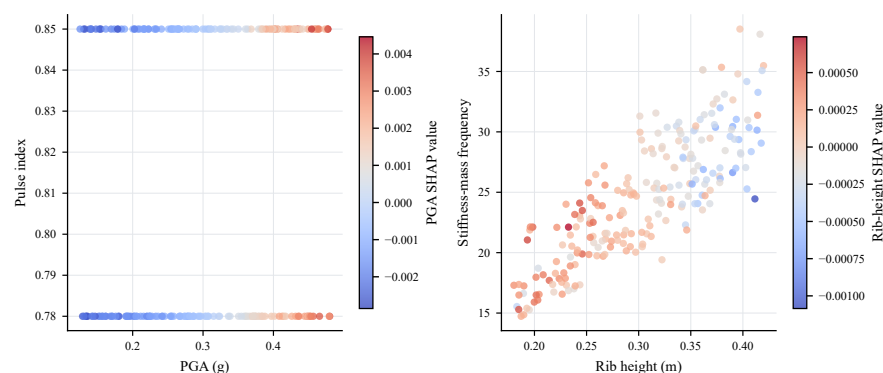


Figure 15. DeepSHAP interaction proxies for PGA–pulse index and rib-height–stiffness–frequency effects.

The 4000-case database also indicates a recurring MCSS damage-demand pattern under pulse-like input: velocity and displacement demands increase more coherently than floor acceleration, and the maximum inter-story drift tends to concentrate in the middle and upper stories when pulse-period matching is unfavorable. This pattern is consistent with the later T_p/T_1 grouping and with the wall-panel damage mapping in Figures 7–9. Therefore, the database is not used only for conventional R^2 fitting; it also identifies the response path by which near-fault pulses translate into drift concentration and wall-panel damage demand.

3.3. Parameterized Conditional Fragility Analysis Based on Inter-Story Drift Ratio

To evaluate the seismic reliability of MCSS under near-fault excitation from a probabilistic perspective, parameterized conditional fragility curves are developed using the 4000 OpenSees nonlinear time-history results. The fragility formulation itself follows the conventional lognormal approach; the contribution of this paper is the use of the surrogate/OpenSees database to accelerate the response evaluation and to connect fragility shifts with mechanically interpretable MCSS parameters. Damage classification follows the idea of using inter-story drift ratio as a structural damage indicator in FEMA 356 and Hazus. Combined with the 1/100 performance control limit, the maximum inter-story drift ratio $\theta_{\max}$ is divided into four damage states: Slight, $\theta_{\max} \geq 1/250$; Moderate, $\theta_{\max} \geq 1/150$; Extensive, $\theta_{\max} \geq 1/100$; and Complete, $\theta_{\max} \geq 1/50$.

It should be emphasized that the curves reflect exceedance probabilities caused by structural-parameter uncertainty, PGA scaling, and duration-window variation under specific Wenchuan near-fault pulse-like records. They are not universal seismic fragility curves that cover different fault mechanisms, propagation paths, and site spectra. They are therefore defined as parameterized conditional fragility curves. The drift thresholds are used because inter-story drift is the most stable global demand measure in the equivalent shear model. Component-level wall-panel damage, connection safety, residual deformation, reinforcement detailing, and reparability are not fully represented by a single drift EDP; these effects are evaluated qualitatively through the wall-panel damage mapping and are listed as mandatory post-screening checks for engineering design use.

The parameterized conditional fragility curve is expressed by a lognormal cumulative distribution function:

$$P(DS \geq ds|PGA) = \Phi \left[\frac{\ln(PGA) - \ln(m_{ds})}{\beta_{ds}} \right], \quad (2)$$

where m_{ds} is the median PGA corresponding to a damage state, β_{ds} is the logarithmic standard deviation, and $\Phi(\cdot)$ is the standard normal cumulative distribution function.

As shown in Table 7 and Figure 16, the PGA-based parameterized conditional fragility curves of MCSS move to the right as the damage state develops from Slight to Complete, and the median PGA increases from 0.214 g to 0.561 g. For the Extensive state corresponding to the performance design limit in this study, the median PGA is 0.442 g, indicating that the structure retains a certain deformation reserve within the sampled space.

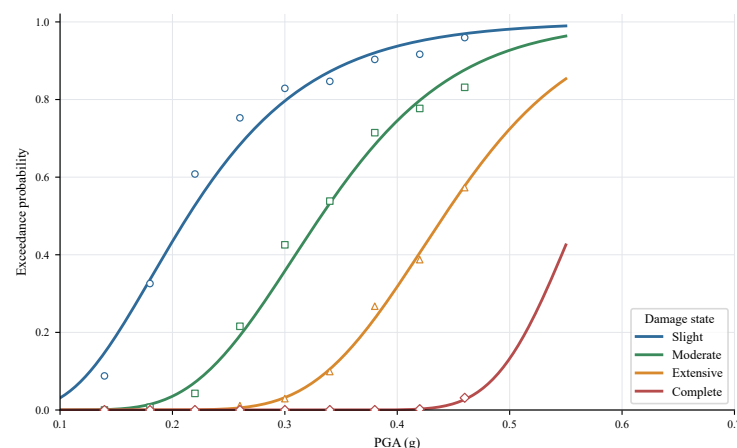


Figure 16. PGA-based parameterized conditional fragility curves of the MCSS. Different marker shapes distinguish Slight, Moderate, Extensive, and Complete damage states.

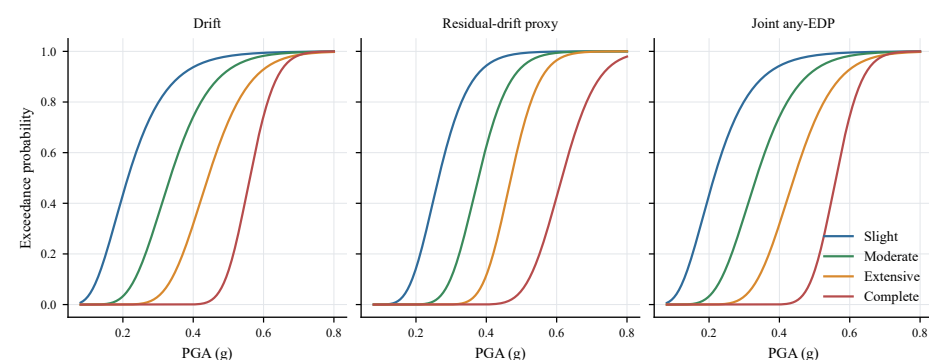
Table 7. Damage-state thresholds and lognormal fitting parameters for MCSS parameterized conditional fragility curves.

Chinese State	Damage State	$\theta_{\max}$ Threshold	Median PGA (g)	β	Exceedance Samples
Slight damage	Slight	0.0040	0.214	0.408	2769/4000
Moderate damage	Moderate	0.0067	0.332	0.281	1579/4000
Extensive damage	Extensive	0.0100	0.442	0.209	608/4000
Complete damage	Complete	0.0200	0.561	0.103	15/4000

To avoid relying on a single global drift EDP, the revision adds a multi-EDP fragility post-processing framework. Four EDP families are evaluated: maximum inter-story drift, wall-panel damage proxy, residual-drift proxy, and demand-capacity-ratio (DCR) proxy. The wall-panel proxy maps drift demand to the previously used four-panel damage interpretation. The residual-drift proxy is estimated conservatively from the OpenSees peak-drift response because residual time-history output was not stored for every original training case. The DCR proxy is derived from the mechanically informed strength-demand ratio and is used as a strength-side screening indicator rather than as a measured component failure variable. A joint “any-EDP” exceedance curve is then fitted by marking a damage state as exceeded if any available EDP proxy exceeds its threshold. Representative fitting parameters are listed in Table 8. As shown in Figure 17, the drift and wall-panel proxies lead to the same median PGA values because the wall-panel mapping is drift-driven in the present equivalent model. The residual-drift proxy gives higher median PGA values, with 0.470 g for the Extensive state, while the DCR proxy does not control failure within the sampled strength range. These results support a cautious engineering use of the fragility curves: global drift remains the primary quantified EDP, but residual deformation, wall-panel damage, and strength-demand checks must be retained as post-screening criteria.

Table 8. Representative multi-EDP fragility parameters added in the revision.

EDP Family	Damage State	Median PGA (g)	β	Exceedance Rate
Drift	Extensive	0.442	0.209	0.152
Residual-drift proxy	Extensive	0.470	0.135	0.079
DCR proxy	Extensive	2.772	0.272	0.000
Joint any-EDP	Extensive	0.442	0.209	0.152
Drift	Complete	0.561	0.103	0.0038
Residual-drift proxy	Complete	0.615	0.129	0.0018
Joint any-EDP	Complete	0.561	0.103	0.0038

**Figure 17.** Multi-EDP fragility curves based on drift, wall-panel, residual-drift, DCR, and joint exceedance proxies.

3.4. Independent Validation and Expanded Ground-Motion Checks

Independent validation is treated in three layers. First, all accuracy metrics for the surrogate are simulation-surrogate validation against withheld OpenSees cases from the

4000-case database. This is the relevant target because the proposed model is intended to reduce repeated nonlinear numerical simulations. Second, the active-learning, out-of-domain, cross-story, and 24 new low-distance interpolation cases are newly calculated OpenSees checks that test numerical reliability near and outside the training boundary. The 24 additional interpolation cases all converged, and the augmented 4024-case retraining check gives a mean multi-output R^2 of 0.9699. Third, the external literature matrix compares the present assumptions with independent experimental and numerical evidence for near-fault slab systems and multi-ribbed composite walls [22–24]. This matrix verifies mechanism consistency, including stiffness degradation, residual deformation, wall-panel damage progression, and the need to limit conclusions to the calibrated equivalent model.

In addition, an independent IDARC anchor check is added using eight fixed PGA cases that were not part of the 4000-case OpenSees training split. The anchor comparison is intentionally reported as a boundary test rather than as a favorable validation claim. As summarized in Table 9, the physically regularized surrogate has a drift MAE of 0.001056 and an acceleration MAE of 130.56 gal relative to the IDARC anchor cases, while several response-wise R^2 values are negative because only eight anchor cases are available and because the surrogate was trained on the OpenSees equivalent-model database rather than on IDARC outputs. This result reinforces the revised usage rule: the MIFE-DNN/stacked surrogate is suitable for OpenSees-domain interpolation and screening, whereas third-party numerical anchors or experimental cases should be used for recalibration before transferring the surrogate to a new modeling or measurement domain.

Table 9. Independent IDARC anchor check for the physically regularized surrogate.

Response Target	<i>n</i>	MAE	RMSE	R^2
Top acceleration (gal)	8	130.56	144.15	−0.581
Top velocity (mm/s)	8	95.95	106.47	−0.630
Top displacement (mm)	8	48.48	49.10	−13.093
Maximum inter-story drift	8	0.001056	0.001080	−5.819
Base shear (kN)	8	1535.67	1568.42	−8.705
Energy-dissipation index	8	0.5305	0.5334	−114.242

The expanded ground-motion check uses the QP, BJ, ISK001_EW, and ISK002_EW records at PGA levels of 0.24, 0.36, and 0.48 g, forming the 12-case four-record auxiliary OpenSees database included in the supplementary files. The external records increase the observed drift demand substantially. The mean maximum inter-story drift is 0.00402 for QP_EW, 0.00410 for BJ_EW, 0.00859 for ISK001_EW, and 0.01804 for ISK002_EW. The maximum drift under ISK002_EW reaches 0.03083, exceeding the Complete-state drift threshold. As shown in Figure 18, record-to-record variability is therefore not a minor detail for near-fault MCSS assessment. The original two-record Wenchuan database is adequate for the proposed surrogate within its training domain, but a broader record suite is required before making regional or code-level fragility claims.

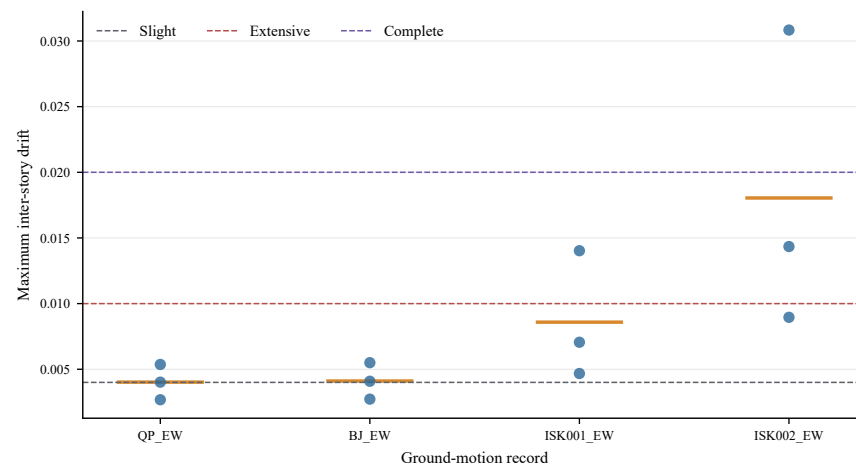


Figure 18. OpenSees response variability for baseline Wenchuan records and two external near-fault records. Blue dots denote individual OpenSees analyses, and yellow lines denote median responses for each record group.

4. Mechanistic Interpretation of Near-Fault MCSS Response

4.1. Floor Acceleration, Velocity, and Displacement Responses

As shown in Figure 19, acceleration decreases from the fifth to the eighth floors, and the floor-acceleration distribution is irregular. This fluctuation in the middle and upper stories is generally associated with higher-mode participation, variation in equivalent story stiffness, and weakening of local whip effects. Structural velocity and displacement generally increase as PGA increases; therefore, these two parameters better reflect cumulative response demand under near-source ground motions.

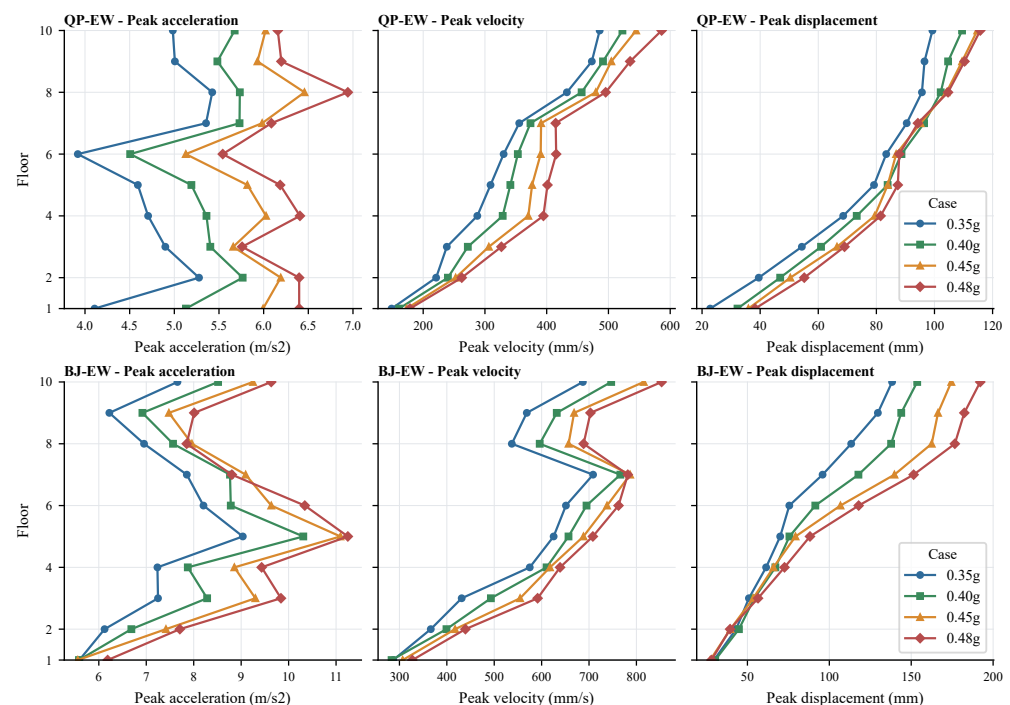


Figure 19. Floor-wise acceleration, velocity, and displacement response distributions under QP and BJ waves.

4.2. Influence of Damping Ratio

The structural damping ratio ε and material loss factor η approximately satisfy $\varepsilon \approx 0.5\eta$. This study does not rebuild the constitutive test model of the infill material, so the damping

variation is not interpreted as the deterministic effect of a new material. Instead, damping ratio is used only as an equivalent parameter for sensitivity analysis. The conventional structural damping ratio is 0.05, and the comparison case is 0.10. QP and BJ waves with PGA of 400 gal are input to calculate the inter-story displacement responses after the damping change, as shown in Figure 20.

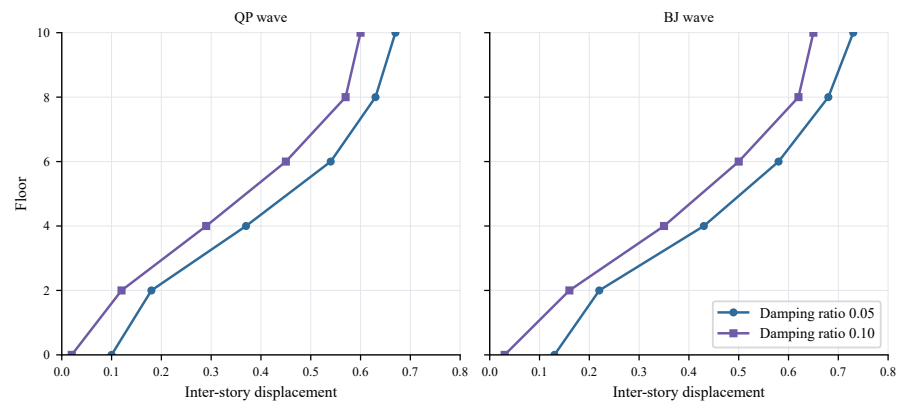


Figure 20. Influence of damping variation on inter-story displacement.

Figure 20 shows that increasing the equivalent damping ratio reduces the inter-story displacement response. This result indicates that damping regulation can improve the seismic response of MCSS.

4.3. Duration Effect

QP and BJ waves with durations of 10, 20, and 30 s and PGA of 400 gal are applied to the MCSS. The corresponding floor acceleration and displacement curves are shown in Figure 21. For shorter ground-motion duration, both floor acceleration and displacement responses decrease. For the QP wave, when the duration is 10 s, the displacement response decreases significantly from the fourth floor upward, and the maximum floor displacement decreases to 77% of the value corresponding to the 30 s duration. However, duration variation has little influence on the acceleration and displacement of the lower structure.

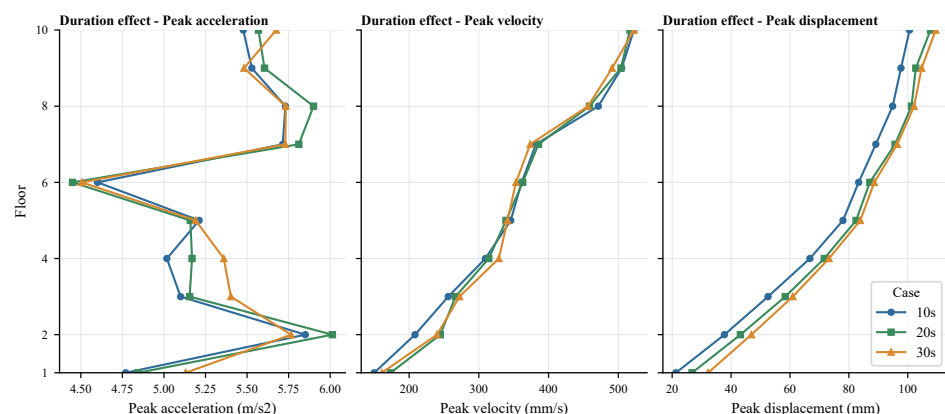


Figure 21. Influence of duration variation on floor acceleration and displacement responses.

5. Surrogate-Based Seismic Design Method

Constrained Design Formulation and Algorithm Comparison

The MIFE-DNN is further used as a design-screening evaluator, but this step is treated as a methodological extension rather than as the main result of the paper. The inverse problem seeks structural parameter combinations that satisfy performance limits under a prescribed seismic input. The design variables include rib spacing, rib height, slab thickness,

concrete strength, frame-column section area, damping ratio, and site class. The objective is to minimize a material-use proxy, subject to $\theta_{\max} \leq 0.01$, roof displacement $u_{\text{roof}} \leq 0.18$ m, and roof acceleration $a_{\text{roof}} \leq 10.0$ m/s².

The MIFE-DNN adopted in this study is a feature-fusion surrogate model with explicit mechanical descriptors. Let the structural parameter vector be x_s , the ground-motion parameter vector be x_g , and the physical prior feature vector be ϕ_p . The network input can be written as $z = [x_s, x_g, \phi_p]$, and the output is $y = [\theta_{\max}, u_{\text{roof}}, v_{\text{roof}}, a_{\text{roof}}, V_{\text{base}}, E]^T$. Network training uses a weighted multi-output mean-squared error:

$$L = \frac{1}{N} \sum \|W_y(f_{\Theta}(z_i) - y_i)\|_2^2 + \lambda \|\Theta\|_2^2, \quad (3)$$

where y_i comes from OpenSees nonlinear time-history analysis, W_y balances responses with different dimensions, and λ is the weight-decay coefficient.

The physical prior features are constructed from low-order structural-dynamics relationships. Equivalent stiffness K_{eq}^* is jointly determined by rib height, rib spacing, slab thickness, column section area, and concrete strength. Equivalent yield strength F_y^* reflects the combined lateral resistance of the frame and rib grid. Mass proxy M^* represents floor inertial demand. Strength-demand ratio ρ_s , PGA-stiffness ratio ρ_k , and damping-stiffness index I_{ξ} are then constructed. These quantities do not replace OpenSees analysis; instead, they explicitly input interpretable mechanical relationships into the neural network.

The inverse-design variable ranges are consistent with the LHS database. Rib spacing s_r ranges from 1.20 to 2.40 m, rib height h_r from 0.18 to 0.42 m, slab thickness t_s from 0.08 to 0.18 m, concrete strength f_c from 30 to 50 MPa, column section area A_c from 0.16 to 0.36 m², damping ratio ζ from 0.035 to 0.120, and site class c_s from I to III. Differential evolution (DE), GA, and PSO all search within these bounds.

Because MCSS damage is not governed by inter-story drift alone, the inverse-design result should pass an additional engineering screening layer before being interpreted as a practical design. This layer includes: (1) wall-panel damage-index limits based on the MLB-1–MLB-4 ductility, stiffness, and Park damage curves; (2) connection and rib-grid constructability checks that prevent unrealistically sparse rib spacing or insufficient rib height; (3) residual-drift and reparability limits when cyclic degradation data are available; and (4) code-based checks on axial compression ratio, reinforcement detailing, and local shear demand. These checks are not all included in the numerical objective function because the present database is a global equivalent-model database. They are therefore stated as mandatory post-screening constraints, which avoids overinterpreting the surrogate optimum as a final engineering design.

To improve reproducibility of the optimization comparison, DE, GA, and PSO use the same surrogate-model evaluator, design-variable bounds, and constraint-penalty function. The penalty function is

$$P = 10^4 \max(0, \theta_{\max} - 0.01)^2 + 10^2 \max(0, u_{\text{roof}} - 0.18)^2 + 10^{-1} \max(0, a_{\text{roof}} - 10.0)^2. \quad (4)$$

DE uses the rand/1/bin strategy, population size 28, maximum iteration number 80, scale factor $F = 0.60$, and crossover probability $CR = 0.70$. GA uses population size 60, maximum generation number 63, crossover probability 0.85, mutation probability 0.08, and tournament size 3. PSO uses 56 particles, maximum iteration number 69, an inertia weight linearly decreasing from 0.90 to 0.40, and individual and global learning factors of 1.60. All three algorithms stop when the maximum iteration number is reached or the best objective improves by less than 1.0×10^{-5} for 15 consecutive generations. The random seed is fixed at 2026.

For seismic input corresponding to intensity 8, site class II, PGA of 0.40 g, and near-fault pulse index of 0.85, the inverse results show that the mechanically informed feature-enhanced surrogate model can rapidly search feasible candidates near the global drift constraint boundary. Under the settings of this study, the mechanically informed feature-enhanced DE method gives a maximum inter-story drift ratio of 0.00966, below the 1/100 control limit, and a roof displacement of 0.172 m, satisfying the 0.18 m control condition.

Figure 22 shows the relationship between inverse-design results and the inter-story drift-ratio limit. The mechanically informed feature-enhanced DE method yields a maximum inter-story drift ratio below 1/100 and close to the constraint boundary. This indicates that the method can avoid overly conservative global-drift design candidates while maintaining the prescribed drift limit, but the candidate still requires the MCSS-specific post-screening checks described above.

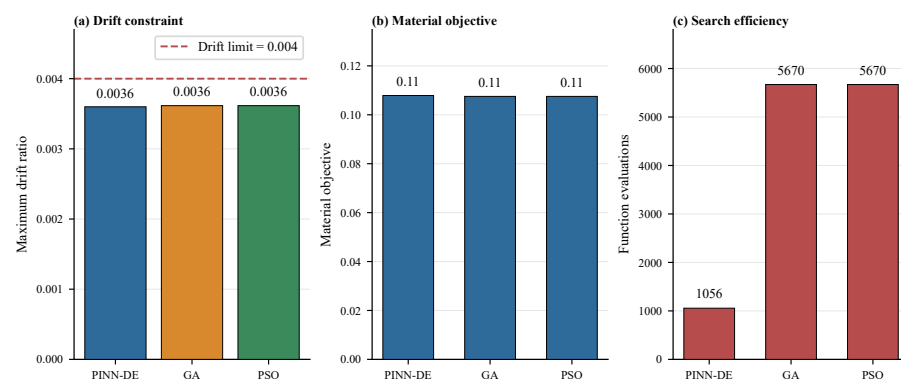


Figure 22. Inverse design comparison under inter-story drift-ratio constraints.

Figure 23 compares the three optimization strategies from the perspective of feasibility. The figure emphasizes the relationship between the maximum inter-story drift ratio, roof displacement, and constraint boundaries obtained by different algorithms. The results show that mechanically informed feature-enhanced DE and GA both obtain feasible solutions satisfying the 1/100 drift limit, whereas the PSO result is close to the constraint boundary but is judged infeasible.

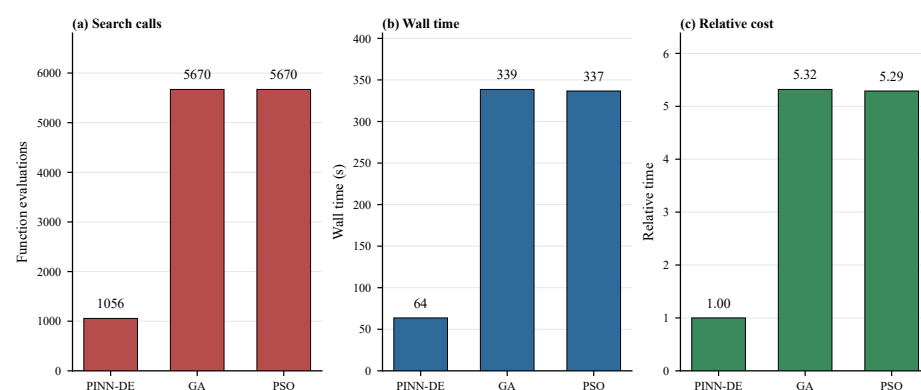


Figure 23. Inverse-design efficiency comparison among mechanically informed feature-enhanced differential evolution, GA, and PSO.

Table 10 quantitatively compares feasibility, material index, response constraints, and computational cost. Mechanically informed feature-enhanced DE achieves a feasible solution with 1792 function evaluations. GA also obtains a feasible solution but requires 3780 function evaluations. PSO performs 3864 evaluations but does not obtain a feasible solution satisfying the inter-story drift-ratio constraint. Therefore, the seemingly lowest PSO material index should not be interpreted as the preferred design. Ta-

ble 10 and Figure 23 jointly show that surrogate-based inverse design should be used as a rapid candidate-generation method. Final adoption still requires wall-panel damage, connection safety, residual deformation, and detailing checks beyond the global drift and roof-response constraints.

Table 10. Inverse-design efficiency comparison among mechanically informed feature-enhanced differential evolution (MIFE-DE), GA, and PSO.

Algorithm	Feasible	Material Index	$\theta_{\max}$	u_{roof} (m)	Evaluations	Time (s)	s_r (m)	h_r (m)
MIFE-DE	Yes	0.1383	0.00966	0.172	1792	11.44	2.378	0.257
GA	Yes	0.1344	0.00996	0.173	3780	23.86	2.400	0.259
PSO	No	0.1342	0.01000	0.173	3864	23.45	2.400	0.257

6. Discussion

The main finding of this study is not that a neural network can fit OpenSees output, but that mechanically normalized features help organize a large nonlinear time-history database into interpretable response and fragility patterns. The improvement over the ordinary DNN is numerically modest because the 4000-case database is already dense and the ordinary DNN, histogram-gradient boosting, and validation-stacked baselines are strong. Therefore, the term mechanically informed feature-enhanced is used deliberately: the model embeds equivalent stiffness, yield strength, mass, and demand-capacity indicators as input features, but it is not claimed to be a full physics-informed neural network with governing-equation residuals or hard equilibrium constraints. The value of the physical features lies in improving drift prediction, stabilizing cross-validation, and making the dominant response drivers traceable to intensity, pulse index, stiffness, damping, and rib geometry.

The database-level response pattern provides a second line of evidence. The floor-response and Wenchuan damage-mapping analyses indicate that acceleration demand is irregular across floors, whereas velocity, displacement, and inter-story drift provide a clearer path from pulse-like input to damage demand. The middle and upper stories are repeatedly identified as critical regions under unfavorable pulse-period matching, and the four-wall-panel damage curves show that the same global displacement demand may correspond to different ductility, stiffness, and Park damage levels. This pattern explains why the fragility analysis is based on inter-story drift but the design extension requires additional wall-panel damage and connection-safety screening.

The residual diagnostics, active-learning enrichment, expanded ground-motion checks, and out-of-domain/cross-story checks provide a clearer boundary assessment for the surrogate model. The residuals do not show monotonic amplification with PGA within the sampled interval, and the inverse-design optimum remains inside the LHS envelope. However, the 16 active-learning OpenSees cases confirm that high-disagreement and near-boundary regions are more difficult for purely surrogate-based prediction. The external-record analyses further show that record-to-record variability can change drift demand by several times, and the cross-story tests show large errors when the ten-story surrogate is applied to seven-story or thirteen-story systems. For this reason, the surrogate model should be used for interpolation and near-boundary screening within the ranges in Table 1; high-disagreement, external-record, out-of-domain, or cross-configuration candidates are recalculated by OpenSees before being used for fragility or design decisions.

These limitations are central to the intended use of the revised workflow. The 4000-case database improves coverage within the selected structural and ground-motion ranges, but it does not define a universal seismic-response model for all MCSS variants, diaphragm con-

ditions, connection details, or near-fault records. Likewise, the mechanically informed features are descriptors of the adopted equivalent OpenSees model. They improve interpretability and reproducibility, but they do not replace component-level calibration or additional records when the method is transferred to a different structural typology, story number, site condition, or design objective. A practical extension route is therefore required before transfer: (1) construct story-specific or configuration-specific OpenSees subsets instead of applying the ten-story surrogate directly; (2) use transfer learning only after recalculating representative boundary cases for the new structure or record suite; and (3) update the admissible parameter envelope in Table 1 before re-estimating fragility curves. These steps are listed as required recalibration actions, not as completed validation in the present study.

The external validation matrix also changes the interpretation of experimental support. The near-fault slab-system shake-table tests of Benavent-Climent et al. [22], the ten-story frame-supported multi-ribbed composite wall shaking-table/numerical study [23], and the low-reversed cyclic wall-panel tests [24] support the mechanical plausibility of stiffness degradation, residual deformation, drift-based damage progression, and wall-panel damage mapping. The numerical accuracy claims, however, are based on OpenSees-domain tests, including the original withheld samples, active-learning enrichment, external-record OpenSees checks, OOD/cross-story OpenSees checks, and the newly added 24-case interpolation audit. This separation keeps the surrogate-model claim aligned with its numerical training target.

The FSWS comparison is retained only as a controlled contextual discussion of structural response tendency, not as a direct superiority claim or a full equivalence proof between two different systems. The FSWS and MCSS models use the same LHS sample size, the same 51MZQ and 51SFB near-fault east-west records, the same PGA scaling range, and the same nonlinear time-history solution procedure. Nevertheless, their mass distribution, stiffness composition, hysteretic mechanism, and energy-dissipation path cannot be made identical without changing the physical meaning of the two structural systems. Therefore, the comparison below is interpreted through normalized or matched-input indicators rather than as an absolute claim that one structural system is universally superior.

As shown in Figure 24, after the 4000 nonlinear time-history data are grouped by PGA interval, the energy-demand proxies of the two structural systems show clear differences. Energy demand increases with PGA for both systems. In the 0.28–0.36 g interval, the median energy-demand proxy of MCSS is 5.18×10^5 N m, higher than the FSWS value of 4.78×10^5 N m. In the 0.36–0.48 g interval, the MCSS median is 7.73×10^5 N m, higher than the FSWS value of 7.00×10^5 N m. Under the current equivalent modeling and energy-proxy definition, this result suggests stronger energy participation of MCSS under high-PGA pulse-like input, but it should be read together with the unit-mass-normalized energy proxy reported below.

Figure 25 further compares the seismic reliability of the two structural systems from a probabilistic perspective, with fitting parameters summarized in Table 11. For the Moderate and Extensive states, the MCSS parameterized conditional fragility curves are generally located to the right of the FSWS curves, indicating that a higher PGA is required to reach the same exceedance probability under matched input and response-processing assumptions. For the Extensive state, the median PGA increases from 0.396 g for FSWS to 0.443 g for MCSS, and the sample exceedance rate decreases from 23.5% to 15.2%. For the Complete state, the median PGAs of the two systems are close, but the sample complete-damage exceedance rate of FSWS is 2.05%, higher than the 0.38% of MCSS. These results support a cautious interpretation: within the adopted equivalent models and parameter ranges,

MCSS shows lower severe-damage exceedance tendency, but broader design conclusions require additional normalization for mass, stiffness, construction cost, and reparability.

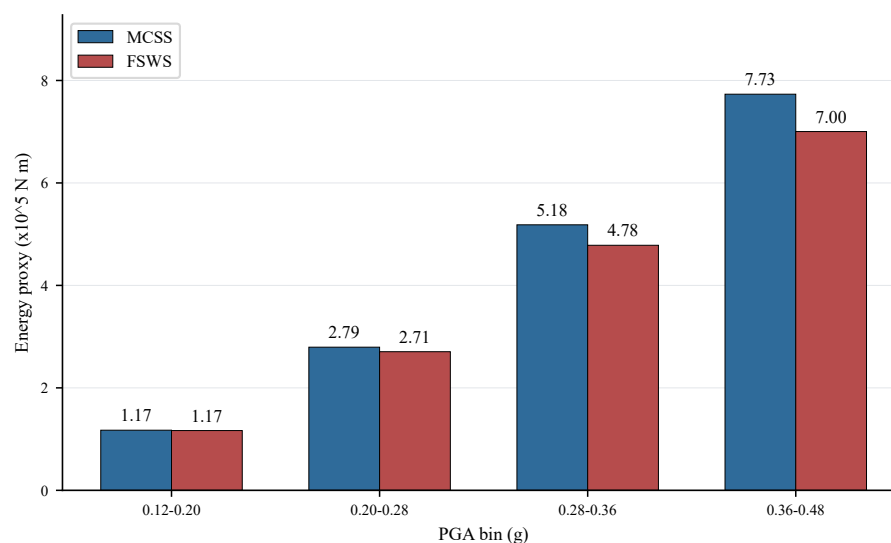


Figure 24. Comparison of cumulative energy-demand proxy between MCSS and FSWS in different PGA intervals.

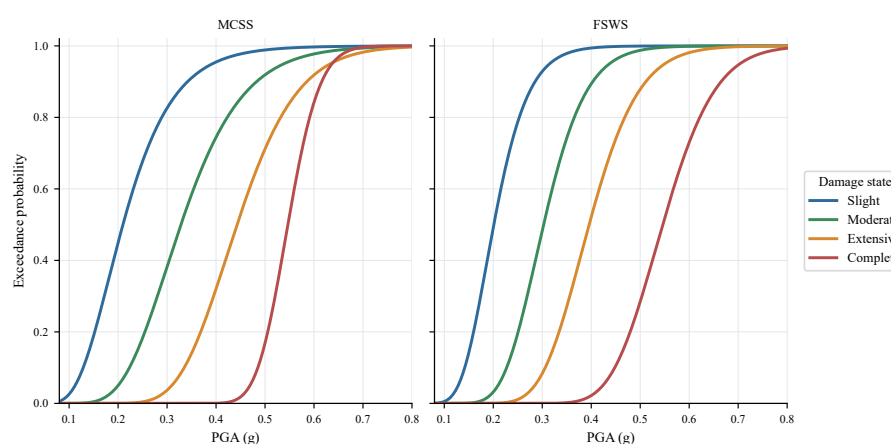


Figure 25. Comparison of PGA-based parameterized conditional fragility curves between MCSS and FSWS.

Table 11. Fitting parameters and sample exceedance rates of MCSS and FSWS parameterized conditional fragility curves.

System	Damage State	Drift Limit	Median PGA (g)	Log. Std. β	Exceedance Rate
MCSS	Slight	0.0040	0.210	0.381	0.692
MCSS	Moderate	0.0067	0.328	0.301	0.395
MCSS	Extensive	0.0100	0.443	0.218	0.152
MCSS	Complete	0.0200	0.547	0.093	0.004
FSWS	Slight	0.0040	0.201	0.273	0.748
FSWS	Moderate	0.0067	0.303	0.223	0.470
FSWS	Extensive	0.0100	0.396	0.200	0.235
FSWS	Complete	0.0200	0.543	0.070	0.021

The discussion therefore closes the loop of the paper. The surrogate model provides fast and interpretable response prediction; the permutation-importance and SHAP results identify how near-fault pulse characteristics and MCSS stiffness-related variables control damage demand; the multi-EDP fragility post-processing shows why global drift should

be supplemented by wall-panel, residual-drift, and strength-demand checks; the design extension shows how the surrogate can generate candidates only after additional MCSS-specific damage constraints are imposed; and the FSWS comparison provides contextual evidence for MCSS energy participation without overstating structural superiority.

7. Data Availability and Applicability Limits

The 51MZQ (Qingping) and 51SFB (Bajiao) east-west, north-south, and vertical strong-motion records used in this study are from the China Strong Motion Networks Center (<https://www.csmnc.net/>). Downloading, citing, and redistributing the original records should comply with the data-source license. OpenSees is available from the official OpenSees platform (<https://opensees.berkeley.edu/> (accessed on 16 July 2026)). The OpenSees Tcl model scripts, LHS input parameter table, 4000-case MCSS response database, 4000-case FSWS comparison database, processed Wenchuan-wave data, four-wall-panel damage-index table, Python training scripts, optimization algorithm configuration files, active-learning OpenSees enrichment files, SHAP analysis files, multi-EDP fragility files, external near-fault-record response checks, out-of-domain/cross-story OpenSees files, and main plotting scripts generated in this study are organized as Supplementary Data S1–S6. If a public repository is required by the journal, the authors will upload the data to Zenodo or Figshare before acceptance and add the data DOI to the final manuscript. The present data package supports reproducibility of the numerical workflow, including the 16 added active-learning OpenSees cases, 12 external-record OpenSees checks, 3 out-of-domain checks, and 100 cross-story checks, but it does not remove the need for future validation using broader near-fault records, additional structural configurations, or component-level experimental measurements.

To examine the boundary risk of the surrogate model, residual diagnostics of the test set with respect to PGA and pulse index are plotted in Figure 26. The residuals do not show monotonic amplification with PGA within the main sample range. The inverse-design optimum also lies within the LHS parameter envelope defined in Table 1; therefore, the inverse result is not interpreted as an extrapolated design outside the parameter space. In addition, the active-learning enrichment in Table 5 adds 16 OpenSees cases selected from high-disagreement and near-boundary candidate samples. These added analyses show that boundary samples can reach larger drift demand and should be recalculated numerically before final fragility or design use. Because the enrichment remains within the current LHS ranges and Wenchuan record family, this study limits its claim to interpolation and near-boundary reliability within the sampled domain.

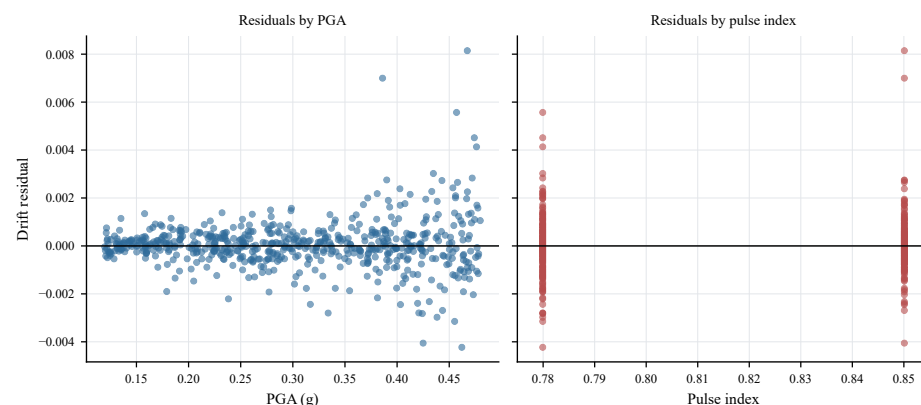


Figure 26. Residual diagnostics of the mechanically informed feature-enhanced DNN predictions. Dots denote test-sample residuals, and reference lines denote zero-residual or fitted trend levels.

The out-of-domain and cross-story OpenSees checks are shown in Figure 27. Blue dots denote recalculated OpenSees cases, the dotted line denotes the ideal one-to-one reference, yellow markers identify out-of-domain parameter checks, and red markers identify cross-story transfer checks.

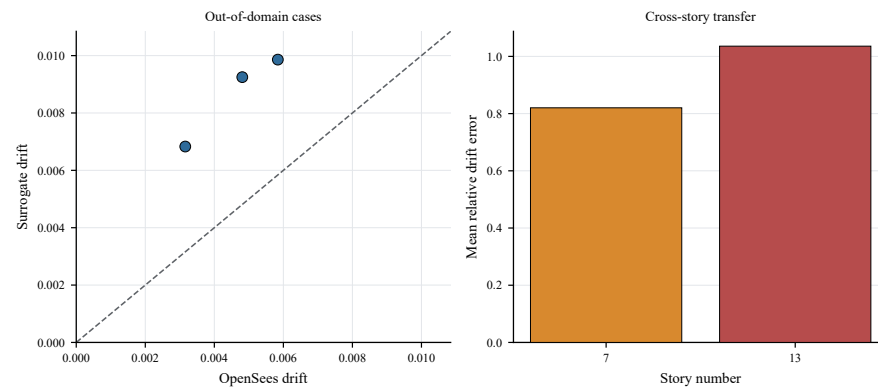


Figure 27. Out-of-domain and cross-story OpenSees checks against the original ten-story surrogate. Blue dots denote recalculated OpenSees cases, the dotted line denotes the ideal one-to-one reference, yellow markers identify out-of-domain parameter checks, and red markers identify cross-story transfer checks.

The destructive potential of near-fault pulse-like ground motions is controlled not only by PGA, but also by the relationship between pulse period and structural period. This study groups samples by T_p/T_1 , where $T_1 = 0.85$ s is the first period of the OpenSees benchmark model. Figure 28 shows that when $T_p/T_1 \geq 0.78$, the median PGA for the Extensive state is 0.410 g and the sample exceedance rate is 19.8%. When $T_p/T_1 < 0.78$, the median PGA is 0.481 g and the sample exceedance rate is 10.6%. This result indicates that inter-story deformation demand in MCSS increases significantly when the pulse period is closer to the structural period.

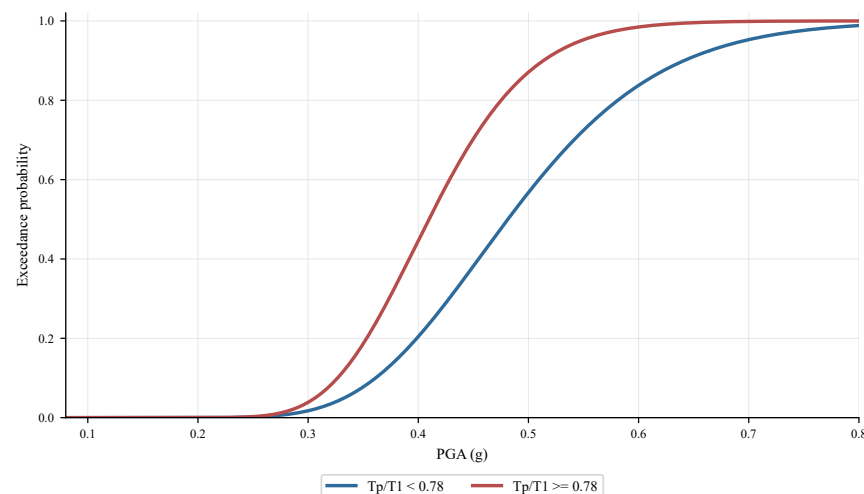


Figure 28. Parameterized conditional fragility curves of MCSS for different T_p/T_1 intervals.

The comparison between MCSS and FSWS uses the same number of stories, story height, story mass setting, ground-motion input, and PGA scaling range where possible. This setting improves comparability of dynamic input and response metrics, but it cannot eliminate differences in stiffness composition and hysteretic mechanism. To reduce the influence of structural quantity on energy comparison, this study further reports the unit-mass-normalized energy-demand proxy, as shown in Figure 29. The results still show

that MCSS has a higher unit-mass energy-demand proxy in the higher PGA interval. Broader structural-system comparison requires stricter matched-period or matched-initial-stiffness comparisons, material cost, residual inter-story drift ratio, repair cost, and post-earthquake recoverability indicators, which are outside the claim scope of the present MCSS surrogate model.

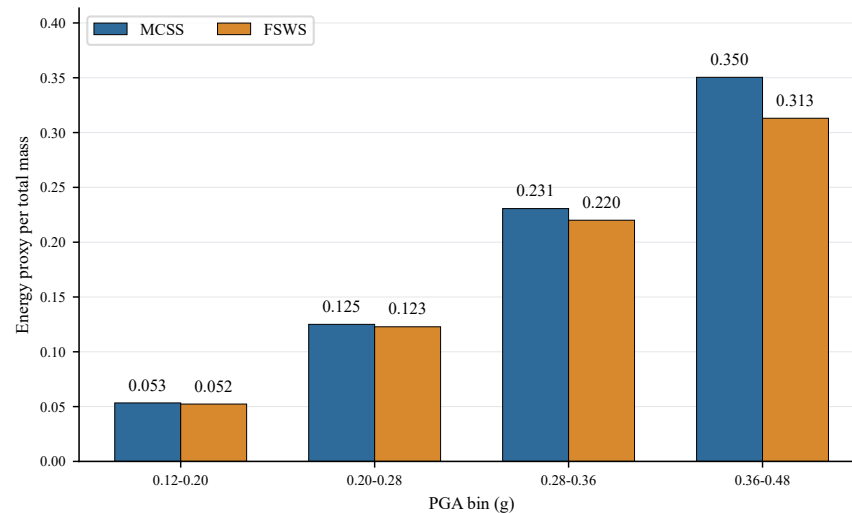


Figure 29. Comparison of unit-mass-normalized energy-demand proxy between MCSS and FSWS.

8. Conclusions

This study addresses the rapid prediction and fragility assessment of MCSS under near-fault pulse-like ground motions by combining a 4000-case OpenSees nonlinear time-history database with a mechanically informed feature-enhanced DNN surrogate model. The main conclusions are as follows.

First, mechanically normalized physical features provide a useful but bounded enhancement to data-driven surrogate modeling. By embedding equivalent stiffness, equivalent yield strength, mass proxy, strength-demand ratio, PGA-stiffness ratio, and damping-stiffness indicators as explicit inputs, the MIFE-DNN obtains a modest and consistent improvement over the ordinary DNN, especially for maximum inter-story drift ratio. The active-learning enrichment further shows that high-disagreement boundary samples should be corrected through OpenSees recalculation rather than accepted from the surrogate alone. The added out-of-domain and cross-story checks confirm that the ten-story surrogate should not be transferred to extrapolated parameters or different story numbers without new OpenSees training data. The result supports the use of mechanically informed feature augmentation for interpretable MCSS response prediction, but it should not be interpreted as a full physics-informed neural network with hard governing-equation constraints.

Second, the large OpenSees database reveals a coherent near-fault damage-demand path for MCSS. Permutation importance and SHAP consistently show that PGA, pulse index, period matching, rib height, rib spacing, and damping-related descriptors dominate drift demand. Under unfavorable pulse-period matching, deformation demand concentrates in the middle and upper stories, and wall-panel damage mapping shows that the same global displacement demand can correspond to different ductility, stiffness, and Park damage levels. These findings explain why MCSS fragility assessment should combine global drift demand with component-level damage interpretation.

Third, the parameterized conditional fragility curves quantify the seismic risk of MCSS within the sampled near-fault parameter space. The median PGA increases from 0.214 g for Slight damage to 0.561 g for Complete damage, and the Extensive-state threshold associated

with the 1/100 drift limit has a median PGA of 0.442 g. The added multi-EDP fragility analysis shows that the residual-drift proxy gives a higher Extensive-state median PGA of 0.470 g, while the DCR proxy does not control failure in the sampled strength range. The T_p/T_1 grouping and the external-record OpenSees checks further show that pulse-period matching and record-to-record variability can substantially increase deformation demand, confirming that PGA alone is insufficient for near-fault MCSS assessment.

Finally, the surrogate model can support rapid design screening, but only with MCSS-specific post-checks. The inverse-design example reduces the number of surrogate evaluations needed to find a feasible global-drift candidate, yet final engineering use must also check wall-panel damage, connection safety, residual deformation, constructability, and code detailing. External experimental and numerical literature supports the adopted mechanism interpretation, while the reported prediction accuracy quantifies how well the surrogate replaces the calibrated OpenSees equivalent model. The MCSS-FSWS comparison is therefore presented as contextual evidence under matched input assumptions. It suggests favorable severe-damage tendencies for MCSS in the present database, but it should not be read as a general structural-system superiority claim without stricter normalization of mass, stiffness, cost, repairability, and record-to-record variability.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app16147225/s1>; Supplementary Data S1: 4000-case MCSS OpenSees NLTHA database and LHS samples; Supplementary Data S2: 4000-case FSWS comparison database and LHS samples; Supplementary Data S3: representative OpenSees model scripts and batch-analysis scripts; Supplementary Data S4: Python scripts and metrics for surrogate-model training, stacking, active learning, inverse design, DeepSHAP interpretation, IDARC anchor checking, and figure regeneration; Supplementary Data S5: wall-panel experimental damage data, processed Wenchuan ground-motion data, response spectra, floor-response profiles, and damage-index mapping data; Supplementary Data S6: external-record OpenSees checks, multi-EDP fragility files, out-of-domain and cross-story checks, DeepSHAP checkpoint outputs, IDARC anchor validation metrics, and the external validation matrix.

Author Contributions: Conceptualization, Y.Z. and S.J.; methodology, Y.Z.; software and numerical simulation, Y.Z.; experimental investigation, S.J.; formal analysis, Y.Z.; data curation, Y.Z.; writing-original draft preparation, Y.Z.; writing-review and editing, S.J. and Z.W.; supervision, S.J.; project administration, S.J. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used to support the findings of this study are available in the supplementary data package. Supplementary Data S1 contains the 4000-case MCSS OpenSees nonlinear time-history analysis database and LHS samples. Supplementary Data S2 contains the 4000-case FSWS comparison database and LHS samples. Supplementary Data S3 contains representative OpenSees model scripts and batch-analysis scripts. Supplementary Data S4 contains Python scripts and metrics for surrogate-model training, hyperparameter search, stacking, active-learning OpenSees enrichment, inverse design, DeepSHAP interpretation, IDARC anchor checking, and figure regeneration. Supplementary Data S5 contains wall-panel experimental damage data, processed Wenchuan ground-motion data, response spectra, floor-response profiles, and damage-index mapping data. Supplementary Data S6 contains the external-record OpenSees response-variability cases, multi-EDP fragility post-processing files, out-of-domain and cross-story OpenSees checks,

MIFE-DNN DeepSHAP checkpoint outputs, independent IDARC anchor validation metrics, and the external experimental/numerical validation matrix. Additional files related to the original strong-motion records are available from the corresponding author upon reasonable request, subject to the data-source license.

Conflicts of Interest: The authors declare no conflicts of interest.

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