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A COMPARATIVE ASSESSMENT OF MECHANISTIC AND DATA-DRIVEN MODELS TO ESTIMAE BUILDING SEISMIC RESPONSES

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Abstract

The second-generation performance-based seismic design (PBSD) framework enables structural engineers to target specific stakeholder-drive building performance objectives. However, due to the labor-intensive and computationally processes of performing iterative response history analyses (NRHAs) and subsequent damage, loss, and downtime assessments, it has not been widely adopted in engineering practice. To address this challenge, several simplified methodologies have been developed for estimating building seismic response demands (i.e. so-called engineering demand parameters). One common theme among these models is that they are all rooted in the fundamental principles of structural dynamics and beam theory. However, while some rely solely on these basic physics and engineering principles, others have attempted to integrate basic statistical regression using structural response data generated from NRHAs performed on parametric structural models. In this study, the authors lay out a spectrum of methodologies for estimating structural response demands to be utilized in PBSD. On one end of the spectrum is a simplified purely mechanistic method, which is often preferred by practicing engineers because it is typically highly generalizable and easy to interpret. However, this method often relies on many simplifications which can influence the accuracy of the response estimates. On the other end of the spectrum is a purely data-driven model which utilizes parametric datasets generated from NRHAs, which is often viewed as a black box. However, these models are less reliant on the convenient simplifications that are adopted in the simplified mechanistic models and thus might achieve higher accuracy. Between these two extremes, there are models that combine elements of basic physics and statistical learning. This paper starts by introducing the development of a comprehensive database, which includes seismic designs of 621 steel moment resisting frames (SMRFs), the corresponding nonlinear structural models, and associated seismic responses (i.e., peak story drifts, peak floor accelerations, and residual story drifts). Then four existing methodologies that fall within the spectrum of seismic response estimation approaches are introduced, critically examined to reveal their benefits and drawbacks, systematically evaluated to quantitatively illustrate the accuracy. Inspired by these existing methods, one hybrid (mechanistic + data-driven) and one purely data-driven models are rigorously developed via training, testing, and validating against the database. Finally, a comparative assessment among mechanistic, hybrid, and data-driven models is performed.

Keywords: seismic response estimation; mechanistic models; data-driven models; steel moment resisting frames

1 Introduction

Currently, several simplified methodologies have been developed and used to estimate seismic drift demands in buildings [1–8]. Some of these techniques are derived solely based on classical mechanics (e.g., shear and flexural beam theory), structural dynamics, and/or linear models coupled with static analyses (referred to as mechanistic models in the remainder of this paper) [1–3], which are often preferred by practicing engineers because they are typically highly generalizable and easy to interpret. However, these methods often rely on many simplifications, which can influence the accuracy of response estimates. Moreover, the assumptions underlying these models may not be applicable to specific conditions. Some other methods [4–6] have been developed based on some combinations of mechanistic models and statistical approaches (e.g., linear regression and other machine learning techniques) (referred to as hybrid models in the remainder of this paper). These models strike a balance between interpretability and applicability, but the coefficients involved in these models are not derived through a rigorous statistical approach. The remaining methods (referred to as data-driven models) [7,8] are proposed using some state-of-the-art machine learning models (e.g., artificial neural network). While these methods are less reliant on convenient simplifications and tend to achieve a higher accuracy, the excessive use of statistical derivations might render them difficult to interpret and less likely to be adopted by structural engineers.

The aforementioned methodologies have greatly enhanced our ability to rapidly estimate structural response demands. However, the following common limitations still exist in their development and implementation: *Method:* these existing approaches either rely on a series of simplifications or involve relatively complex deep learning models, both of which pose an impediment to their adoption in structural engineering practice. *Data used for calibration and/or validation:* most of the available methods are validated against a few (three to five) buildings subjected to a very small number of ground motions (maximum of five). As a result, whether they can provide reliable prediction under a broad range of conditions remains unknown. *Model development and testing approach*: For the existing data-driven or hybrid (mechanistic + data-driven) methods, none of them utilized rigorous model performance evaluation, which, again, brings into question the breadth of their applicability. A rigorous data-driven model development and evaluation procedure would include training, testing, and validating using three different datasets without any overlaps. The validation set should be independent of the training and testing sets. *Prediction accuracy*: most of the existing methods are evaluated using a single error metric (e.g., mean squared error, relative difference, or mean absolute relative deviation), which only reveal partial information about the model accuracy. Ideally, the proposed methods should be assessed such that their accuracy are fully transparent to the users. To address these limitations, there is a need to develop a framework that strikes a balance among accuracy, convenience, and interpretability. Additionally, newly developed models should be developed using a rigorous process and large diverse dataset, then evaluated using a range of error indicators.

This study introduces a framework to develop data-driven and hybrid (mechanistic + data-driven) models for estimating seismic story drift demands of steel moment resisting frames (SRMFs). A spectrum of methodologies for estimating structural response demands are presented. On one end of the spectrum is a simplified purely mechanistic model and on the other end is a purely data-driven model that utilizes parametric datasets generated from NRHAs. Between these two extreme cases, there are models that combine elements of basic mechanics and statistical learning. As shown in Fig. 1, the paper starts by introducing the development of a comprehensive database that includes seismic designs for 621 buildings, the corresponding ready-to-run OpenSees [9] nonlinear structural models, and structural responses obtained by subjecting them to 240 ground motions. The database also includes the response of a subgroup of 100 buildings subjected to three groups of systematically selected site-specific ground motions (different from the 240 used to develop the models) at the service-level earthquake (SLE), design-based earthquake (DBE), and maximum considered earthquake (MCE) levels. Four previously developed methodologies that fall within the spectrum of seismic response estimation approaches are briefly introduced, critically examined to reveal their benefits and drawbacks, and quantitatively evaluated. Inspired by these existing methods, one hybrid and one purely data-driven models are rigorously developed via training, testing, and validating against the database. Finally, a comparative assessment among mechanistic, hybrid, and data-driven models is performed.

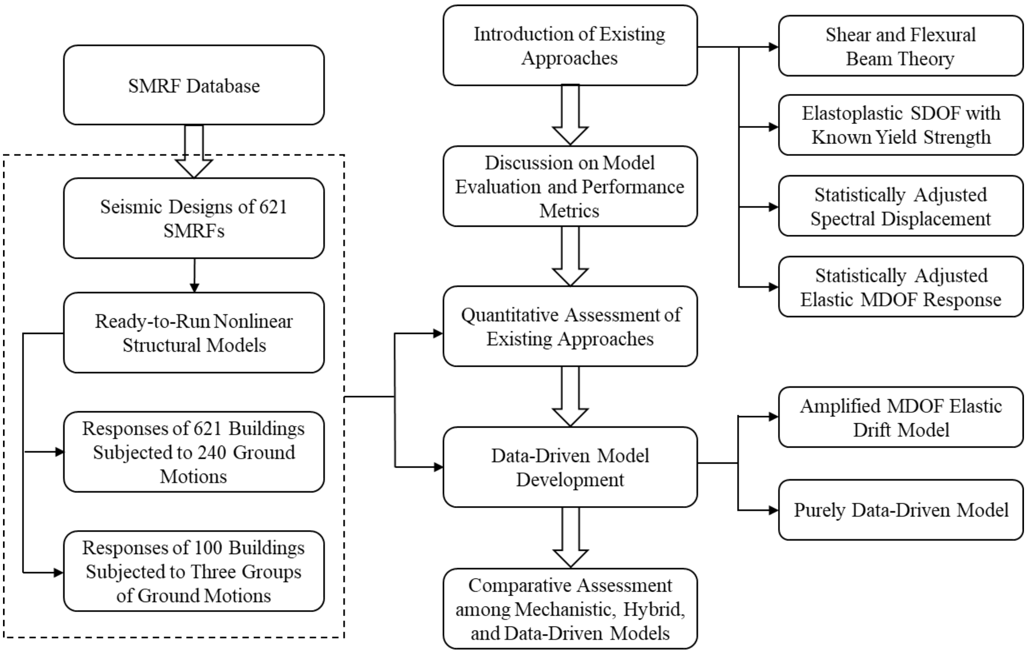

Fig. 1 – Overview of study

2. Database of SMRF Designs, Nonlinear Models and Seismic Responses

As explained in the Introduction section, a common limitation of the existing simplified seismic response estimation methodologies is that they were all validated or tested on a relatively limited dataset (e.g., three buildings subjected to five ground motions). This is attributed to the fact that a large database of building designs, nonlinear structural models and responses under earthquake ground motions is currently unavailable. Such a comprehensive database would be invaluable in training, testing, and/or validating seismic response estimation methods. As part of the current study, 621 SMRFs with various geometric configurations and loads are designed in accordance with current building codes and design standards [10–13]. Based on the developed code-conforming designs, two-dimensional (2D) nonlinear structural models are constructed in OpenSees. NRHAs are then performed on these models by subjecting them to a set of 240 ground motions and corresponding engineering demand parameters (EDPs) (peak story drifts, peak floor accelerations, and residual story drifts) are extracted. Additionally, the EDPs for a subgroup of 100 SMRFs subjected to three groups of site-specific ground motions (with 40 in each) at the SLE, DBE, and MCE levels, are also obtained. The overview of the database is presented in Fig. 2.

3. Existing Simplified Methods for Estimating Seismic Drift Demands

3.1 Overview

Within the current literature, there are several simplified methodologies for estimating seismic drift demands. One common theme among these methods is that they are all rooted in the fundamental principles of structural dynamics and/or beam theory. Some of them rely solely on basic physics, whereas others have attempted to integrate statistical regression using the structural response data generated from NRHAs performed on nonlinear structural models. These existing methods form a spectrum with purely mechanistic models on one end and purely data-driven models on the other. Between these two extremes, there are models that combine elements of engineering mechanics and statistical learning. Four representative methods that fall within this spectrum are introduced in this section.

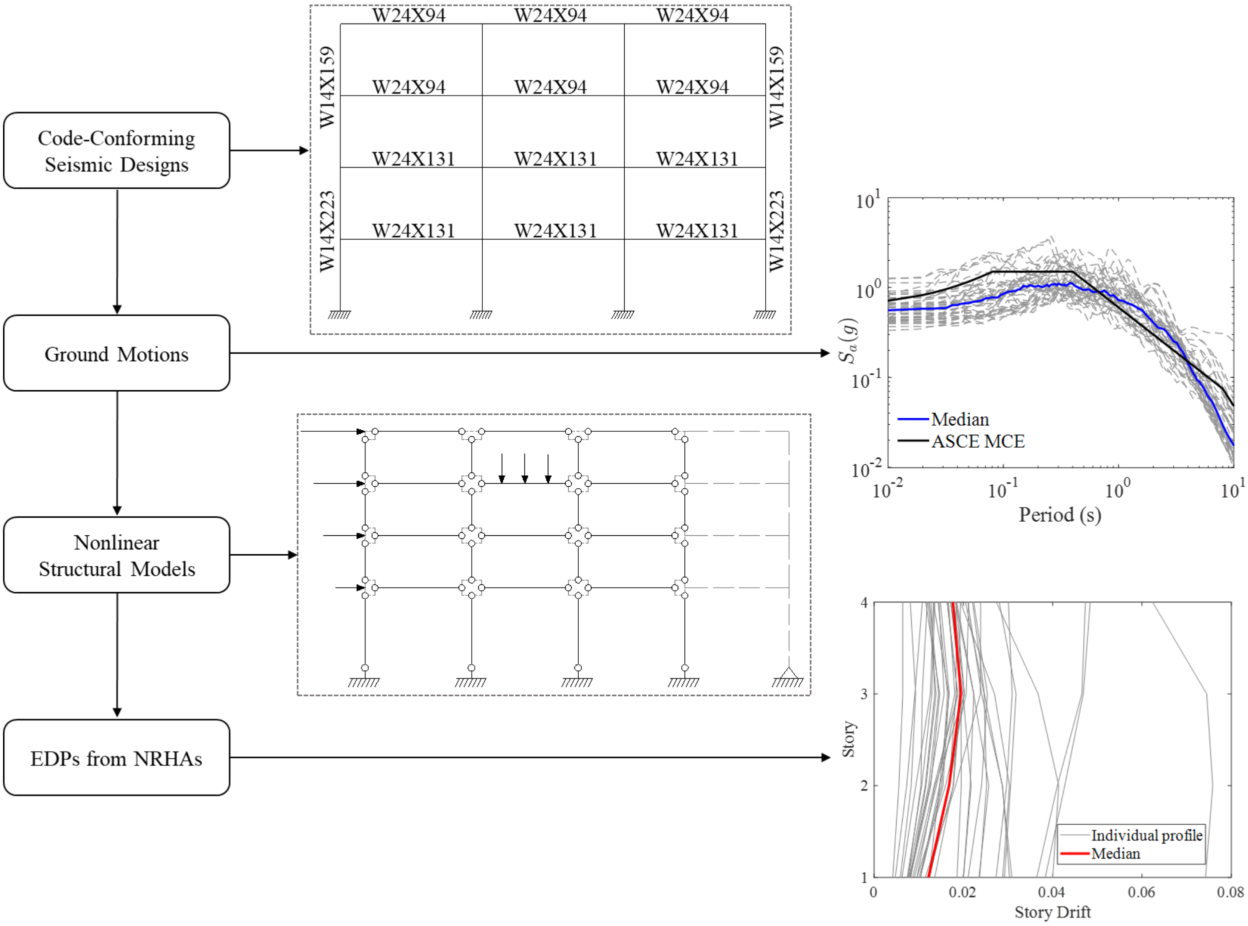

Fig. 2 – Overview of the database

3.2 Shear and flexural beam theory

Miranda [1,2] developed an approximate method to estimate the maximum lateral drift demands in multistory buildings using beam theory. This method is relatively easy to interpret and provides an approximation for the preliminary design of new buildings. However, it has several limitations. First, the underlying assumption that the mass is uniformly distributed along the building height might not be applicable since the weight of the roof is generally different from that of typical floors in real buildings. Second, the determination of an important parameter α_0 for actual buildings requires a tremendous effort. Consequently, the value of α_0 is typically determined based on engineering judgement and established rule of thumbs, which might be unreliable enough. Third, the differential equation set only has a closed-form solution for buildings that have uniform lateral stiffness. For buildings with varying lateral stiffness, the differential equation set is relatively difficult to solve. Last, the output of this method is a single maximum story drift not the peak story drift profile, which is critical for performance-based earthquake engineering (PBEE) type evaluations. All of these aforementioned drawbacks reduce the effectiveness and efficiency this method in engineering practice.

3.3 Elastoplastic single-degree-of-freedom system with known building yield strength

Lin and Miranda [3] proposed a methodology that uses an equivalent elastoplastic single-degree-of-freedom (SDOF) system coupled with the lateral yielding strength of the building to estimate the maximum inelastic roof displacement demand of regular steel frame buildings. Despite the fact that the method is developed based on elementary structural dynamics, it is was validated on a relatively small dataset that includes the structural responses of three SMRFs subjected to 72 earthquake ground motions records. Moreover, the method requires the yielding strength of the building (which is typically obtained by performing a nonlinear static analysis on the entire structure) and nonlinear response history analyses on an elastoplastic SDOF. As such, a reasonable argument can be made that the level of effort required is comparable to performing nonlinear response history analyses on a multi-degree-of-freedom (MDOF) system.

3.4 Statistically adjusted spectral displacement

Gupta and Krawinkler proposed a framework that provides the estimation for inelastic story drift demands by multiplying the elastic spectral displacement with a set of four empirical coefficients [6]. This framework provides a clear path from spectral displacement demand to individual story drift demand by using a set of four coefficients. While the framework is helpful in the conceptual design phase and is rooted in a fundamental understanding of the seismic behavior of SMRFs, it has two key limitations. First, the generalized formula for two of the coefficients are not immediately available. Additionally, the framework is developed using nonlinear analysis results from nine SMRFs subjected to three sets of 40 ground motions, which brings its generalizability into question.

3.5 Statistically adjusted elastic MDOF response

FEMA P-58 [5] provides a simplified seismic response estimation method to estimate the EDPs that are needed for a 2nd generation PBEE-type assessment. The procedure uses a linear elastic MDOF structural models, static analyses, an estimate of the lateral yield strength, and linear regression, to generate median estimates of the seismic drift demands. The details can be found in Chapter 5.3 of FEMA P-58 [5]. This method be viewed as a employing a combination of mechanics (i.e., an elastic analysis) and statistical learning (i.e., simple linear regression). It is relatively straightforward to apply and interpret. However, this method was developed based on assumptions that the story drift ratios are limited to 4% and the building should be less than 15 stories tall. Additionally, this method is validated on a relatively small dataset that includes four SMRFs subjected to 50 pairs of ground motions.

3.6 Evaluation of existing simplified seismic drift demand estimation models

3.6.1 Model evaluation and performance metrics

Previous studies evaluate the model performance using the following metrics: mean and standard deviation of relative difference [14], median absolute relative deviation (MARD) [15], mean squared error (MSE), the slope of a straight line obtained from applying linear regression on dataset comprised on the predicted and actual values of the response variable [7].

Apart from the aforementioned metrics, a new performance metric is proposed for the current study. It is the fraction of the dataset whose relative difference does not exceed *X*%. Mathematically, it is defined as

$$D_{X\%} = \text{countif}\ [\text{abs}(\frac{\hat{y}_i - y_i}{y_i}) <= X\%] / N$$

where *countif* is a function that counts the number of data points satisfying the condition in the square brackets, *abs* is a function that takes the absolute value of its argument, $\hat{y}_i$ is the predicted value, y_i is the actual value, *X* is a threshold defined by the user, and *N* is the total number of data points. In this study, $D_{10\%}$ and $D_{25\%}$ together with aforementioned metrics are adopted to provide a complete and transparent assessment for the simplified seismic drift estimation models.

Two of simplified seismic drift estimation methods presented earlier (i.e., shear and flexural beam theory and statistically adjusted spectral displacement) do not provide closed-form solution for buildings with varying lateral stiffness. Consequently, only the remaining two methods (i.e., elastoplastic SDOF with known building yield strength and statistically adjusted elastic MDOF response) are evaluated herein. The median drift demands from a set of ground motions is used to validate the methods. More specifically, the maximum story drift profile for a subgroup of 100 buildings subjected to three groups of site-specific ground motions at the SLE, DBE, and MCE levels, are used to evaluate the two simplified methods. Also, the evaluation datasets (100 buildings) are divided into two subgroups: low-to-mid-rise buildings (stories < 10) and high-rise buildings (stories >= 10). The methods are evaluated on two subgroups separately.

3.6.2 Evaluating the method of elastoplastic SDOF with known building yield strength

The peak story drift profiles obtained from NRHAs for the low-to-mid-rise buildings subjected to SLE, DBE, and MCE ground motions are compared with those predicted by the methodology of elastoplastic SDOF with known building yield strength, as shown in Fig. 3(a). The horizontal and vertical axes are the predicted and NRHA-based story drifts, respectively. A total of 1131 data points is included in the figure. If the predicted and NRHA-based results are the same, the datapoint would lie on the reference line whose slope is 1.0. Fig. 3(a) shows that the data points are located at the lower right side of the reference line for all three cases, which indicates that the method of elastoplastic SDOF with known building yield strength tends to overestimate the peak story drift. A histogram of the relative difference between predicted and NRHA-based results for the low-to-mid-rise buildings is shown Fig. 3(b). The horizontal and vertical axes represent the lumped bins of the relative difference and the normalized number of predictions, respectively. The relative differences are concentrated in the bin of 125% to 500%, which indicates the story drifts estimated by elastoplastic SDOF with known building yield strength are much higher that the NRHA-based values. The similar observations are made for the high-rise building dataset though the figures are not shown here. The performance metric values for the method of elastoplastic SDOF with known building yield strength evaluated on the low-to-midrise and high-rise buildings are summarized in Table 1. In general, they reveal that the model has equally poor performance at all intensities for both building groups.

3.6.3 Evaluating the method of statistically adjusted MDOF response

The method of statistically adjusted MDOF response is evaluated against the NRHA-based story drift demands for the low-to-mid-rise buildings subjected to the site-specific SLE, DBE, and MCE level ground motions. The comparison is presented in Fig. 4(a) where the data points corresponding to the SLE and DBE are clustered around the reference line. However, for the MCE level ground motions, the data points are clustered on the lower right side of the reference line. This observation indicates that the statistically adjusted MDOF response method provides a roughly unbiased prediction for drift demands under SLE and DBE ground motions but overestimates the MCE level demands. A histogram showing the relative difference between the statistically adjusted MDOF response method and NRHA results is shown in Fig. 4(b). The relative difference is mostly within the range of -25% to +25%. As presented in Table 2, across all metrics, the model performance at MCE level is worse than the SLE and DBE cases. A similar evaluation process is performed on the data set of high-rise buildings and the performance evaluation metrics are also summarized in Table 2.

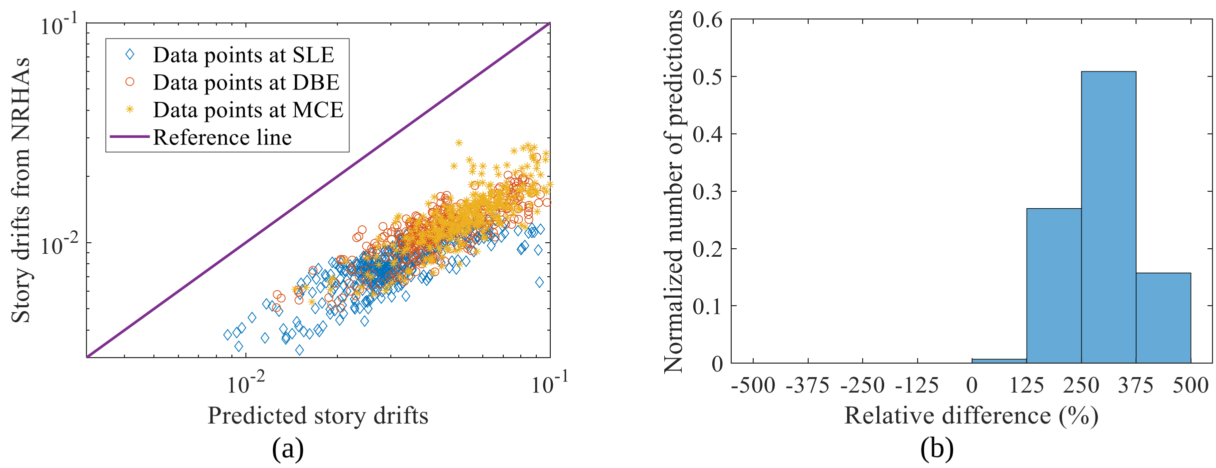

Fig. 3 – Evaluation results for the method of elastoplastic SDOF with known yield strength on low-to-mid-rise building dataset: (a) NRHA-based versus predicted peak story drifts, (b) distribution of relative difference between predicted and NRHA-based peak story drifts

Table 1 – Multi-metric performance evaluation for the method of elastoplastic SDOF with known building yield strength

Building group	Indicators	Validating at MCE	Validating at DBE	Validating at SLE
Low-to-mid-rise buildings	MARD	3.10	2.86	2.97
	μ	3.32	3.09	3.18
	σ	1.22	1.29	1.40
	$D_{10\%}$	0.00%	0.00%	0.00%
	$D_{25\%}$	0.00%	0.00%	0.00%
	Slope of linear fitting	y = 0.21x	y = 0.21x	y = 0.21x
	MSE	2.8E-03	1.8E-03	9.00E-04
High-rise buildings	MARD	2.14	1.91	1.87
	μ	2.15	1.96	1.92
	σ	0.61	0.67	0.51
	$D_{10\%}$	0.00%	0.00%	0.00%
	$D_{25\%}$	0.18%	0.00%	0.00%
	Slope of linear fitting	y = 0.303x	y = 0.34x	y = 0.33x
	MSE	4.30E-04	1.90E-04	9.80E-05

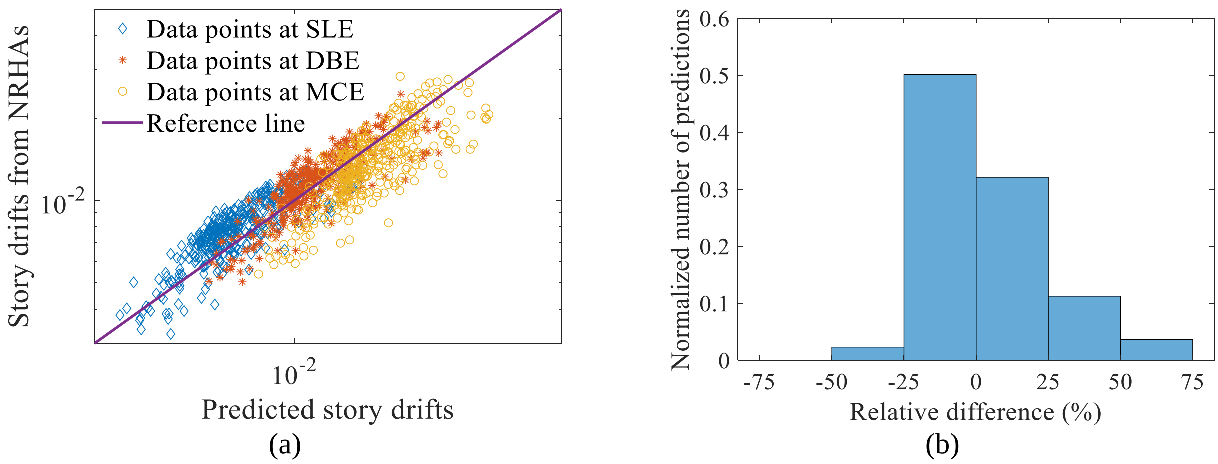

Fig. 4 – Evaluation results for the method of statistically adjusted MDOF response method on low-to-mid-rise building dataset: (a) NRHA-based versus predicted peak story drifts, (b) distribution of relative difference between predicted and NRHA-based peak story drifts

Overall, the approach of statistically adjusted MDOF response provides more accurate seismic drift estimates for low-to-midrise buildings compared to high-rise buildings. Additionally, the accuracy at the MCE level is lower than the SLE and DBE estimates. However, across all intensity levels and building heights, the performance is much better than the method of elastoplastic SDOF with known building yield strength. This result suggests that the statistically adjusted MDOF response method that integrate mechanistic and statistical learning models are likely to be superior to those that solely rely on the fundamentals of physics /dynamics, which, in part, motivates the development of the data-driven models developed in the next section.

Table 2 – Multi-metric performance evaluation for the method of statistically adjusted MDOF response

Building group	Indicators	Validating at MCE	Validating at DBE	Validating at SLE
Low-to-mid-rise buildings	MARD	0.16	0.10	0.15
	μ	0.19	0.00	-0.08
	σ	0.24	0.16	0.15
	$D_{10\%}$	33.16%	47.21%	30.24%
	$D_{25\%}$	65.78%	90.98%	80.92%
	Slope of linear fitting	y = 0.86x	y = 1.01x	y = 1.08x
	MSE	1.30E-05	4.20E-06	2.00E-06
High-rise buildings	MARD	0.24	0.17	0.13
	μ	-0.24	-0.14	-0.11
	σ	0.15	0.14	0.09
	$D_{10\%}$	14.46%	28.04%	36.97%
	$D_{25\%}$	53.21%	75.00%	97.97%
	Slope of linear fitting	y = 1.30x	y = 1.19x	y = 1.13x
	MSE	8.50E-06	2.70E-06	5.40E-07

4. Developing Data-Driven Models to Estimate Seismic Drift Demands

4.1 Overview of model development approach

Inspired by the existing methods, one hybrid and one data-driven models are developed to estimate median drift demands in SMRFs. The models are developed separately for low-to-mid-rise and high-rise buildings. The databased described in Section 2 is used to formulate the data-driven models. The entire database is divided into two sub-datasets: the drift demands obtained for 621 SMRFs subjected to 240 ground motions and the demands for 100 SMRFs subjected to three groups of site-specific ground motions at the SLE, DBE, and MCE levels. The first dataset (from the 621 SMRFs) is further randomly divided into two subsets comprised of 80% and 20% of the original data. The former used to train the machine learning model and the latter is used for testing purposes. Once the model has been trained and tested, it is further validated using the second dataset (100 SMRFs). This strategy ensures that there are no shared data points among the training, testing, and validation subsets.

The 240 ground motions used to develop the training/testing dataset are first binned based on the $S_a(T_1)$ value. A total of six bins are formed ensuring that none of them have less than 10 ground motions. The median intensity measure value (e.g., $S_a(T_1)$) is used as one of the predictor variables. In the section dataset, the ground motions associated with each hazard level (SLE, DBE, or MCE) are considered as one group, and their median intensity measure is used to validate the data-driven model.

A total of 34 variables which have been identified as having an influence on seismic story drift demands are grouped into four categories: building information, modal analysis results, spectral intensity parameters, and nonlinear pushover analysis results. There are 7 building information predictors: the number of stories (N_s), number of bays (N_b), story height (h_i), bay width (W_b), floor dead load (DL_{floor}), roof dead load (DL_{roof}), and fundamental period (T) determined using the equation specified in Chapter 12 of ASCE 7-16 [13]. There are 12 modal analysis result predictors: the first to fourth modal periods (T_1, T_2, T_3, and T_4), the associated four modal shapes (ϕ_1, ϕ_2, ϕ_3, and ϕ_4), and mass participation factors (MMP_1, MMP_2, MMP_3, and MMP_4). The 10 spectral intensity parameter predictors include the spectral acceleration and displacement values evaluated at the first to fourth modal periods ($S_a(T)$, $S_a(T_1)$, $S_a(T_2)$, $S_a(T_3)$, $S_a(T_4)$, $S_d(T)$, $S_d(T_1)$, $S_d(T_2)$, $S_d(T_3)$, and $S_d(T_4)$). The following 5 predictors are obtained from the results of nonlinear static analysis: the force and drift corresponding to yield point, the peak force and associated drift and the force at 2% drift.

4.2 Amplified MDOF elastic drift model

The amplified MODF elastic response model is derived by adapting the method of statistically adjusted MDOF response. The overall workflow involved in the model development is shown in Fig. 5. To begin, an elastic MDOF model of the building is subjected to the pseudo lateral force and the associated story drifts are recorded. Subsequently, the ratios between the drift demands from NRHAs and the elastic MDOF analysis is determined. These "amplification factors", which are unique to each story, are taken as adjustment factors for the latter. In other words, a model user would determine the elastic MDOF drift demands and use the amplification factors predicted by the data-driven model to arrive at nonlinear response drift estimates. The aforementioned 34 predictor variables are the machine learning model inputs and the MDOF elastic drift amplification factor is the output. In this study, random forest [16] is selected as the machine learning model.

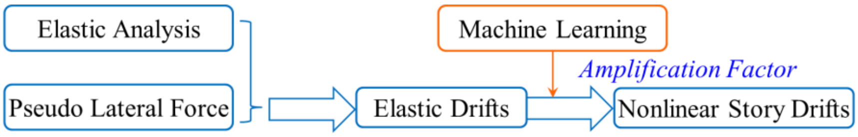

Fig. 5 – Workflow for amplified MDOF elastic drift model

After training and testing the random forest algorithm, the performance is also assessed using the and validation dataset. The random forest predicted and NRHA observed amplification factors are compared in Fig. 6(a) and the associated distribution of relative difference is shown in Fig. 6(b). While the proposed model seems to provide slightly biased prediction at the DBE and MCE levels, the overall relative difference is mostly within the range of -25% to +25%. As Table 4 shows, the $D_{10\%}$ and $D_{25\%}$ in all three cases are greater than 50% and 90%. Moreover, $D_{10\%}$ varies significantly across all intensities whereas other metrics do not change much, implying $D_{10\%}$ is highly sensitive to model performance. A similar evaluation process is performed on high-rise building dataset and the metrics listed in Table 4 indicate that the amplified MDOF elastic drift model performs equally well on both building groups.

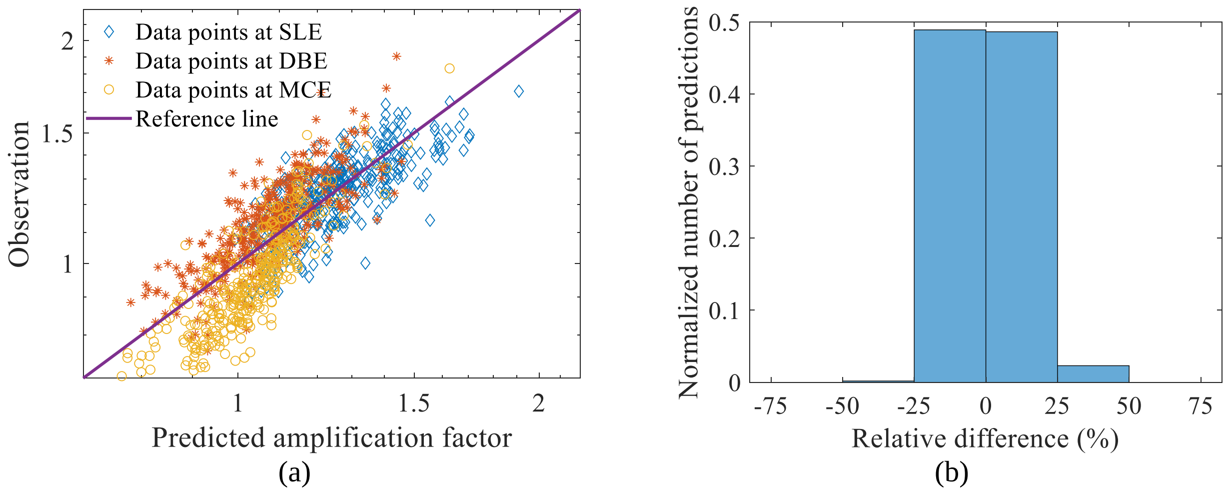

Fig. 6 – Evaluation results of the amplified MDOF elastic drift model on low-to-mid-rise building dataset: (a) observed versus predicted amplification factors, (b) distribution of relative difference between random forest predicted and NRHA observed amplification factors

Table 4 – Multi-metric performance evaluation for the amplified MDOF elastic drift model

Building group	Indicators	Validating at MCE	Validating at DBE	Validating at SLE
Low-to-mid-rise buildings	MARD	0.10	0.07	0.06
	μ	0.09	-0.05	0.01
	σ	0.10	0.08	0.09
	$D_{10\%}$	49.87%	69.76%	74.54%

	$D_{25\%}$	93.90%	99.20%	99.47%
	Slope of linear fitting	y = 0.93x	y = 1.06x	y = 0.99x
	MSE	1.4E-02	1.4E-0.2	1.1E-02
High-rise buildings	MARD	0.08	0.10	0.07
	μ	-0.02	-0.06	0.00
	σ	0.11	0.11	0.10
	$D_{10\%}$	62.50%	51.07%	69.50%
	$D_{25\%}$	96.07%	96.07%	98.71%
	Slope of linear fitting	y = 1.04x	y = 1.07x	y = 1.00x
	MSE	1.9E-02	2.4E-02	1.3E-02

4.3 Purely data-driven model

A purely statistical model that is solely based on machine learning is developed to provide a direct link between the 34 input variables and the nonlinear story drift demands (Fig. 7) and random forest is selected to be used as the machine learning model. After training and testing the random forest algorithm, its performance is further evaluated on the validation dataset. The performance evaluation results are summarized in Table 5. While the estimates generated by this model tends to underestimate the story drift demand at all three intensity levels, $D_{25\%}$ in all cases are greater than 80%. Additionally, different metrics show the same trend across different intensities. For example, the MARD, μ, $D_{10\%}$, and $D_{25\%}$ of high-rise buildings indicate that the model has best performance in the SLE case. This observation demonstrates that these metrics are consistent in evaluating model performance. Table 5 also reveals that the model provides more accurate drift demand estimations for high-rise buildings than for low-to-mid-rise buildings.

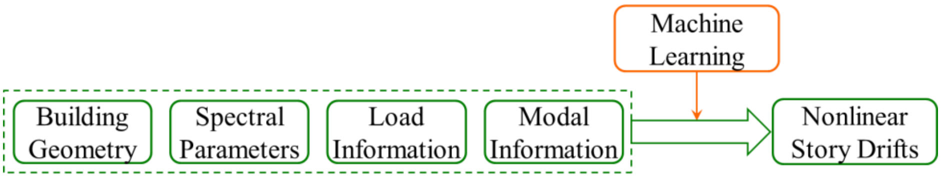

Fig. 7 – Workflow of purely data-driven model

Table 5 – Multi-metric performance evaluation for the purely data-driven model

Building group	Indicators	Validating at MCE	Validating at DBE	Validating at SLE
Low-to-mid-rise buildings	MARD	0.12	0.08	0.13
	μ	-0.08	-0.04	-0.07
	σ	0.14	0.11	0.16
	$D_{10\%}$	44.30%	59.15%	36.34%
	$D_{25\%}$	86.21%	97.61%	84.88%
	Slope of linear fitting	y = 1.14x	Y = 1.07x	y = 1.09x
	MSE	8.19E-06	2.48E-06	2.04E-06
High-rise buildings	MARD	0.10	0.09	0.08
	μ	-0.10	0.05	-0.02
	σ	0.10	0.13	0.11
	$D_{10\%}$	49.29%	56.25%	62.85%
	$D_{25\%}$	95.89%	93.04%	97.04%
	Slope of linear fitting	y = 1.13x	y = 0.97x	y = 1.04x
	MSE	2.40E-06	8.50E-07	3.08E-07

4.4 Comparative assessment among mechanstic, hybrid, and data-driven models

To compare the performance of the mechanistic, hybrid and data-driven models, $D_{25\%}$ values for both building groups are shown in Fig. 8. Methods 1 to 4 on the horizontal axis represent the method of elastoplastic SDOF with known build yield strength, statistically adjusted elastic MDOF response, pure data-driven model, and amplified MDOF elastic drift model, respectively. From the figure, several conclusions could be drawn: First, the purely mechanistic model (i.e., elastoplastic SDOF with known building yield strength) shows poor performance having almost zero $D_{25\%}$ at all intensity levels. The hybrid model (i.e., amplified MDOF elastic drift model) performs reasonably well with $D_{25\%}$ greater than 95% in all cases. Second, the hybrid and purely statistical models developed in the current study generally outperform the existing models with $D_{25\%}$ values that are almost exclusively in the range of 90% to 100% for both low-to-mid-rise and high-rise buildings and across all hazard levels. Last, compared with the purely data-driven model, the amplified MDOF elastic drift model has a higher $D_{25\%}$ value, indicating that the models that integrate both mechanics and statistical learning outperform ones that are purely data-driven.

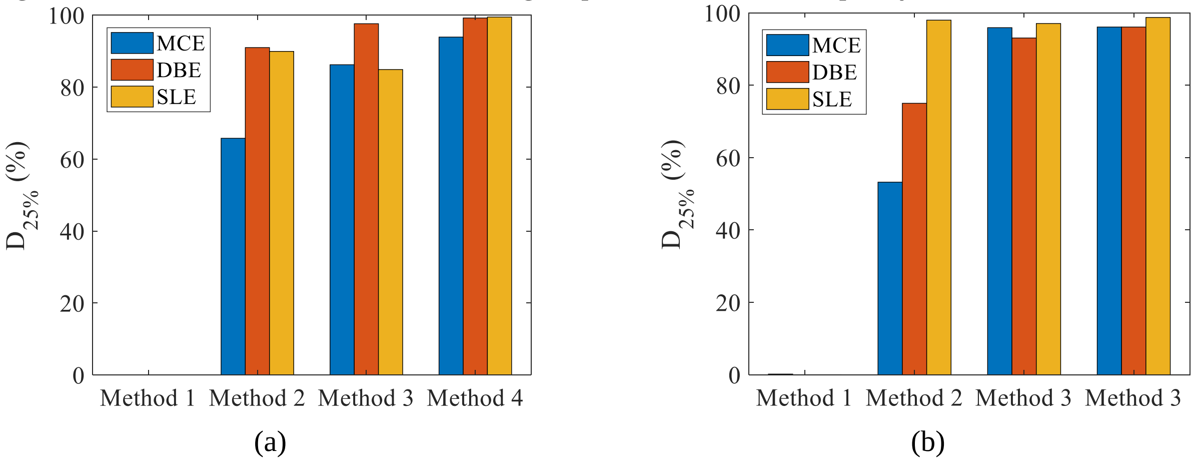

Fig. 8 – Comparing the performance across the mechanistic, hybrid, and data-driven models: (a) low-to-mid-rise buildings and (b) high-rise buildings

5. Conclusions

This study introduces a framework to develop data-driven and hybrid (mechanistic + data-driven) models that could be used to estimate seismic deformation demands of SMRFs. To start with, a comprehensive database is developed. The database includes the seismic designs for 621 buildings, the corresponding ready-to-run OpenSees nonlinear structural models, the structural responses of 621 buildings subjected to 240 ground motions, and the responses of a subgroup of 100 buildings subjected to three groups of ground motions at SLE, DBE, and MCE levels, respectively. Then four existing methodologies (including shear and flexural beam theory, elastoplastic SDOF with known building yield strength, statistically adjusted spectral displacement, and statistically adjusted elastic MDOF response) for predicting seismic demands are outlined, critically examined to reveal their advantages and drawbacks, and evaluated to quantitatively illustrate their prediction accuracy. The examination indicates that the methods of shear and flexural beam theory and Gupta and Krawinkler framework did not provide generalized closed-form solution for the buildings in practice. The accuracy for the method of elastoplastic SDOF with known building yield strength is extremely small, whereas the statistically adjusted elastic MDOF response shows a generally good prediction ability. Based on these existing methods, one hybrid and one data-driven models are rigorously developed via training, testing, and validating against the created database. Finally, a comparative assessment among mechanistic, hybrid, and data-driven models is performed. The assessment shows that the two models developed in this study have a relative higher accuracy compared with existing methods. Moreover, the comparison implies that the model integrating both mechanistic and statistical learning outperform than the models that only rely on mechanics or are purely data-driven.

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