EXPERIMENTALLY VALIDATED MACHINE LEARNING PREDICTION OF SEISMIC PERFORMANCE FOR RC DOUBLE-COLUMN PIERS

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Extended Abstract

Reinforced concrete (RC) double-column piers are critical load-bearing components within bridge seismic systems. Accurately defining their seismic performance levels and deformation capacity limits under varying earthquake intensities is essential for rapid post-earthquake assessment and resilient design. However, traditional assessment methods have notable limitations. Physical testing directly reflects the force and damage evolution characteristics of structural components, but it is costly, time-consuming, and limited by the number of samples. Numerical simulations can expand the parameter space but are sensitive to material constitutive models, boundary conditions, and nonlinear analysis processes. Empirical formulas, while convenient, have limited applicability and fail to accurately capture the complex response behavior under the interaction of multiple parameters. To address these challenges, this study proposes a seismic performance prediction framework for RC double-column piers that integrates experimental validation, numerical simulation, and interpretable machine learning.

The proposed framework for RC double-column piers consists of three stages, as shown in Figure 1. In stage 1, quasi-static tests were conducted on seven RC double-column piers with a scale ratio of 1:5.6 to reveal the damage evolution laws under low-cycle cyclic loading. The observed damage progression, including initial cracking, concrete spalling, longitudinal reinforcement buckling, and core concrete crushing, was examined. Based on CSA S6-29 standards, four seismic performance levels (DS1 to DS4) were established by integrating macroscopic damage observations with microscopic material strain responses. In stage 2, a finite element model of the RC double-column piers was developed on the OpenSees platform and validated using experimental results. The validation indicated that the average error

for the model's peak load was only 7.48%, confirming its reliability. Subsequently, seven key design parameters, namely concrete strength, yield strength of longitudinal and stirrup reinforcement, longitudinal reinforcement ratio, volumetric stirrup ratio, shear span ratio, and axial load ratio, were selected as input features. Their value ranges determined based on current standards and available quasi-static test results. Latin hypercube sampling was used to uniformly sample the parameter space, resulting in 3600 finite element models. Pushover analysis was conducted to extract corresponding force-displacement responses and material strain evolution at critical cross-sections, and the drift ratio thresholds corresponding to each performance level were then obtained to form the seismic performance database. In stage 3, six machine learning algorithms, namely Ridge Regression, Lasso Regression, Decision Tree (DT), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Multilayer Perceptron (MLP), were selected to evaluate their prediction accuracy for the drift ratio thresholds of the four performance levels. SHAP (Shapley Additive Explanations) analysis was then performed on the most accurate predictive model to identify the dominant control parameters at different damage stages.

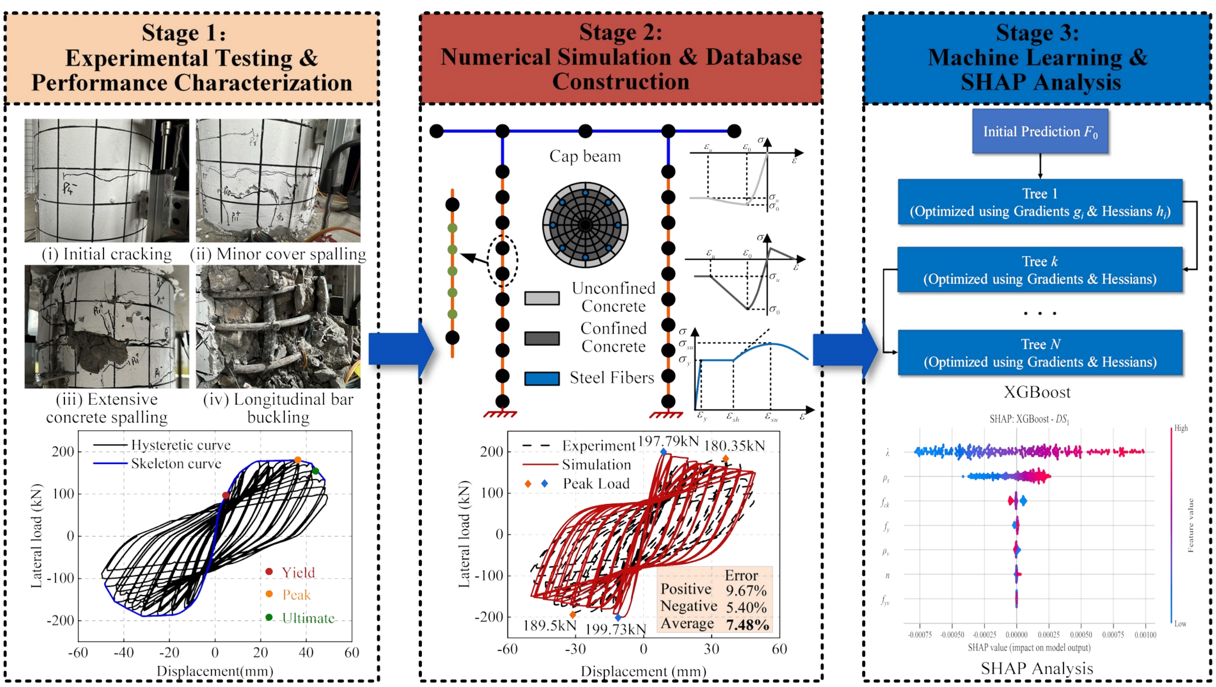

Figure 1- Seismic performance prediction framework for RC double-column piers.

The evaluation results from the test set indicated that all models demonstrated high prediction accuracy for the slight to severe damage stages (DS1 to DS3), with the coefficient of determination (R^2) remaining above 0.95. However, in the near-collapse stage (DS4), significant differences in predictive performance were observed due to the concurrent control of both the reinforcement strain threshold and the degradation criteria of bearing capacity. This resulted in a clear failure competition mechanism, leading to substantial variation in the performance of different models. Linear regression models, such as Ridge and Lasso, exhibited notable limitations, with R^2 values around 0.55 at this stage. In contrast, the XGBoost model achieved the best performance, with an R^2 of 0.945 in DS4 and an average R^2 of 0.98 across the four performance levels, demonstrating its ability to effectively capture the complex nonlinear relationships between the multiple damage thresholds and input parameters of RC double-column piers.

Furthermore, the SHAP analysis of the XGBoost model revealed a distinct stage-specific governing mechanism for the drift ratio thresholds. In the slight to moderate damage stages (DS1 and DS2), geometric and reinforcement characteristics, such as shear span ratio (λ) and longitudinal reinforcement ratio (ρ_s), played a dominant role in controlling deformation capacity. At the severe damage stage (DS3), the contributions of reinforcement yield strength (f_y) and concrete strength (f_{ck}) were further intensified as the influence of material properties became increasingly apparent. At the near-collapse state (DS4), the dominant roles of concrete strength (f_{ck}), volumetric stirrup ratio (ρ_v), and axial load ratio (n) were significantly enhanced.

The main conclusions are as follows. First, the damage evolution laws of RC double-column piers under low-cycle cyclic loading were revealed through seven sets of quasi-static tests, and four seismic performance levels were established utilizing material strains. A seismic performance database consisting of 3,600 samples was constructed with an experimentally validated OpenSees finite element model, addressing the limitations of restricted parameter coverage in physical experiments. Second, among the six machine learning models, XGBoost demonstrated the optimal prediction accuracy and generalization capability for predicting drift ratio thresholds at each performance level, while maintaining high predictive precision even in the near-collapse stage characterized by a failure competition mechanism. Third, SHAP analysis indicated that the dominant factors for the drift ratio thresholds of RC double-column piers exhibited distinct stage-specific characteristics: DS1 to DS3 were primarily governed by geometric and reinforcement features, whereas DS4 was more significantly influenced by material properties and confinement efficiency. These findings verify the applicability and effectiveness of interpretable machine learning for predicting multi-level damage states and provides a robust reference for rapid damage-state identification and post-earthquake emergency decision-making for bridges.

Keywords*: RC double-column pier; seismic performance level; pushover analysis; machine learning; SHAP; interpretability analysis.*