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SEISMIC PERFORMANCE PREDICTION OF RCC BUILDINGS HAVING SHEAR WALL USING MACHINE LEARNING

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Abstract - The seismic performance of reinforced concrete (RCC) buildings is highly influenced by the configuration and properties of shear walls, as well as key structural indices that govern lateral strength, stiffness, and ductility. Conventional seismic response assessment methods often rely on computationally expensive nonlinear analyses, making them less practical for rapid classification of building performance. In this study, a machine learning (ML)-based framework is developed to classify the seismic response of RCC buildings by integrating shear wall characteristics (location, aspect ratio, and wall density). A comprehensive dataset is generated through nonlinear time-history analyses of prototype RCC building models subjected to varying ground motions. The extracted response parameters are used to train and validate using machine learning classifier. The findings highlight the potential of combining structural engineering principles with data-driven techniques for rapid seismic performance assessment, aiding in resilient design and risk-informed decision-making for RCC buildings.

Keywords: Shear wall, Machine Learning, Regression, Displacement

1. Introduction

The seismic safety of reinforced cement concrete (RCC) buildings remains a critical concern in structural engineering, particularly in earthquake-prone regions. Among various structural components, shear walls play a significant role in enhancing lateral stiffness and strength, thereby improving the overall seismic performance of buildings. The arrangement, geometry, and distribution of shear walls, when combined with key structural indices such as stiffness ratio, ductility index, and slenderness parameters, largely govern the dynamic response of RCC systems. Traditionally, seismic performance evaluation has relied on nonlinear dynamic analyses, which, though accurate, are computationally intensive and impractical for large-scale applications. In this context, machine learning (ML) offers an efficient data-driven alternative for rapid seismic response classification, enabling engineers to predict structural behavior without exhaustive numerical simulations.

Several studies have emphasized the importance of shear wall configuration in improving seismic resilience. Paulay and Priestley (1992) highlighted the effectiveness of ductile shear walls in resisting earthquake-induced lateral forces, while Wallace (1995) provided insights into shear wall failure mechanisms under cyclic loading. Subsequent research by Kabeyasawa et al. (2000) demonstrated that the location and aspect ratio of shear walls significantly influence lateral stiffness distribution in multi-storey RCC buildings. More recently, Boivin and Paultre (2012) studied shear wall–frame interaction and reported that balanced distribution of stiffness is crucial for minimizing torsional effects during earthquakes. Parallel to structural advancements, researchers have also focused on performance-based seismic design approaches. Chopra and Goel (2002) introduced modal pushover analyses as a means of evaluating building response indices, while Fajfar (2000) proposed the capacity spectrum method for estimating seismic demand and capacity interaction. These methods laid the groundwork for quantifying seismic indices, which are now being explored as input parameters in data-driven frameworks.

In recent years, machine learning applications in earthquake engineering have gained momentum. Ghaboussi et al. (1991) were among the first to apply neural networks for structural system identification, establishing a foundation for predictive modeling in seismic analysis. More recently, Kiani and Ghodrati (2015) utilized support vector machines to classify seismic vulnerability of RC frames, while Chakraborty and Roy (2016) demonstrated the potential of decision tree algorithms for rapid damage state prediction. Similarly, Tena-Colunga et al. (2019) incorporated structural indices with ML models for vulnerability assessment, showing significant improvements in prediction accuracy. Advances in ensemble methods, such as random forests (Breiman, 2001), further strengthened classification robustness in structural engineering applications. The convergence of structural engineering knowledge with modern ML algorithms presents a transformative opportunity for rapid seismic assessment. Studies such as Zhang et al. (2020) applied deep learning to predict seismic damage patterns, while Bansal and Saini (2021) integrated structural indices with ML classifiers to evaluate RC frame responses. These efforts collectively indicate that ML-driven frameworks can reduce dependency on computationally expensive time-history analyses, while maintaining reliability in response classification. Building on these foundations, the present study aims to develop an ML-aided classification framework that integrates shear wall characteristics and structural indices for seismic response prediction of RCC buildings. By training multiple ML classifiers on response datasets generated through nonlinear time-history analyses, this work seeks to identify efficient prediction models capable of supporting risk-informed design and rapid decision-making for resilient urban infrastructure.

3. Methodology

The structural configuration adopted in this study is based on insights from prior literature. A building with a plan aspect ratio of 2 (37 m × 18.5 m) and a total height of 72 m is modeled, consistent with mid-rise RCC designs in seismic Zone V. The structure comprises 12 storeys, each 3 m high, with beams sized 0.3 m × 0.45 m and columns 0.6 m × 0.6 m to ensure stiffness and ductility. A slab thickness of 150 mm and shear walls of 200–230 mm are provided, in line with established design practices. Seismic and load combinations are considered as per IS 875 and IS 1893:2016.

The following below are the sample of the building with different shear wall locations:

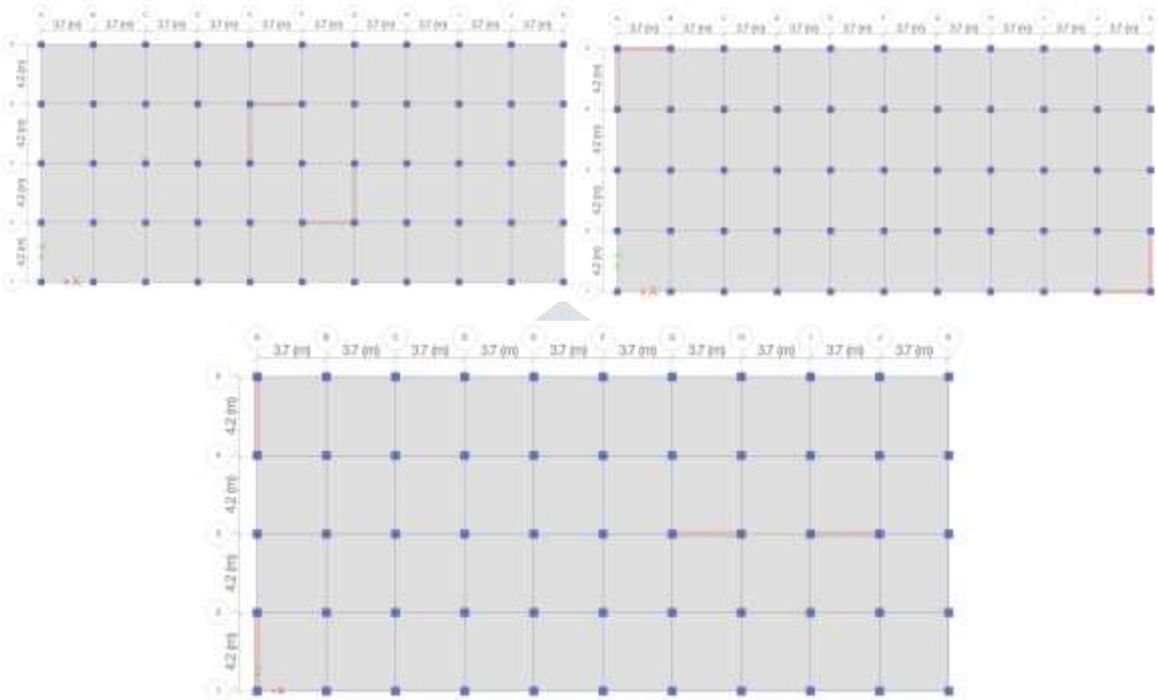

Fig. 1 Models with Corner, Periphery & Core placed shear wall

An effort is made in the present study to analyze the seismic response of RCC frame buildings by varying three fundamental parameters—location of shear wall, thickness of shear wall, and height of the building (number of storeys)—based on typical configurations observed in existing literature. Some of the sample datasets used in the working

Table 3.1 Description of Models

Building Height (m)	Shear Wall Location	Thickness (mm)	Roof Displacement (mm)	Reference Paper	Time Period (sec)
12	Corner	230	22.1	Azam & Hosur, 2013	0.36
12	Corner	200	23.8	Azam & Hosur, 2013	0.42
12	Diagonal	230	21	Dahesh et al., 2015	0.37
12	Diagonal	200	23.4	Dahesh et al., 2015	0.41
12	Core	230	20.9	Yaghmaei-Sabegh et al., 2024	0.35
12	Core	200	23.1	Yaghmaei-Sabegh et al., 2024	0.4

4. Results & Discussion

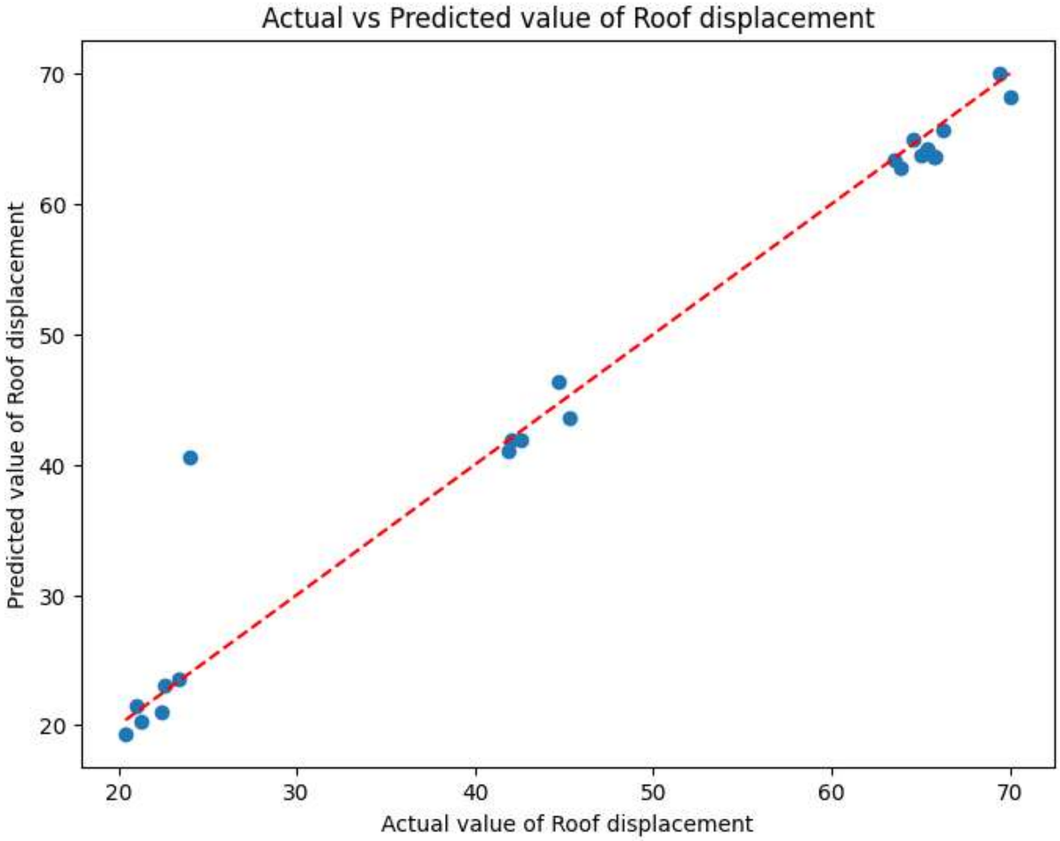

Fig. 2 Actual vs Predicted value of Displacement

The Multi Linear Regression model achieved an R^2 of 0.9954, indicating that it explains 99.54% of the variance in the target variable. The correlation coefficient (R) of 0.9978 suggests a very strong positive relationship between the predicted and actual values. Additionally, the Mean Absolute Error (MAE) of 0.0145 and Root Mean Squared Error (RMSE) of 0.0178 reflect minimal prediction errors, confirming the model's high accuracy and reliability in capturing the underlying data patterns.

Table 4.2 Evaluation of the Performance Indices

ML Model	R^2	R	MAE	RMSE
Multi Linear Regression	0.99537	0.9978	0.014549	0.01777

Conclusions

The multi-linear regression model demonstrated excellent predictive capability, with an R^2 value of 0.9954 and correlation coefficient of 0.9978, indicating a near-perfect fit between actual and predicted displacements. Very low MAE (0.0145) and RMSE (0.0178) further confirm its high accuracy and reliability, making it a robust tool for seismic response prediction.

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