Proceedings of the 10th World Congress on New Technologies (NewTech'24)
Barcelona, Spain - August 25-27, 2024
Paper No. ICCEIA 164
DOI: 10.11159/icceia24.164

Kernel-based Column Drift Ratios Prediction in Highway Bridges

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Abstract **-** This study focuses on quantifying the critical parameter of column drift ratio in bridge engineering and proposes a novel kernel-based regression approach to enhance the performance-based seismic assessment of bridge systems. Traditionally, analytical methods in this field have relied on power-law functions of a single ground motion intensity measure. However, recent research has explored alternative models, though the application of machine learning (ML) approaches for bridge demand quantification and performance-based seismic assessment remains largely untapped. To address this gap, we introduce an advanced ML algorithm, specifically a kernel-based Gaussian regression approach, to estimate the column drift ratio metric for bridges. The effectiveness of the proposed model is demonstrated through its application to a representative class of highway bridges in California. The results reveal that the kernel-based model performs comparably to conventional approaches, underscoring its significance in efficiently estimating column drift ratio within the performance-based engineering framework. Importantly, the model's implications extend beyond accurate estimation, as it can inform infrastructure resilience assessments and facilitate rapid decision-making processes post-seismic events. By harnessing the capabilities of ML algorithms, this approach presents a compelling alternative to conventional methods, advancing earthquake engineering practices and providing valuable insights into the behavior of bridge systems under seismic conditions.

Keywords**:** Probabilistic seismic demand model, performance-based analysis, machine learning, bridge seismic performance, Kernel-based regression, column drift ratio, bridge engineering, highway bridges.

1. Introduction

Bridges are critical components of transportation infrastructure, upon which global economies and societies heavily depend [1]. Research has shown that these structures are highly vulnerable to seismic hazards, and their potential failure could have substantial consequences for transportation system operations [2]. Consequently, it is imperative to comprehensively assess the fragility and seismic risk of bridges by evaluating their seismic responses, commonly referred to as Engineering Demand Parameters (EDPs) [3].

Within the framework of Performance-Based Earthquake Engineering (PBEE), Probabilistic Seismic Demand Models (PSDMs) are commonly used to predict various bridge EDPs, such as deformations, drifts, and accelerations [4]. The development of effective PSDMs plays a crucial role in risk and hazard quantification, as well as in informed decision-making [5]. These models establish functional relationships between ground motion intensity measures (IMs) and EDPs [6], [7], like column drift ratio. PSDMs provide estimates of the demands imposed on bridge columns under simulated seismic scenarios, enabling engineers to evaluate the probability of exceeding specific drift levels and the associated dispersion [8].

In recent years, there has been a growing emphasis on performance-based seismic design, wherein bridge's column relative drift is considered a critical index for determining the need for post-earthquake column repair or full reconstruction [9]. While significant advancements have been made in estimating this crucial demand component, conventional methodologies employed for the assessment of column relative drift often entail computationally intensive analyses and may not comprehensively account for the complex dynamic characteristics of bridge performance under seismic excitation [10].

Amidst these challenges, the field of earthquake engineering has witnessed a surge of interest in the application of machine learning (ML) techniques, which hold the potential to enhance the accuracy and efficiency of EDP assessment [7],

[11], [12]. Among the emerging ML approaches, kernel-based methods have demonstrated promising capabilities for modelling complex relationships within data and generating probabilistic predictions [13]. By leveraging the capabilities of kernel-based frameworks, researchers aim to address the computational hurdles associated with traditional methodologies, while simultaneously providing valuable insights into the intricate dynamics underlying bridge performance under seismic loading [14]. These advancements hold the promise of advancing the state-of-the-art in performance-based earthquake engineering and supporting more informed decision-making processes.

This research paper's endeavour presents a novel kernel-based modelling approach to quantifying the column drift ratio of highway bridges. By conducting a case study focused on a representative class of California highway bridges, the proposed methodology seeks to demonstrate its efficacy in estimating the critical seismic demand metric of column drift ratio. Through the introduction of this kernel-based framework for demand assessment, the study contributes to the advancement of computational methods employed in the domain of infrastructure Probabilistic Seismic Demand evaluation, offering insights that can inform and enhance emergency preparedness efforts, as well as support more robust decision-making processes in regions prone to seismic hazards.

2. Methodology

2.1. Gaussian Kernel

This study presents a novel and influential methodology for predicting and quantifying column drift ratios in highway bridges using the Gaussian Kernel (GK) algorithm, a powerful nonlinear regression technique. In contrast to conventional learning approaches, the GK algorithm eliminates the need for time-consuming iterative learning processes, such as gradient descent, thus offering distinct advantages [15]. As demonstrated in Figure 1, at the core of the GK algorithm lies the calculation of a weighted average of neighboring data points to predict the column drift ratio at a query point. Equation 1 represents this calculation, where y^* represents the predicted column drift ratio at the query point x^*. The weights assigned to these neighboring points are determined by the Gaussian Kernel function, as given by equation 2, where $k\ (x^*, x_k)$ represents the weight between the query data point x^* and its neighboring location x_k [15], [20], [21], *and* [7].

The Gaussian Kernel function incorporates the variance (σ^2) serves as a bandwidth parameter to determine the weights, with the spatial distance between x^* and x_k influencing the weighting scheme [16], as shown in Figure 1. The variance parameter determines the width of the Gaussian distribution controlling the extent of influence that each neighboring point has on the prediction at the query point [17]. A higher variance value results in a broader Gaussian distribution, assigning relatively higher weights to data points that are further away from x^*, while a lower variance value leads to a narrower Gaussian distribution, giving more prominence to neighboring points in the immediate vicinity to x^*. By adjusting the value of the variance, the GK algorithm achieves a balance by effectively trading off variance and bias. This trade-off takes into consideration the spatial distance of neighboring data points, resulting in the prevention of overfitting and underfitting [17]. As a result, the algorithm can accurately estimate column drift ratios, leading to more precise estimations [18], [19], [15], [20], [21].

$$y_i^* = \frac{\sum_{k=1}^{q} (k\ (x^*, x_k) y_k)}{\sum_{k=1}^{q} k\ (x^*, x_k)} \tag{1}$$

$$k\ (x^*, x_k) = \exp\left(-\frac{(x^* - x_k)^2}{2\sigma^2}\right) \tag{2}$$

This adaptive weighting scheme, influenced by the gaussian variance in equation 2, ensures that the regression model focuses on the most relevant and informative data points, making it resilient to noise and outliers. Additionally, the nonlinearity of the GK algorithm enables it to capture complex relationships between input variables and column drift ratios.

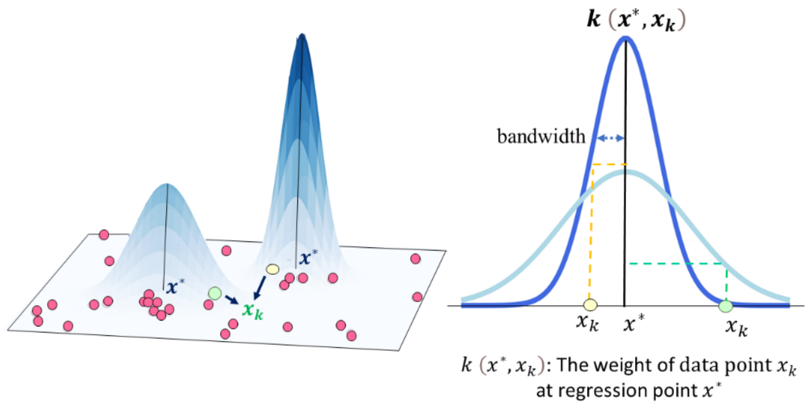

Fig. 1. Illustration of a Gaussian kernel function.

2.2. Implementation

In this paper, the nonlinear estimation of the column drift ratio using Gaussian kernel regression modelling was implemented exclusively in MATLAB. Specifically, the fitrkernel function from MATLAB's Statistics and Machine Learning Toolbox was employed to fit the Gaussian kernel regression model [22]. The input features for the Gaussian kernel regression model included bridge structural properties and ground motion intensity measures (IMs), namely peak ground acceleration (PGA) and spectral acceleration at 0.5 seconds (SA_05).

The OptimizeHyperparameters parameter in the fitrkernel function was set to 'auto', enabling the tuning of critical hyperparameters with a Bayesian optimization algorithm. Over the course of 30 training epochs, this adaptive algorithm dynamically adjusted the kernel scale, regularization coefficient (λ), and tolerance threshold (ε) to determine the optimal configuration for enhanced model performance [22], [23], [24].

This auto option also facilitated the standardization of the input features, a common pre-processing step in regression to ensure numerical stability and improve the model's performance. To ensure result reproducibility, a set of random seeds was applied prior to fitting the Gaussian kernel regression model. For each training epoch, the kernel scale, lambda, epsilon (measured as mean squared error), and objective function were estimated, with the optimal model ultimately selected based on the lowest cross-validation loss across the 5 folds. The minimum observed objective and estimated minimum objective are depicted in Figure 6, respectively showing the performance of the model [22].

It is noteworthy that the large number of parameters involved during the training phase of machine learning models can potentially lead to overfitting, whereby the model achieves high accuracy on the training dataset but exhibits comparatively lower performance on the validation dataset. To mitigate this issue, a regularization method, like Ridge regularization, automatically have been introduced for this modelling framework, offering encouraging outcomes in terms of enhancing prediction accuracy and generalization [22].

3. Case Study

Multi-span Simply Supported concrete girder bridges representative of bridges in the Central and Eastern United States was considered herein. The bridge parameters considered in this study are listed in Table 1. The space of these parameters was spanned by Latin Hypercube Sampling [25] to develop a training set consisting of 1044 bridge parameters and a test set consisting of 108 bridge parameter combinations. For each bridge parameter combination, a finite element model was developed. The bridge model consisted of a grillage deck model wherein the longitudinal elements represented the girders and the transverse elements represented the bridge deck slab. The columns and bent beams were modelled using displacement-based beam column elements with fiber sections which included separate fibers representing cover concrete, confined concrete, and rebars. The effects of transverse reinforcement were modelled following previous research [26]. The elastomeric bearings, abutments, and foundations were modelled using phenomenological models, details can be found in another references [27]. It must be noted that each bridge parameter combination leads to a bridge with different geometry, material properties, and deterioration condition for columns and bearings. Each of these bridges was paired with a randomly selected ground motion from the combined suite of synthetic ground motions developed by Wen and Wu [28] and Rix and Fernandez [29]. Correspondingly, the response of the bridge components – columns, bearings, and abutments, were determined. Specifically, the key engineering demand parameter of interest in this paper is the relative column drift ratio which is used as the output of the Kernel-based predictive demand model. This data is also available publicly at DesignSafe cyberinfrastructre [30].

Table 1. The list of input variables for the kernel regression model

Input	Seismic analysis characteristic	Input	Seismic analysis characteristic
$\boldsymbol{x_1}$	Concrete compressive strength	x_{24}	Concrete cover depth
$\boldsymbol{x_2}$	Steel yield strength	x_{25}	Number of girders along the width of the deck
$\boldsymbol{x_3}$	Coefficient of friction for bearing pad	x_{26}	Girder spacing
$\boldsymbol{x_4}$	Stiffness of bearing pad	x_{27}	Column spacing
$\boldsymbol{x_5}$	Dowel strength	x_{28}	Deck slab c/s area
$\boldsymbol{x_6}$	Dowel gap	x_{29}	Girder steel area
$\boldsymbol{x_7}$	Abutment passive stiffness	x_{30}	Girder concrete strength
$\boldsymbol{x_8}$	Abutment active stiffness	x_{31}	I_x of deck slab
$\boldsymbol{x_9}$	Foundation vertical stiffness	x_{32}	I_z of deck slab
$\boldsymbol{x_{10}}$	Foundation transverse stiffness	x_{33}	I_x of girder
$\boldsymbol{x_{11}}$	Mass participation ratio	x_{34}	I_z of girder
$\boldsymbol{x_{12}}$	Damping ratio	x_{35}	EQ direction
$\boldsymbol{x_{13}}$	Gap 1 (used for bearing model)	x_{36}	Earthquake ground motion number
$\boldsymbol{x_{14}}$	Gap 2 (used for bearing model)	x_{37}	Weight of one AASHTO prestressed girder
$\boldsymbol{x_{15}}$	Gap 3 (used for bearing model)	x_{38}	Slab thickness
$\boldsymbol{x_{16}}$	Gap 4 (used for bearing model)	x_{39}	Bearing pad area
$\boldsymbol{x_{17}}$	Number of spans	x_{40}	Bearing pad thickness
$\boldsymbol{x_{18}}$	Span length	x_{41}	Decrease in rebar diameter
$\boldsymbol{x_{19}}$	Number of columns	x_{42}	Stiffness factor to account for oxidation of elastomeric bearings
$\boldsymbol{x_{20}}$	Column height	x_{43}	Decrease in bearing dowel diameter
$\boldsymbol{x_{21}}$	Column diameter	x_{44}	PGA
$\boldsymbol{x_{22}}$	Longitudinal steel reinforcement ratio	x_{45}	Sa at 0.5 seconds
$\boldsymbol{x_{23}}$	Transverse steel reinforcement ratio		

*Sa represents spectral acceleration, and PGA represents arithmetic mean of the two ground motion components

4. Discussion

This study introduces a novel approach to predicting and quantifying column drift ratios in highway bridges using a Gaussian Kernel-based regression model. The integration of this machine learning technique addresses some of the key limitations inherent in conventional seismic demand modeling methods, which often rely on power-law functions of a single ground motion intensity measure. By leveraging the capabilities of Gaussian Kernel regression, the proposed model effectively captures the complex nonlinear relationships between input variables and the column drift ratio, enhancing the accuracy and efficiency of seismic performance assessments.

The methodology was rigorously tested on a dataset representative of multi-span simply supported concrete girder girder bridges in the Central and Eastern United States. The use of Latin Hypercube Sampling to develop a comprehensive training and test set ensured that the model was exposed to a diverse range of bridge configurations and ground motion scenarios. The Gaussian Kernel-based model demonstrated strong performance, as indicated by its ability to produce accurate predictions of the column drift ratio. The tuning of hyperparameters through Bayesian optimization further refined the model, balancing variance and bias to prevent overfitting and enhance generalization.

Fig. 2. illustrates the distributions of the seismic demand parameter "Column Drift Ratio" for the bridge, along with seismic analysis structural characteristics including column height, column diameter, span length, and deck slab I_z for a given set of peak ground acceleration records "PGA". A noteworthy observation from each plot is the presence of distinct areas wherein larger ratios of column drift are observed, in response to seismic characteristic components and notably the PGA records. This finding suggests that these areas are more susceptible to increased column drift, highlighting the importance of considering the combined effects of PGA records and seismic characteristics in comprehensively assessing the bridge's behaviour, vulnerability, and conducting fragility analyses.

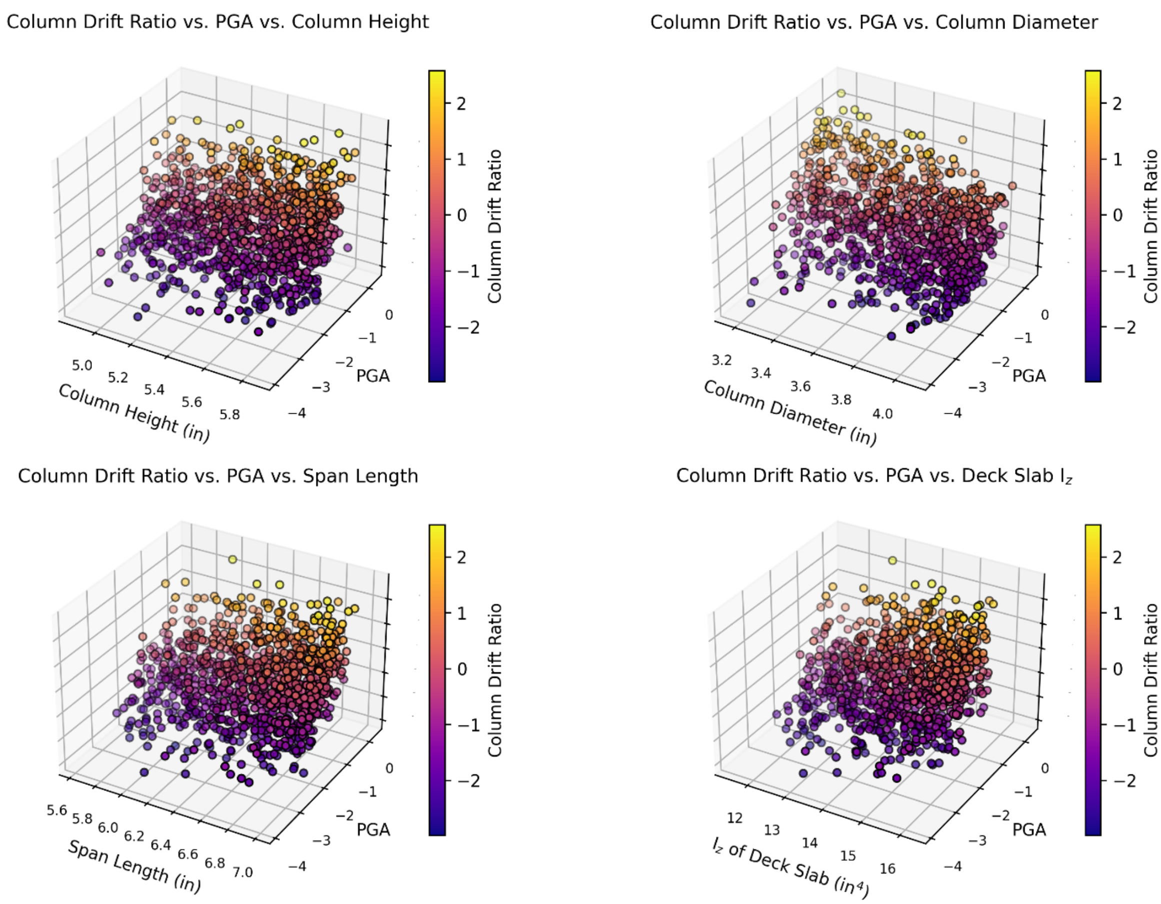

Fig. 2. Column drift ratio variability in response to PGA records and seismic characteristics

Fig. 3. and Fig. 4. illustrate the objective function values and the hyperparameters obtained throughout the optimization process. The plot presents the best estimated objective function value in red, plotted against the corresponding iteration number. Simultaneously, the best observed objective function value is represented in blue. The red and blue lines depict the achieved fit, resulting in an approximate 21% loss for the default 5-fold cross-validation after the 9th iteration. This visualization provides a clear and concise representation of the optimization algorithm's convergence and the performance of the objective function throughout the iterative process.

One of the significant advantages of the proposed model is its computational efficiency. Unlike traditional methods that require iterative learning processes, the Gaussian Kernel approach eliminates the need for such processes, making it a more time-efficient solution for seismic demand estimation. This efficiency, combined with the model's robust performance, underscores its potential as a valuable tool in performance-based earthquake engineering.

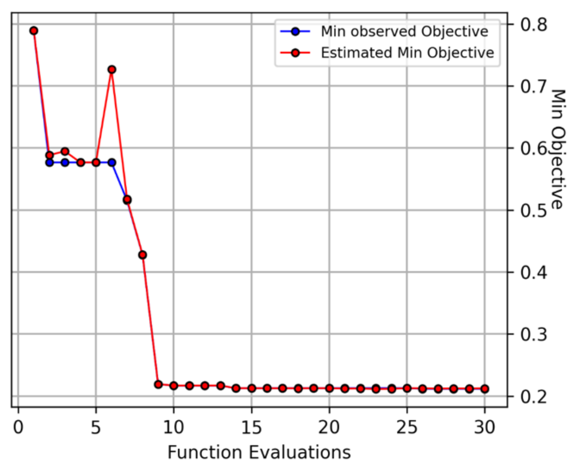

Fig. 3. The performance of the objective function during the iterative process using Bayesian optimization.

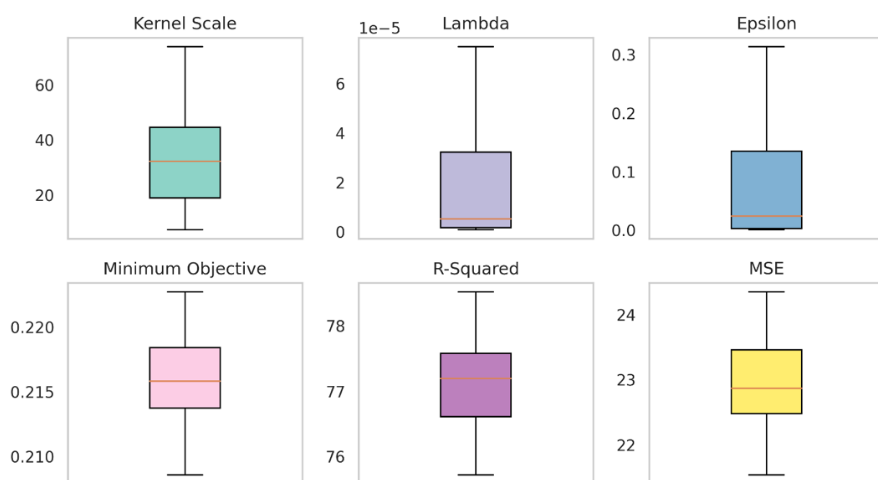

Fig. 4. Results of Kernel algorithm for 66 iterations

5. Conclusion

In conclusion, this study presents a Gaussian Kernel-based regression model for predicting column drift ratios in highway bridges, offering a novel and efficient approach to seismic performance assessment. By leveraging the strengths of of machine learning, particularly the Gaussian Kernel algorithm, the proposed model addresses the limitations of conventional seismic demand modeling methods and provides accurate, computationally efficient predictions. The methodology was validated through a comprehensive case study involving multi-span simply supported concrete girder bridges in the Central and Eastern United States, with hyperparameter tuning via Bayesian optimization ensuring robust performance. The successful application of this model demonstrates its potential to enhance performance-based earthquake engineering, offering valuable insights into bridge behavior under seismic loading and supporting informed decision-making in regions prone to seismic hazards. The availability of the dataset on the DesignSafe platform further underscores the model's applicability and potential for future research.

Acknowledgements

The authors acknowledge the support and funding provided by the School of Civil and Construction Engineering at Oregon State University.

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