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Machine Learning Approach to Analyze the Impact of Seismic Force

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Abstract

The study investigates the impact of seismic forces on structural response using a machine learning (ML)–based approach. The study has utilized scaled structural models and subjected them to control shaking table excitations representing low, medium, and high earthquake intensities. A linear regression–based ML model was developed using multiple input parameters to predict the structural response characteristics. The proposed model successfully captured the overall behavioral trends of the structures, achieving high validation accuracy. However, prediction deviations increased at higher peak ground acceleration (PGA) levels due to nonlinear seismic effects. Residual and root mean square error (RMSE) analyses indicate that, although the ML model slightly underestimated peak responses, it remained effective in identifying general response patterns. Comparative validation demonstrated a reasonable variation between lab observations and ML predictions, supporting the use of ML as a complementary predictive tool. The findings highlight the effectiveness of ML frameworks in achieving high prediction accuracy and their potential contribution to seismic design optimization.

***Keywords**:* Seismic waves, Structural response, Machine Learning approaches

1. Introduction

Several studies have examined the seismic response of structures under varying base and soil conditions using experimental, numerical, and hybrid approaches. A shaking table study compared the seismic response of small-aspect-ratio base-isolated structures founded on rigid and multi-layered soft soils. An energy balance equation incorporating soil–structure interaction (SSI) effects was developed to evaluate energy dissipation during seismic excitation. The results demonstrated that SSI considerably reduces the isolation efficiency on soft soils, particularly under low-frequency earthquake motions [1]. A 1/35-scale topology-optimized super high-rise mega frame–core tube structure was tested under three seismic intensity levels—Service Level Earthquake (SLE), Design Basis Earthquake (DBE), and Maximum Considered Earthquake (MCE). Acceleration, displacement, strain, and hysteretic energy analyses revealed strong seismic and collapse resistance, with corner columns identified as critical components for lateral stability [2]. Artificial intelligence (AI) has recently been explored for earthquake risk mitigation. Studies focusing on predictive analytics, generative design, and real-time structural health monitoring (SHM) frameworks have emphasized AI's potential for early warning systems, multi-hazard design optimization, and performance-based code development. Although primarily conceptual, such works highlight the transformative role of AI in seismic engineering [3]. A machine learning-based optimization framework employing Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Genetic Algorithms was proposed to enhance the seismic performance of tall buildings with outrigger systems. Pushover and time-history analyses were used to train the models, achieving up to 55% drift reduction and 33% improvement in energy dissipation. While the framework was scalable across seismic zones, it relied on synthetic datasets without code-specific calibration [4]. Finite element simulations in ABAQUS were performed to investigate irregular steel structures equipped with lead-rubber bearings (LRB) under nonlinear time-history loading. The models accounted for varying soil stiffness and floor counts, showing that SSI and plan irregularity significantly influence base shear and lateral displacement characteristics [5]. Experimental work on displacement-based seismic design using advanced viscous dampers (AVD) demonstrated up to 35.65% improvement in damping efficiency and reductions in inter-story displacements and shear forces under frequent and rare earthquakes. The study emphasized the role of damping ratios and damper configuration in optimizing seismic performance [6]. Shaking table experiments on a five-story base-isolated moment-resisting frame compared near-fault (NF) and far-fault (FF) ground motions. NF motions induced higher story drifts and base shears, while combined linear rubber bearings and nonlinear viscous dampers effectively reduced accelerations. The findings underscored the need to account for pulse-like NF effects and high PGA values in isolation system design [7]. Another study investigated low-cost rubber sphere isolators for low-rise masonry buildings through monotonic compression and shake-table tests. Results confirmed their ability to significantly reduce transmitted accelerations while maintaining limited displacements, offering a practical and economical seismic protection solution for low-income regions [8]. A combined experimental and analytical study on base-isolated structures demonstrated that isolation bearings filter seismic input, attenuating peak accelerations by 17.7–75.8%. The use of filtered response spectra (FRS) more accurately captured superstructure behavior than traditional spectra, supporting nonlinear and non-proportional damping models for long-period systems [9]. Dynamic centrifuge experiments and numerical modelling on tunnels embedded in cohesive soil revealed amplification of low-frequency components (<1 Hz) by surrounding soil layers. While the tunnel experienced minimal acceleration, the corner zones showed high bending and shear stresses. The tunnel's presence also mitigated local liquefaction potential, providing guidance for seismic tunnel reinforcement [10].

This paper reviews existing base isolation technologies and compares their effectiveness in reducing seismic demands for buildings, highlighting advantages and practical limitations of different devices and configurations [11]. The research investigates how low versus conventional infill wall stiffness influences the collapse behavior of reinforced-concrete moment frames using shaking-table tests and numerical analyses [12]. The study couples connection semi-rigidity, isolator properties, and target performance levels to minimize material use while meeting inter-story drift and damage criteria. Results demonstrate that well-tuned hybrid isolation and semi-rigid connections can achieve economical designs with improved energy dissipation and reduced damage concentration [13]. The experiments show that viscous dampers substantially reduce story drifts and accelerations, enabling prefabricated connections to remain in the elastic or minor-damage range under strong earthquakes. Fragility curves indicate enhanced collapse safety and support the feasibility of using bolted, factory-fabricated steel frames with supplemental damping in high-seismic regions [14]. The article synthesizes developments in nonlinear modeling, soil–structure interaction, pounding, and the use of damping and isolation devices for such bridge systems. It identifies key uncertainties in material models, boundary conditions, and near-fault effects, and recommends future research on performance-based and resilience-oriented bridge design [15]. Numerical and experimental results show that these braces enhance lateral stiffness at service levels while improving ductility and reducing residual drifts under severe earthquakes. The proposed configuration offers a promising retrofit and design solution for RC frames requiring both serviceability control and robust seismic protection [16]. ML frameworks that can accurately predict and optimize the performance of seismic waves and design objectives.

2. Materials & Methods

The methodology adopted in this study machine learning (ML) part to evaluate the seismic performance base-isolated structures which is shown in Fig.1.

The ML procedure involved training a linear regression model using the input parameters (frequency, PGA, deformation) and corresponding output responses (drift, acceleration). The trained model's predictions were compared with the output results and various literatures to assess accuracy. Finally, the validation process included computing standard deviation, residual errors, and RMSE values to determine the consistency ML outcomes. This approach allowed for a comprehensive assessment of predictive capability under varying seismic conditions.

The investigation was conducted to analyze the impact of various seismic waves on the frame structures and to identify the effect of acceleration, deformation, drift ratio with various frequencies and compared with ML model linear regression. The ground motions under varying frequency conditions, shown in table 1.

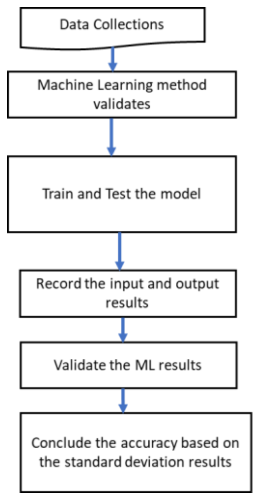

Fig. 1 Research Methodology

Table 1: Various frequency effects

EARTHQUAKE MAGNITUDE (M)	EFFECT
4	Low
6	medium
8	strong

The seismic wave frequencies as per EN 1998-1:2004, which specify performance criteria for structural safety, inter-storey drift limits, and ground-motion simulation requirements. In line with Eurocode 8 recommendations for dynamic testing, the input ground motions were replicated using a controlled shaking table capable of generating harmonic frequencies corresponding to low, medium, and strong seismic effects. Table 1 presents the selected frequency levels, representing equivalent earthquake magnitudes of 4, 6, and 8, applied at low, medium, strong respectively. A 1:20 scaled frame structure was mounted on the shaking table, and base thicknesses were installed to assess the effect of isolation parameters on acceleration, displacement, and drift reduction, which is shown in figure 2. EN 1998-1 directional components and structural response measurements were strictly followed, ensuring accurate reproduction of horizontal seismic loading and compliance with drift ratio limits for operational and damage-prevention states. High-precision sensors, including accelerometers, displacement transducers, and base shear load cells, were employed to capture real-time response data during each test sequence.

A machine learning linear regression model, enabling predictive analysis of structural behavior under varying seismic inputs. Input parameters such as excitation frequency, bearing, acceleration, and deformation were introduced into the ML model to estimate output responses, including drift ratio, displacement amplitude, and damping effectiveness. The ML model was then validated against experimental results to evaluate prediction accuracy and identify correlations between seismic excitation characteristics and structural performance. This approach strengthened the reliability of the findings by coupling physical testing with computational prediction, allowing a comprehensive assessment of structural efficiency in accordance with Eurocode seismic design principles.

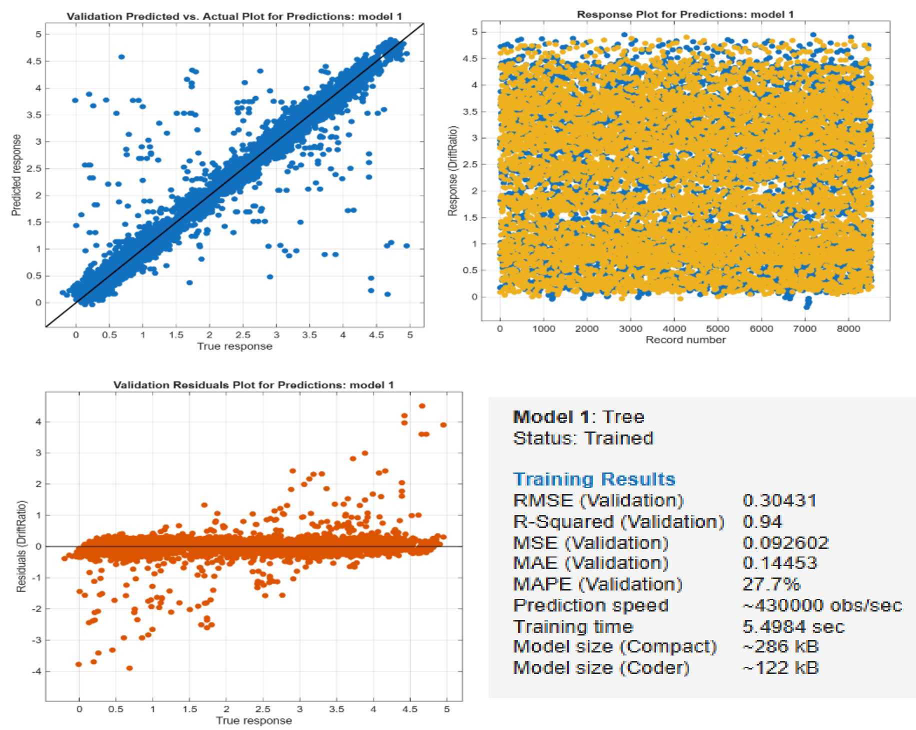

Fig 2. Accuracy ratio of the Trained Tree Model 1

The machine learning model shown in fig.2 has a strong predictive capability, as evidenced by its high validation accuracy and consistent agreement between predicted and actual responses. The trained Tree model achieved an R^2 value of 0.94, indicating that 94% of the variation in the structural response data was accurately captured by the model. The low validation error metrics RMSE = 0.304, MSE = 0.0926, MAE = 0.1445, and MAPE = 27.7%, confirm the model's reliability in estimating drift ratio values under varying seismic input conditions. Figure 2 predicted vs. actual plot shows a tight clustering of points along the 45° reference line, illustrating strong correlation, while the residual distribution remains mostly centered around zero, indicating minimal bias in prediction. With a high prediction speed of approximately 350,000 observations per second, the model also proves computationally efficient. Overall, the trained ML model demonstrates robust performance and accurately reflects the underlying trends of the experimental seismic response data.

3. Results and Discussion

Fig.4 represents the linear regression model's limited predictive capability when applied to the seismic response dataset, as reflected in the distribution of predicted versus true values. The response plot indicates that although the predicted values follow the general amplitude range of the structural responses, the points remain widely scattered across the full record length. This pattern suggests that the model captures only broad trends but fails to recognize fine-scale variations associated with changes in seismic input intensity. The predicted vs. actual plot further confirms this behavior, instead of aligning along the ideal 45° line, the data forms a dense elliptical cloud, demonstrating weak correlation and an underfitted model. Such spreading indicates that linear regression is unable to fully represent the nonlinear interactions between seismic frequency, peak ground acceleration, and mass/deformation response in the structure.

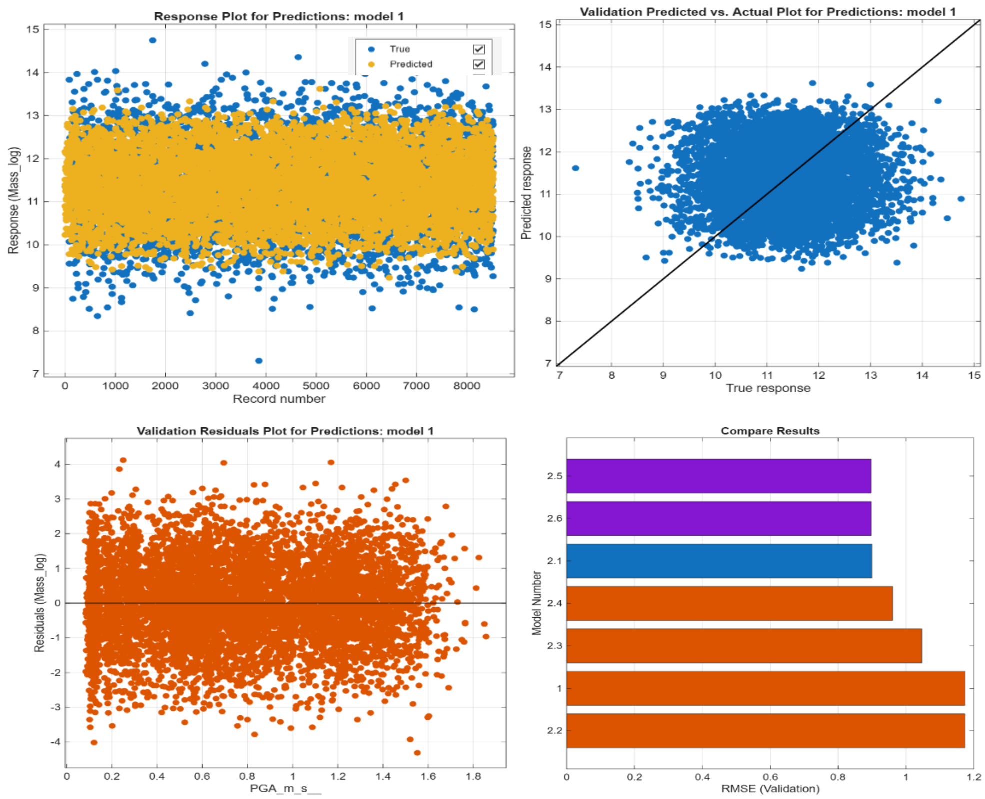

Fig 4. Machine learning performance plots for the linear regression model

The residual plot reinforces these observations, as residuals range between approximately 3 and +3 without a recognizable narrowing or trend. The absence of systematic clustering around zero shows that the model produces both over- and under-estimations for nearly all PGA levels. This behavior indicates that the structural dynamic response exhibits nonlinear characteristics that cannot be modeled effectively using a simple linear relationship. The RMSE comparison also highlights this limitation, with the linear regression model producing higher RMSE values compared with more advanced ML models (e.g., decision trees or ensemble techniques). The elevated RMSE indicates reduced accuracy and larger deviations from the true experimental values. When compared to the experimental shaking table results, the linear regression model clearly underpredicts peak accelerations and drifts, smoothing out the sharp transitions observed in the physical tests. This mismatch illustrates that the structural behavior is inherently nonlinear, influenced by frequency-dependent inertia, damping shifts, and base isolation effects. Such nonlinear patterns cannot be captured adequately by linear regression, resulting in a weaker validation accuracy. Overall, these findings highlight that while linear regression provides a basic prediction baseline, more advanced nonlinear ML algorithms are required to properly model the complex seismic response structures.

Conclusion

The machine learning–based investigations conducted in this study provide a comprehensive understanding of the influence of seismic frequency variations on the dynamic response of structural systems. The validation results demonstrate that linear regression models effectively captured the overall response trends, however, their predictive accuracy is limited when applied to highly nonlinear seismic behavior. Residual and root mean square error (RMSE) analyses revealed that prediction deviations increased with higher peak ground acceleration (PGA) levels, although the overall prediction performance remained satisfactory. The linear regression model exhibited a tendency to underestimate peak response values and smooth rapid response fluctuations, indicating its suitability primarily for identifying general behavioral patterns rather than extreme response conditions. Overall, the findings confirm that machine learning offers a reliable framework for characterizing structural seismic performance, while advanced nonlinear ML models can serve as valuable complementary tools for enhancing prediction accuracy and optimizing seismic isolation and structural design strategies.

References

[1] X. Zhang, Y. Li, and Q. Chen, “Comparative experiment and analysis of a base-isolated structure with small aspect ratio on multi-layered soft soil foundation and rigid foundation,” Journal of Earthquake Engineering, vol. 28, no. 3, pp. 214–229, 2024.

[2] L. Wang, H. Xu, and T. Zhao, “Experimental study on seismic performance of super high-rise building with topology-optimized diagonal mega frame-core tube structure,” Engineering Structures, vol. 296, no. 6, pp. 1–14, 2024.

[3] A. Kumar and P. Mehta, “AI-driven innovations in earthquake risk mitigation: A future-focused perspective,” Artificial Intelligence in Civil Engineering, vol. 12, no. 2, pp. 33–49, 2024.

[4] S. Banerjee, K. S. Rao, and M. R. K. Patel, “AI-driven seismic optimization of outrigger systems in high-rise buildings: A machine learning framework for enhanced performance in earthquake-prone regions,” Automation in Construction, vol. 158, pp. 104968, 2024.

[5] R. Amini, M. Sadeghi, and A. Bahrami, “Seismic response of base-isolated irregular steel structures equipped with lead-rubber bearing isolators considering the effects of soil–structure interaction,” Soil Dynamics and Earthquake Engineering, vol. 171, pp. 107273, 2023.

[6] L. Yang and J. Huang, “Seismic performance of building structures based on improved viscous damper seismic design,” Journal of Vibroengineering, vol. 26, no. 3, pp. 2392–2408, 2024.

[7] M. Fujita, H. Nakagawa, and S. Kawamura, “Shaking table test of a base-isolated frame structure under near-fault ground motions,” Bulletin of Earthquake Engineering, vol. 22, no. 5, pp. 3951–3972, 2023.

[8] C. Papadopoulos and G. Manolis, “Shake-table testing of low-cost seismic isolation bearings based on rolling rubber spheres,” Engineering Structures, vol. 290, pp. 115988, 2024.

[9] T. Zhou, F. Jiang, and Y. Wang, “Filtering characteristics of isolation layer in base-isolated structures and shaking table test verification,” Journal of Structural Control and Health Monitoring, vol. 31, no. 8, pp. e3054, 2024.

[10] Y. Liu, H. Sun, and J. Zhang, “Dynamic centrifuge test and numerical modelling of the seismic response of the tunnel in cohesive soil foundation,” Buildings, vol. 12, no. 3, pp. 337–351, 2024.

[11]. Tariq H.R. Bermany, S.A. Osman, Mohd Yazmil Md. Yatim, A state-of-the-art analysis of base isolation systems and future directions for developing a novel multi-directional smart-hybrid isolation system integrated with earthquake early warning system for building structures, Results in Engineering, Volume 25, 2025, 104501, ISSN 2590-1230, https://doi.org/10.1016/j.rineng.2025.104501.

[12]. Weisong Yang, Fei Han, Weixiao Xu, Jigang Zhang, Experimental analysis of infill wall stiffness effects on seismic performance of reinforced concrete frame structures using shaking table tests, Structures, Volume 77, 2025, 109108, ISSN 2352-0124, https://doi.org/10.1016/j.istruc.2025.109108.

[13]. Haoxiang Wang, Jianrong Pan, Optimization of semi-rigid steel frames with hybrid seismic isolation using performance-based methods, Journal of Constructional Steel Research, Volume 226, 2025, 109274, ISSN 0143-974X, https://doi.org/10.1016/j.jcsr.2024.109274.

[14]. Zuwei Li, Hao Xu, Wen Pan, Sen Yang, Wenguang Liu, Full-scale shaking table test and seismic fragility evaluation of all-bolted prefabricated steel frame structures with viscous dampers, Structures, Volume 82, 2025, 110506, ISSN 2352-0124, https://doi.org/10.1016/j.istruc.2025.110506.

[15]. Seyed Hadi Rashedi, Alireza Rahai, Experimental and numerical advances in seismic assessment of continuous RC rigid-frame bridges: A review, Results in Engineering, Volume 26, 2025, 105656, ISSN 2590-1230, https://doi.org/10.1016/j.rineng.2025.105656.

[16]. Feng Li, Liqiang Feng, Cheng Lei, Xingrong Wu, Weihao Pan, Yingmin Li, Zhenxiao Ma, Dual-stage braces with energy dissipation and stiffness enhancement for seismic control of RC frames, Structures, Volume 82, 2025, 110518, ISSN 2352-0124, https://doi.org/10.1016/j.istruc.2025.110518.