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SEISMIC DEMAND MODELING LEVERAGING CONDITIONAL GENERATIVE ADVERSARIAL NETWORK

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ABSTRACT

Prediction of structural seismic responses under varying ground motion intensities is critical for advancing seismic resilience and optimizing structural designs. Surrogate models offer a cost-effective alternative to computationally expensive high-fidelity numerical simulations. However, past surrogate modeling research largely focused on supervised machine learning techniques (Random Foresting, ANN, k-NN). Generative AI models, particularly the generative adversarial network (GAN), have received emerging research interest, but have yet to be explored for seismic surrogate modeling. This study proposes a surrogate modeling approach leveraging conditional variational auto-encoder generative adversarial network (CVAE-GAN) as a robust means to predict the engineering demand parameters (EDPs) of bridges subjected to varying ground motion intensity measures (IMs). We consider a case-study dataset of highway bridge seismic responses encompassing various input variables including intensity measures, geometrical properties, and material properties and six EDPs. The CVAE-GAN framework integrates an encoder, decoder, and discriminator to ensure accurate and realistic predictions. The encoder maps input conditioning structural features and a noise vector into a latent space representation, which is then fed into the decoder to reconstruct the structural responses. The discriminator refines the predictions even more by differentiating real from generated data, using a composite loss function combining the mean squared error for reconstruction accuracy with Kullback-Leibler (KL) divergence as a regularization term in latent space and adversarial loss for statistical realism. These features give cGANs significant advantages compared with conventional supervised machine learning paradigms in a context such as seismic surrogate modeling because they build the underlying data distribution in an adversarial framework and give rise, therefore, to context-aware predictions that better capture the inherent variability across responses of structural systems. The training through adversarial means engendered by a generator-discriminator duo has a factored regularizing effect on the model, insulating it against those topmost forms of overfitting indicative of conventional, supervised techniques.

Besides, the representation in the encoder latent space partially lessens the impact of the highly dimensional data through true compression of essential information, thereby ensuring computational efficiency and focusing on critical dependencies. Through addressing computational demands and overcoming the limitations of existing techniques, the cGAN-based surrogate model makes hazard analysis and performance-based design within structural engineering scalable and accurate.

1. INTRODUCTION

Earthquakes remain one of the most devastating natural hazards, capable of causing tremendous human and economic losses worldwide. The potential impacts of earthquakes on communities and economies emphasize the importance of establishing reliable seismic risk assessment frameworks to promote resilient structural design and enhance disaster preparedness [1–3].

Performance-based earthquake engineering traditionally relies on nonlinear finite element (FE) time-history analyses to estimate engineering demand parameters (EDPs) such as peak drifts, accelerations, and member forces under a spectrum of ground motion scenarios. While these high-fidelity simulations provide detailed insights, they demand substantial computational resources and time. This computational burden limits their practical use, particularly in probabilistic risk assessment, motivating the development of efficient surrogate demand models (SDMs) that approximate FE outputs with dramatically lowered computational cost [4–7]

Surrogate modeling techniques in seismic engineering fall broadly into physics-based and data-driven categories [8]. Physics-based surrogates employ simplified mechanical representations (e.g., equivalent single-degree-of-freedom systems or reduced-order models) to retain interpretability within known parameter ranges. Data-driven surrogates, by contrast, leverage statistical and machine learning methods to learn the input-output mapping directly from simulation or monitoring data, offering flexibility to capture highly nonlinear behavior beyond simplified formulations [9].

The advent of advanced machine learning (ML) and deep learning (DL) has propelled data-driven surrogate modeling forward. Deep neural networks automatically extract complex features and model intricate nonlinear relationships, enabling fast, near-real-time predictions once trained. However, most existing data-driven surrogate models yield deterministic point estimates and do not directly characterize the uncertainty inherent in seismic responses. In probabilistic seismic risk assessment, capturing the full distribution of EDPs given uncertain ground motions is critical [10].

Generative adversarial networks (GANs) [11] offer a powerful framework for learning and sampling complex probability distributions. In particular, the conditional GAN (cGAN) [12] architecture extends GANs by conditioning both generator and discriminator on input variables, thus enabling the generation of synthetic outputs tailored to specified contexts (e.g., ground motion intensity measures, structural properties). This adversarial training not only yields realistic, context-aware predictions but also mitigates overfitting through the interplay of competing networks, preserving variability often lost in deterministic models [13]. Nevertheless, cGAN has yet to be explored for the purpose of seismic surrogate modeling.

Built on these advances, a Conditional Variational Autoencoder Generative Adversarial Network (CVAE-GAN) surrogate modeling framework is developed to predict seismic responses based on varying ground motion intensity measures and structural features. Using a case-study dataset of highway bridges, the CVAE-GAN is benchmarked against traditional supervised learning surrogate models like artificial neural networks (ANNs) and extreme gradient boosting (Xgboost), consistently demonstrating superior predictive accuracy, response variability preservation, and generalization to unseen seismic scenarios.

2. GENERATIVE MODELS

2.1 Generative Adversarial Network (GAN)

Generative Adversarial Networks (GANs) are a powerful deep learning approach introduced in 2014 [6], designed to generate highly realistic synthetic data. Fundamentally, GANs consist of two neural networks known as the generator (G) and the discriminator (D) that engage in a competitive training process. The generator's objective is to produce synthetic data that closely mimics authentic data, effectively trying to fool the discriminator. Conversely, the discriminator's task is to accurately distinguish between the synthetic data produced by the generator and the genuine data from the original dataset. Through this adversarial interplay, GANs aim to reach a state of equilibrium (known as Nash equilibrium), resulting in generated data that is nearly indistinguishable from real-world examples.

2.2 Conditional Generative Adversarial Network (cGAN)

Conditional Generative Adversarial Networks (cGANs) represent an advanced variation of GANs, incorporating conditional adversarial training to improve data generation accuracy. Unlike standard GANs, cGANs supply additional contextual information to both the generator and discriminator, beyond just the random noise input. This supplementary context, often represented as class labels or specific attributes, guides the generator to produce synthetic samples that not only closely resemble real data but also align precisely with the provided labels. Consequently, the discriminator in cGANs must evaluate not just the authenticity of the generated samples, but also their consistency with the intended labels. Through this enhanced conditional approach, cGANs achieve greater precision and relevance in the generated outputs, effectively aligning synthetic data more closely with specified conditions or categories.

2.3 Conditional Variational Auto-Encoder GAN (CVAE-GAN)

In the CVAE-GAN [7] architecture, an encoder is used to map the input data along with its corresponding condition such as seismic intensity measures (IMs) and structural properties into a latent space representation (z). This process captures the underlying variability and uncertainty of the input data. The decoder, also called the generator, reconstructs a realistic output $\hat{x}$ from z and c. A discriminator network is then employed to distinguish between real data and generated samples, further refining the quality of outputs through adversarial training

The training objective of the CVAE-GAN incorporates two critical components. First, the variational autoencoder component targets reconstruction accuracy while maintaining latent space regularity, formalized by the loss function:

$$\mathcal{L}_{\text{VAE}} = \mathbb{E}_{q(z|x,c)}[\log\, p(\boldsymbol{x} \mid \boldsymbol{z}, \boldsymbol{c})] - \text{KL}(q(\boldsymbol{z} \mid \boldsymbol{x}, \boldsymbol{c}) \parallel p(\boldsymbol{z})) \tag{1}$$

Here, $q(\boldsymbol{z} \mid \boldsymbol{x}, \boldsymbol{c})$ approximates the posterior distribution from the encoder $p(\boldsymbol{z} \mid \boldsymbol{x}, \boldsymbol{c})$, denotes the decoder probability of accurately reconstructing data, and the Kullback-Leibler (KL) divergence ensures latent space regularization. The adversarial component actively guides the generator to produce indistinguishable data from real samples. The GAN-based adversarial loss is defined as:

$$\mathcal{L}_{\text{GAN}} = \mathbb{E}_{x \sim p_{\text{data}}}[\log\ D(\boldsymbol{x}, \boldsymbol{c})] + \mathbb{E}_{z \sim p(z)}[\log\ (1 - D(G(\boldsymbol{z}, \boldsymbol{c}), \boldsymbol{c}))] \tag{2}$$

This loss function encourages the generator to produce samples that can fool the discriminator, while the discriminator learns to better differentiate between real and synthetic data.

3. CVAE-GAN FOR PREDICTING THE SEISMIC RESPONSE OF BRIDGE STRUCTURE

In this study, structural response prediction is formulated as a conditional variational autoencoding and adversarial generation task, and implemented using a CVAE-GAN architecture in PyTorch. Each sample consists of an input vector $\boldsymbol{x}$. and its corresponding target response $\boldsymbol{y}$. The generator is designed as a Conditional Variational Autoencoder (CVAE), where the encoder network $q_\phi(\mathbf{z} \mid \boldsymbol{x}, \boldsymbol{y})$ maps the concatenated input-output pair $[\boldsymbol{x}, \boldsymbol{y}]$ to a latent space $\boldsymbol{z}$. In this latent space, the encoder neural network outputs two vectors: a mean vector $\boldsymbol{\mu}(\boldsymbol{x}, \boldsymbol{y})$ and a log-variance vector $\mathbf{log}\ \boldsymbol{\sigma}^{\mathbf{2}}(\boldsymbol{x}, \boldsymbol{y})$, both of dimension $\mathbb{R}^d$ where d is the latent dimension, as shown in Figure 1. A latent vector $\boldsymbol{z}$ is then sampled using the reparameterization trick, expressed as:

$$\boldsymbol{z} = \boldsymbol{\mu}(\boldsymbol{x}, \boldsymbol{y}) + \boldsymbol{\sigma}(\boldsymbol{x}, \boldsymbol{y}) \odot \boldsymbol{\varepsilon}, \qquad \boldsymbol{\varepsilon} \sim N(0, 1), \tag{3}$$

where $\boldsymbol{\varepsilon} \sim N(0, \mathrm{I})$ is standard Gaussian noise and $\odot$ denotes element-wise multiplication. This formulation enables controlled stochastic sampling in the latent space, introducing variability during training while keeping the overall process differentiable for backpropagation. The latent vector $\boldsymbol{z}$, together with the conditioning input $\boldsymbol{x}$, is fed into the decoder to reconstruct the predicted target response $\widehat{\boldsymbol{y}} = f_\theta(\boldsymbol{x}, \boldsymbol{z})$. Training optimises the evidence-lower-bound style objective.

$$\mathcal{L}(\phi, \theta) = \underbrace{\frac{1}{N} \sum_{i=1}^{6} w_i \parallel \widehat{\boldsymbol{y}}_{\boldsymbol{i}} - \boldsymbol{y}_{\boldsymbol{i}} \parallel^2}_{\text{weighted reconstruction}} + \beta D_{\text{KL}}(q_\phi(\boldsymbol{z} \mid \boldsymbol{x}, \boldsymbol{y}) \parallel \mathcal{N}(0, I)) \tag{4}$$

where w emphasizes the more critical response components and $\beta = 10^{-3}$ tempers the Kullback–Leibler regulariser. The Adam optimizer ($\alpha = 10^{-4}$) coupled with a step-decay scheduler fine-tunes thousands of parameters over optimized number of epochs until the loss stabilizes. After convergence the decoder is repurposed as a generative predictor for an unseen $\widehat{\boldsymbol{x}}$ along with the noise ($\boldsymbol{\varepsilon}$) to obtain $\boldsymbol{z}$ and decode $\widehat{\boldsymbol{y}}$, thereby producing diverse yet consistent estimates whose marginal distributions mirror the original data. To enhance prediction realism and match the distribution of $\widehat{\boldsymbol{y}}$ to real data, adversarial training is incorporated through a discriminator network (D). The discriminator receives concatenated pairs $[\boldsymbol{x}, \boldsymbol{y}]$ from real samples and $[\boldsymbol{x}, \widehat{\boldsymbol{y}}]$ from the generator and learns to distinguish between them.

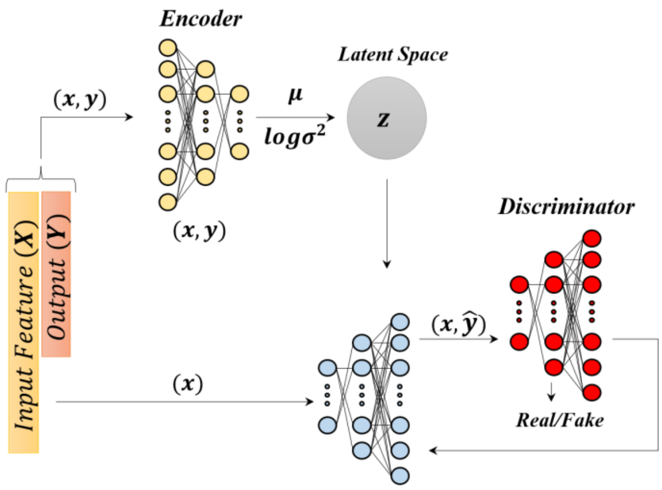


Figure 1: Architecture of CVAE-GAN Model

4. BRIDGE SIMULATION DATA FOR CASE STUDY

For demonstration purposes, the multi-span simply-supported concrete girder bridge portfolio located in the Shelby County, TN, are considered herein. To reflect the bridge parameter variability for the individual bridges within the bridge portfolio, Latin Hypercube Sampling is performed to generate 5,000 random bridge parameter realizations, by considering uncertainties in several bridge related parameters including geometric parameters such as number of spans, span length, deck width, column height, as well as parameters related to material properties such as steel reinforcement yield strength, shear modulus of bearings, among others. More details about the case-study bridge portfolio and parameter uncertainties can be found in Du & Padgett [4]. As for the ground motion inputs, the hazard-consistent ground motion suite assembled by Du & Padgett [14] for the case-study region is adopted. The ground motion suite includes 360 ground motion records covering a wide range of return periods. Each of the 5,000 random bridge samples are then randomly paired with one of the 360 ground motion records. 5,000 nonlinear time history analyses are then performed in OpenSees [14] to obtain bridge dynamic response data for six engineering demand parameters including column drift ratio, expansion bearing deformation, fixed bearing deformation, active abutment deformation, passive abutment deformation, and transverse abutment deformation.

Based on this dataset, a Conditional Variational Autoencoder Generative Adversarial Network (CVAE-GAN) is implemented in PyTorch, where each sample consists of an input vector $\boldsymbol{x} \in \mathbb{R}^{\mathbf{24}}$ representing the intensity measures, geometric attributes, and material properties, and a target output vector $\boldsymbol{y} \in \mathbb{R}^{\mathbf{6}}$ corresponding to the six engineering demand parameters: (a) Column drift ratio (%), (b) Expansion bearing deformation, (c) Fixed bearing deformation (mm), (d) Abutment deformation- Active (mm), and (e) Abutment deformation-Passive (mm).

For benchmarking purposes, two conventional surrogate modeling techniques, Artificial Neural Networks (ANNs) [15] and Extreme Gradient Boosting (Xgboost) [16], are implemented. The ANN model employs a multilayer feed-forward architecture with backpropagation training, where interconnected neurons with nonlinear activation functions map input variables to predicted responses through optimized synaptic weights. In contrast, Xgboost constructs an ensemble of decision trees using the gradient boosting framework, where each tree corrects errors from previous iterations. Incorporating regularization techniques to control model complexity and prevent overfitting, Xgboost offers high predictive accuracy and computational efficiency, making it widely adopted in civil and structural engineering applications.

5. MODEL VALIDATION

To evaluate the predictive performance of the proposed model in forecasting carbon credit prices within the emissions trading market, four statistical metrics were employed: Mean Squared Error (MSE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2) [17]. These indicators were selected to comprehensively assess both the accuracy and robustness of the model predictions. The MAE quantifies the average magnitude of errors between actual and predicted values, offering a straightforward measure of prediction accuracy without considering the direction of the error. The Mean Squared Error (MSE), calculated as the average of the squared differences between actual and predicted values, emphasizes larger errors more than smaller ones and is particularly informative in capturing variance and sensitivity of the model. The RMSE, being the square root of MSE, retains the unit of the original target variable and is more responsive to outliers due to its squared error aggregation, thereby providing insight into the dispersion of prediction errors. Finally, the R^2 score represents the proportion of the variance in the dependent variable that is predictable from the independent variables, serving as an overall indicator of model fit. The mathematical expressions for these evaluation metrics are provided in Equations (5) to (7).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - p_i)^2 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - p_i)^2} \tag{6}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - p_i)^2}{\sum_{i=1}^{N}(p_i - \bar{p}_i)^2} \tag{7}$$

where: y_i denotes the predicted value, p_i represents the corresponding actual value, $\bar{p}$ refers to the mean of the actual values, and N indicates the total number of samples. In general, lower values of MSE, and RMSE imply reduced prediction error, while a higher R^2 value reflects a better fit between the predicted and actual data. Together, these trends indicate a decrease in the deviation between the forecasted and observed structural response of the bridge, thereby demonstrating an enhancement in the model predictive accuracy.

6. RESUTLS AND DISSCUSSION

To evaluate the predictive performance of the proposed Conditional Variational Autoencoder–Generative Adversarial Network (CVAE-GAN) model, we conducted a comparative study against two widely used machine learning techniques: Artificial Neural Network (ANN) and Xgboost. The evaluation was based on three standard regression metrics, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2) for both training and testing datasets across six distinct cases (Tables 1–6, Figure 2-4).

Across all scenarios, the CVAE-GAN consistently achieved superior or comparable performance to traditional methods. In case of column drift response**,** Xgboost and ANN exhibited nearly identical results with a test R^2 of 0.93 as evident for Figure (3a) and Figure (4a), while CVAE-GA slightly outperformed both with a test R^2 of 0.95 but a notably lower test MSE of 0.04 as shown in Figure (2a). Starting from expansion bearing deformation**,** CVAE-GAN began to demonstrate clear advantages. It achieved the highest test R^2 of 0.95 compared to 0.89 for both ANN and Xgboost, along with the lowest error metrics (MSE = 0.06; RMSE = 0.24) as shown Figure (3b) and (4b). Similar observations persist in predicting fixed bearing deformation, where CVAE-GAN attained the best generalization ability with a test R^2 of 0.96 as shown Figure (2c), outperforming ANN (0.88) and Xgboost (0.88) by a noticeable margin. Similarly, in active abutment deformation, CVAE-GAN maintained a high level of performance (R^2 = 0.95) shown Figure 2(d), whereas the competing models scored slightly lower (ANN = 0.91, Xgboost = 0.90). In predicting passive abutment deformation**,** the performance gap became more pronounced. CVAE-GAN achieved a test R^2 of 0.94 as shown in Figure 2(e) with significantly lower error values compared to ANN (R^2 = 0.82) and Xgboost (R^2 = 0.82). The improvements are especially notable in test MSE, with CVAE-GAN scoring 0.09 versus 0.30 for both ANN and Xgboost. Forecasting transverse abutment deformation further consolidates the robustness of the CVAE-GAN framework. It yielded a test R^2 of 0.93 Figure 2(f), higher than both ANN (0.89) and Xgboost (0.88). The test RMSE of 0.30 was also the lowest among the three models, confirming its reliability in preserving the accuracy of predictions across diverse data configurations.

Table 1: Statistical evaluation of column drift ratio (%)

	Train MSE	Train RMSE	Train R^2	Test MSE	Test RMSE	Test R^2
CVAE-GAN	0.04	0.20	0.95	0.04	0.20	0.95
ANN	0.06	0.24	0.93	0.06	0.24	0.93
Xgboost	0.03	0.17	0.96	0.06	0.24	0.93

Table 2: Statistical evaluation of expansion bearing deformation

	Train MSE	Train RMSE	Train R^2	Test MSE	Test RMSE	Test R^2
CVAE-GAN	0.06	0.24	0.96	0.06	0.24	0.95
ANN	0.14	0.37	0.90	0.14	0.37	0.89
Xgboost	0.11	0.33	0.92	0.15	0.38	0.89

Table 3: Statistical evaluation of fixed bearing deformation (mm)

	Train MSE	Train RMSE	Train R^2	Test MSE	Test RMSE	Test R^2
CVAE-GAN	0.06	0.24	0.97	0.06	0.24	0.96
ANN	0.19	0.43	0.89	0.21	0.45	0.88
Xgboost	0.16	0.40	0.91	0.21	0.45	0.88

Table 4: Statistical evaluation of Abutment deformation- Active (mm)

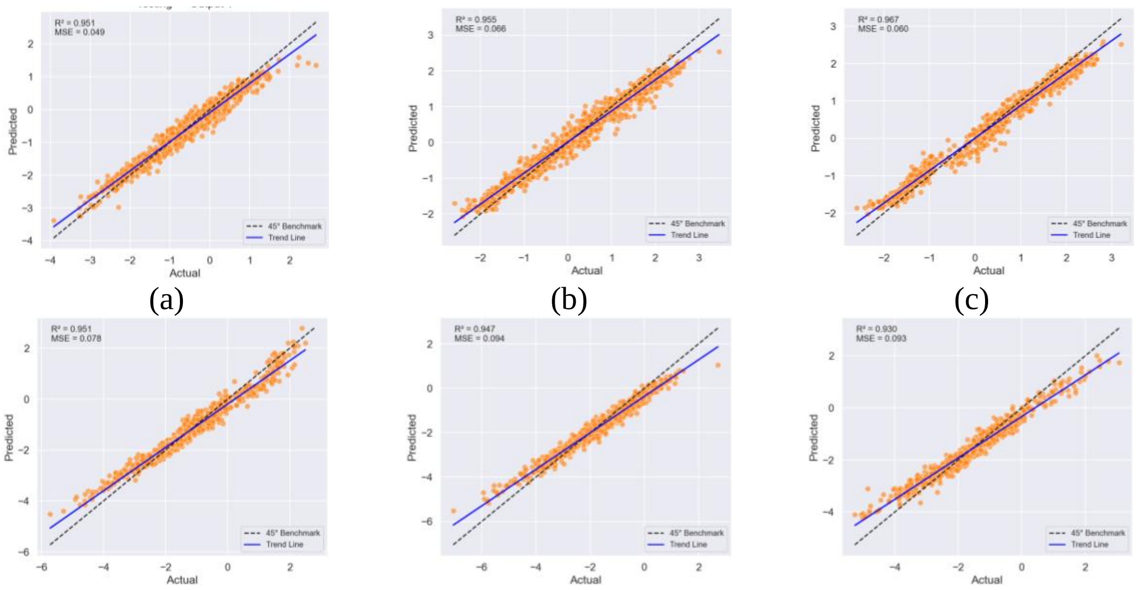
	Train MSE	Train RMSE	Train R^2	Test MSE	Test RMSE	Test R^2
CVAE-GAN	0.07	0.26	0.95	0.07	0.26	0.95
ANN	0.13	0.36	0.91	0.13	0.36	0.91
Xgboost	0.11	0.33	0.93	0.15	0.38	0.90

Table 5: Statistical evaluation of Abutment deformation- Passive (mm)

	Train MSE	Train RMSE	Train R^2	Test MSE	Test RMSE	Test R^2
CVAE GAN	0.09	0.30	0.95	0.09	0.30	0.94
ANN	0.26	0.50	0.85	0.30	0.54	0.82
Xgboost	0.23	0.47	0.86	0.30	0.54	0.82

Table 6: Statistical evaluation of Abutment deformation- Transverse (mm)

	Train MSE	Train RMSE	Train R^2	Test MSE	Test RMSE	Test R^2
CVAE GAN	0.09	0.30	0.93	0.09	0.30	0.93
ANN	0.12	0.34	0.91	0.13	0.36	0.89
Xgboost	0.13	0.36	0.90	0.15	0.38	0.88



(a) (b) (c)
(d) (e) (f)

Figure 2: Testing scatter plots for CVAE-GAN for (a) Column drift ratio (%) (b) Expansion bearing deformation (c) Fixed bearing deformation (mm) (d) Abutment deformation- Active (mm) (e) Abutment deformation- Passive (mm) (f) Abutment deformation- Transverse (mm)

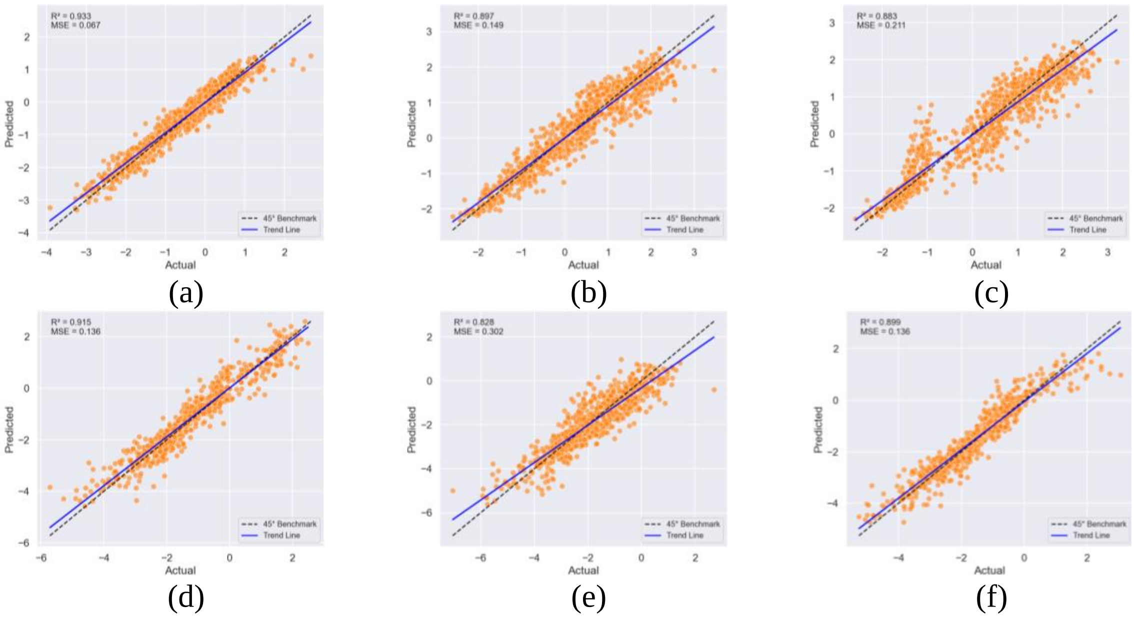


Figure 3: Testing scatter plots for ANN for (a) Column drift ratio (%) (b) Expansion bearing deformation (c) Fixed bearing deformation (mm) (d) Abutment deformation- Active (mm) (e) Abutment deformation- Passive (mm) (f) Abutment deformation- Transverse (mm)

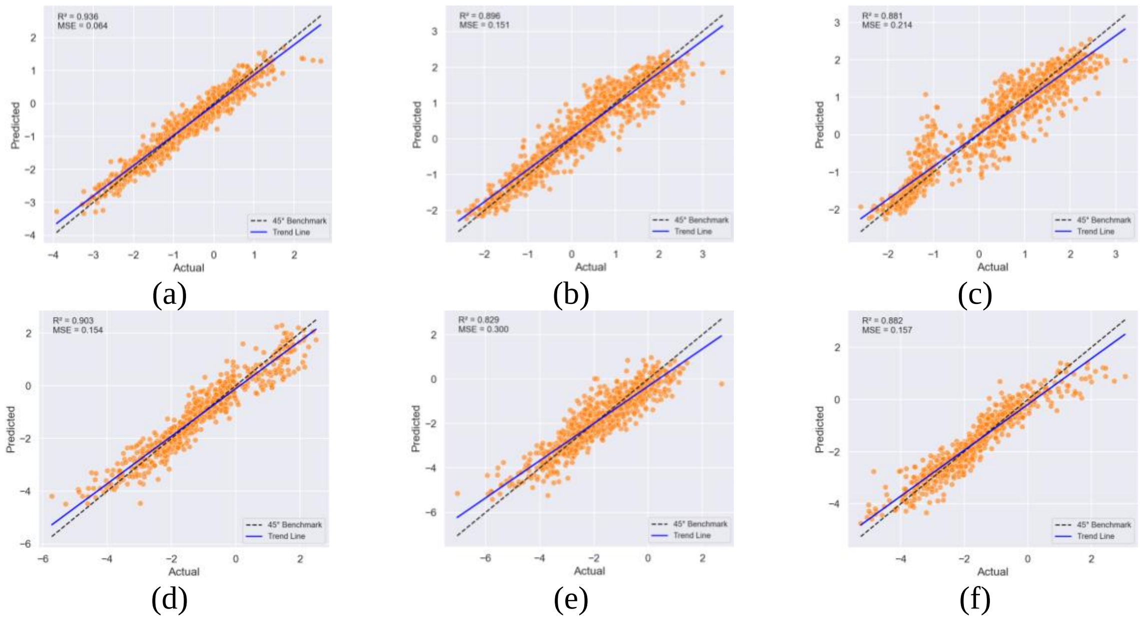


Figure 4: Testing scatter plots for Xgboost for (a) Column drift ratio (%) (b) Expansion bearing deformation (c) Fixed bearing deformation (mm) (d) Abutment deformation- Active (mm) (e) Abutment deformation- Passive (mm) (f) Abutment deformation- Transverse (mm)

7. CONCLUSIONS

This study presents a novel surrogate modeling framework for seismic demand prediction based on the Conditional Variational Autoencoder–Generative Adversarial Network (CVAE-

GAN). Through extensive experimentation on a case-study dataset of highway bridge responses, the proposed model demonstrated its capability to outperform conventional supervised learning approaches, including Artificial Neural Networks (ANN) and Xgboost, across various statistical benchmarks.

By integrating an encoder, decoder, and adversarial discriminator into a unified pipeline, the CVAE-GAN framework not only achieved high predictive accuracy but also preserved the variability and realism of structural responses, a key limitation of traditional models. The hybrid loss formulation combining reconstruction fidelity, latent space regularization, and adversarial realism ensured that the generated predictions were not only statistically robust but also physically meaningful.

Unlike point-estimate models, CVAE-GAN captures the full distribution of engineering demand parameters (EDPs), enabling more reliable seismic risk assessments under uncertainty. The model ability to generalize across diverse ground motion and structural parameter scenarios underscores its potential as a practical tool for performance-based seismic design and hazard analysis in civil infrastructure systems.

Overall, this work contributes to advancing data-driven modeling in structural engineering by highlighting the value of generative AI frameworks. The CVAE-GAN model stands out as a scalable, efficient, and interpretable alternative to resource-intensive numerical simulations, paving the way for future applications in probabilistic design, rapid post-earthquake damage assessment, and resilient infrastructure planning.

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