

DFBI 2025 aims to encourage the international exchange of innovative ideas between researchers from academia and industry. In addition to knowledge dissemination, the conference offers a valuable platform for professional networking, particularly benefiting university professors, graduate students, and postdoctoral researchers.

Research Article

# Health Monitoring of Outriggers of Tall Structures Under Lateral Force Using Machine Learning

Masoumeh Cheraghi<sup>1</sup>, Zahra Khakshour<sup>1</sup>, Yaser Shahbazi<sup>1</sup>, Mohsen Mokhtari Kashavar<sup>1</sup>, Mohammad Fotouhi<sup>2</sup> and Siamak Pedrammehr<sup>3</sup>

1 Faculty of Architecture and Urbanism, Tabriz Islamic Art University, Tabriz 5164736931, Iran; [ma.cheraghi@tabriziau.ac.ir](mailto:ma.cheraghi@tabriziau.ac.ir) (M.C.); [Za.khakshour@tabriziau.ac.ir](mailto:Za.khakshour@tabriziau.ac.ir) (Z.K.); [mo.mokhtari@tabriziau.ac.ir](mailto:mo.mokhtari@tabriziau.ac.ir) (M.M.K.);

2 Faculty of Civil Engineering and Geosciences, Delft University of Technology, 2628 CN Delft, The Netherlands

3 Faculty of Design, Tabriz Islamic Art University, Tabriz 5164736931, Iran

Correspondence: [y.shahbazi@tabriziau.ac.ir](mailto:y.shahbazi@tabriziau.ac.ir) (Y.S.); [m.fotouhi-1@tudelft.nl](mailto:m.fotouhi-1@tudelft.nl) (M.F.)

Copyright: Copyright: © 2026 by the authors.

DFBI is an open-access proceedings distributed under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0). View this license's legal deed at <https://creativecommons.org/licenses/by/4.0/>



## Abstract

High-rise buildings face significant challenges in withstanding lateral forces, such as wind and seismic activity, which can cause excessive drift and vibrations. Outriggers, integral to stabilizing these structures, are particularly susceptible to stress under such forces. This paper presents a novel approach utilizing Machine Learning (ML) for the Structural Health Monitoring (SHM) of outrigger systems in tall buildings, with the aim of enhancing damage detection and long-term structural integrity predictions. The proposed ML framework uses data from sensor networks and focuses on key stress indicators, including average maximum stress ( $\sigma_{max}$ ) and maximum shear stress ( $\tau_{max}$ ), to identify early signs of failure. Through the integration of advanced ML algorithms, such as Long Short-Term Memory (LSTM) networks, the study demonstrates the model's high predictive accuracy in forecasting displacements and stress levels under typical lateral loads. The framework offers a proactive approach for monitoring and maintaining structural health in high-rise buildings, reducing risks and optimizing maintenance schedules. By leveraging real-time sensor data, the proposed system supports a continuous evaluation process, contributing to the development of resilient urban infrastructure. This research underscores the potential of ML to revolutionize SHM practices, ensuring the safety and longevity of critical structural systems in tall buildings.

**Keywords:** High-rise buildings; Outriggers; Structural Health Monitoring; Machine Learning; Lateral force

Cite this article:  
Lastname, F. M., & Lastname, F. M.  
(Year). Title of the article, Title of the  
Journal, Volume (Issue), Page range.  
<https://doi.org/10.66408/dfbi.2026.26321>

# 1 Introduction

High-rise buildings need strong wind resistance. Structural Health Monitoring (SHM) ensures safety. This paper utilizes Machine Learning (ML) for SHM of outriggers under lateral forces, thereby enhancing damage detection and predicting integrity in steel structures under typical loads.

## 1.1 Existing Theories and Frameworks

As cities expand, the construction of high-rise buildings is unavoidable. These structures, known for their lightweight design, flexibility, and ever-increasing height, present significant challenges in wind-resistant design (Lin et al., 2022; Shelake, 2025). Critical stresses from lateral forces can result in unwanted vibrations and excessive lateral sway, known as drift. Drift measures the sideways movement of a building's top compared to its base (Pujari & Gunjal, 2024). Outriggers are crucial for stabilizing tall buildings against lateral loads like wind and earthquakes. They stiffen the structure by connecting the core to perimeter columns, acting as a unified system to resist these forces. The number, placement, and rigidity of outriggers significantly impact structural stiffness (Fang, 2023; Tobber et al., 2025). ML techniques have shown significant potential in SHM of tall structures, including arm monitoring under lateral forces. SHM is essential for structural engineering, providing continuous or periodic assessment to detect damage and guarantee safety, reliability, and longevity (Li et al., 2024). Effective SHM involves four critical steps: data gathering, system analysis, condition assessment, and maintenance. Sensor data, collected through contact (accelerometers, strain gauges) and non-contact (cameras, drones) methods, is crucial. This data is processed using ML, deep learning, or signal processing to pinpoint damage indicators. Maintenance actions follow based on the assessment, ensuring structural safety and lifespan (Jia & Li, 2023). SHM and nondestructive evaluation utilize various techniques, such as piezoelectric, magnetostrictive, and magnetic effects, to assess structural safety. Effective safety evaluation relies on deploying suitable sensors and sensor arrays to collect data, which is then analyzed through signal processing (Liu, 2024). Combining physics and ML enhances high-rise arm health monitoring under lateral forces. Existing work shows ML potential for accurate displacement prediction in tall structures (Ghaffari et al., 2024), and the emerging PINN approach suggests that similar techniques can be adapted for brachial monitoring under lateral forces (Langat et al., 2025). ML shows promise for SHM in tall buildings. Outriggers require integrated data for failure analysis under lateral loads, enhancing stability by linking core to columns. Current SHM lacks real-time data; ML offers automation for predicting responses and detecting damage in outriggers, supporting resilient urban infrastructure design (Altabey & Noori, 2022; Wang et al., 2023). However, current research often focuses on single data types, such as accelerometer data (Armijo & Zamora-Sanchez, 2024) or ultrasonic guided waves (Perfetto et al., 2023; Tanveer et al., 2024), which explore the growing influence of artificial intelligence on SHM, highlighting its potential in predictive maintenance and real-time risk assessment (Plevris & Papazafeiropoulos, 2024). ML improves post-earthquake structural assessment by using velocity features for accurate damage identification. A review of ML techniques in structural health monitoring (SHM) highlights the importance of data-driven models for system reliability and performance (Gomez-Cabrera & Escamilla-Ambrosio, 2022; Muin & Mosalam, 2021). Beyond machine learning methods, multi-objective optimization plays a critical role in structural design, with the resulting Pareto-optimal solution data serving as a valuable dataset for the training and validation of SHM models (Shahbazi et al., 2024).

## 1.2 Knowledge Gaps and Research Opportunities

Despite progress in smart sensors and deep learning for SHM, a key research gap remains in specifically utilizing ML for monitoring the health of outrigger systems in tall buildings (Jia & Li, 2023; Liu, 2024; Yusuf et al., 2023). Additionally, further research in wind engineering is crucial for developing aerodynamic buildings and advancing architectural design (Yusuf et al., 2023). Specifically, AI applications in sensor data processing, including multi-sensor integration, handling data issues, and continuous learning, as well as deterioration prediction for risk assessment, such as multi-defect modeling, large-scale validation, and event evolution, should be emphasized (Di Mucci et al., 2024). One of the notable architectures that can be used for structural prediction and demonstrates robustness to noisy data is CISMN(Shahbazi et al., 2025). researches should focus on developing specific ML models for arm systems, which include data- and physics-based approaches to improve the accuracy and reliability of health monitoring in tall structures.

This study explores using machine learning to improve the resilience of tall buildings by monitoring the structural health of outrigger systems. The primary objective is to more accurately detect potential damage and develop reliable models to predict the long-term health of these systems under normal lateral forces, such as wind and moderate earthquakes. The research focuses on how well-advanced machine learning algorithms can improve prediction reliability, using traditional materials such as steel, and evaluating typical loading scenarios, while excluding extreme earthquakes for practical reasons.

## 2 Methodology

The objective of this research is to develop a ML framework for SHM of outrigger systems in tall structures, specifically under lateral forces. Outriggers, being essential components in stabilizing high-rise buildings, are subjected to varying degrees of stress induced by lateral loads, such as wind and seismic activity. The research focuses on detecting potential failure in outrigger components by using average (sig-max) and average (tau-max) values as indicators of imposed stress. These indicators allow the framework to detect when the outrigger system is approaching critical stress levels, providing an early warning system for failure.

### 2.1 Base Structure Modeling

A precise digital representation of a high-rise building was developed to accurately simulate its behavior under various loads. Using Grasshopper 3D, a visual programming tool within Rhinoceros 3D, we enabled parametric modeling, allowing for efficient adjustments and iterations of the building's structural design. The model is a 20-story structure with a large base and an internal shear core, crucial for resisting lateral forces in seismic regions. Tabriz, Iran, a high-risk seismic zone according to their building codes, provided the context for this model, with its seismic zone factor reflecting expected ground acceleration. Figure 1 displays the model, and predefined specifications for the building's cross-sections and materials ensured its structural accuracy. Table 1 provides the comprehensive cross-sectional and material details of the structure.

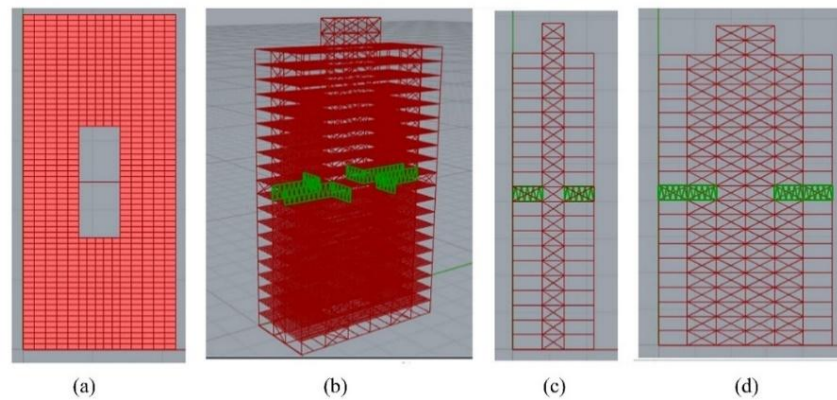


Figure 1. The high-rise structure modeled in Grasshopper and karamba3D: (a) top; (b) perspective; (c) right; and (d) front view.

Table 1. The building structure cross sections and material specifications.

|                    | Dimensions (cm) |           | Cross section | Material Properties |                         |                           |                          |
|--------------------|-----------------|-----------|---------------|---------------------|-------------------------|---------------------------|--------------------------|
|                    | H               | Max Width |               | Material            | E (kN/cm <sup>2</sup> ) | G12 (kN/cm <sup>2</sup> ) | G3 (kN/cm <sup>2</sup> ) |
| Outer beams        | 97              | 30        | I             | Steel               | 21000                   | 8076                      | 8076                     |
| Inner main beams   | 87              | 30        | I             |                     |                         |                           |                          |
| Inner sub-beams    | 62              | 30        | I             |                     |                         |                           |                          |
| Exterior columns   | 80              | 80        | []            |                     |                         |                           |                          |
| Inner columns      | 80              | 80        | []            |                     |                         |                           |                          |
| Exterior bracing   | 87              | 30        | I             |                     |                         |                           |                          |
| Shear core beams   | 52.2            | 30        | I             |                     |                         |                           |                          |
| Shear core columns | 60              | 60        | []            |                     |                         |                           |                          |
| Shear core bracing | 28.3            | 30        | I             |                     |                         |                           |                          |
| Outriggers(X)      | 40              | 80        | I             |                     |                         |                           |                          |
| Outriggers(Y)      | 40              | 160       | I             |                     |                         |                           |                          |
| Floor shells       | 20              | -         | -             | Reinforced concrete | 3000                    | 1375                      | 1375                     |

## 2.2 Data Set Generation

A parametric model of high-rise buildings, combined with a multi-objective genetic algorithm, was used to create a robust ML model. This model predicts structural responses under various conditions, generating a diverse dataset of 2004 solutions. The dataset includes floor loads and lateral forces from wind and seismic activity. The variables and their respective domains are further detailed in Table 2.

Table 2. The variables and their respective domains.

|                                                                   | Min | Max  |
|-------------------------------------------------------------------|-----|------|
| Lateral load (X direction)<br>(m <sup>2</sup> of building façade) | 0   | 4.8  |
| Lateral load (Y direction)<br>(m <sup>2</sup> of building façade) | 0   | 5.9  |
| Floors 1–20 vertical load (m <sup>2</sup> )                       | 0   | 6.24 |

Beyond creating ML datasets, the research framework develops a digital twin of the high-rise building. This digital twin simulates various loads to assess building performance. With real-time sensor data, it enables continuous SHM and dynamic evaluations. Figure 2 illustrates the framework for predicting displacements in vertical and lateral directions

## 2.3 Data Processing

The first step in constructing the ML model was to train it through dataset preparation. The dataset, consisting of 2004 data points in CSV file format, was uploaded. Each data point represented a specific load scenario and its corresponding displacement outcomes. The input feature set (X) included floor load values and lateral forces, which were applied in the X and Y directions, and these values ranged from Floor 0 to Floor 20. The target variable set (y) included vertical displacement and lateral displacements along the X and Y axes.

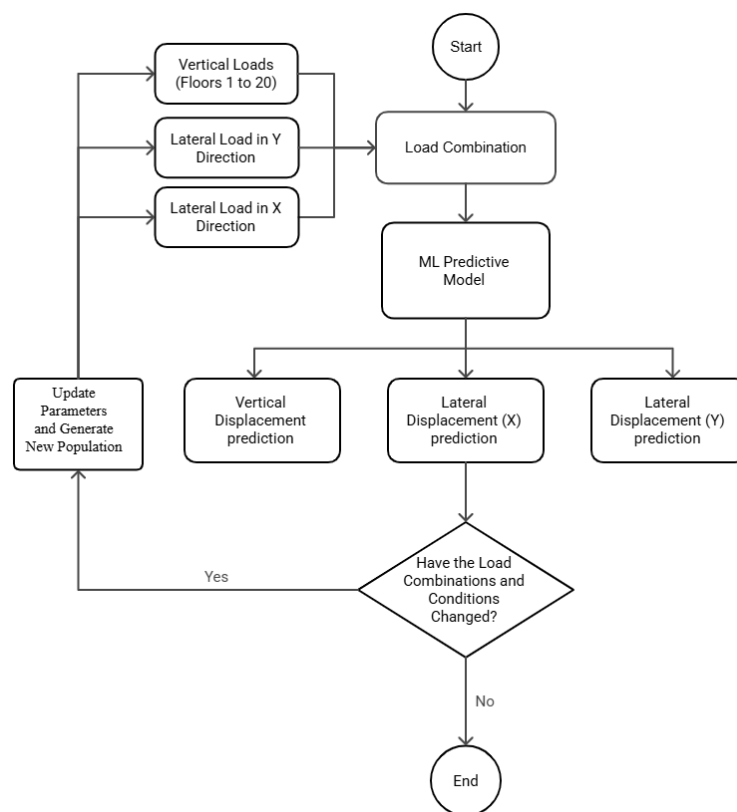


Figure 2. Flowchart of the proposed framework to predict structure displacements.

## 2.4 Model Selection

Given the time-dependent nature of structural displacements under dynamic loads, a Recurrent Neural Network (RNN) architecture with LSTM cells was chosen for its proficiency in handling sequential data. LSTMs' internal memory enables them to capture complex temporal correlations between forces and displacements, which is crucial for SHM's continuous loading conditions. LSTMs offer a balance between predictive power and interpretability, unlike more complex models. Training on a large dataset

(7,347 conditions) enabled the LSTM to learn discernible patterns, thereby improving the model's interpretability and practical application in structural engineering.

## 2.5 Performance Metrics and Evaluation

Against the backdrop of intrinsic time-dependent correlations in structural displacement records under dynamic loads, a Recurrent Neural Network (RNN) architecture comprised of Long Short-Term Memory (LSTM) cells was deliberately employed. LSTMs are proficient at handling sequential data and are thus particularly well-suited for forecasting displacement responses at various levels under dynamic loading conditions. Unlike traditional feedforward models, LSTM networks possess an internal memory mechanism that enables them to track intricate time-dependent correlations between the applied forces and subsequent displacements. This architecture was prompted by the necessity of simulating patterns that evolve over future time steps, a fundamental need of Structural Health Monitoring (SHM) where loading conditions vary continuously. Secondly, LSTMs offer a pragmatic balance between predictive power and interpretability of models. More complex architectures such as Transformers or Deep Convolutional Neural Networks can provide incremental gains in accuracy but sacrifice transparency in the process. LSTMs, in contrast, offer a more transparent method of tracking predictive behavior across various load conditions, a crucial consideration for structural engineering applications in real-world settings. By training the LSTM on a large dataset of 7,347 different loading conditions, the model was induced to learn patterns that could be easily identified. The traceability enhances our ability to interpret the model's predictive reasoning in various conditions, thereby improving interpretability and practical usability.

## 3 Results

The objective of this research is to develop a Machine Learning (ML) framework for Structural Health Monitoring (SHM) of outrigger systems in tall structures, specifically under lateral forces. Outriggers, being essential components in stabilizing high-rise buildings, are subjected to varying degrees of stress induced by lateral loads, such as wind and seismic activity. The research focuses on detecting potential failure in outrigger components by using average (sig-max) and average (tau-max) values as indicators of imposed stress. These indicators allow the framework to detect when the outrigger system is approaching critical stress levels, providing an early warning system for failure.

### 3.1 Model Performance

The performance of the proposed model was assessed using several regression metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination ( $R^2$ ). These metrics were calculated for both the displacement (in the X, Y, and Z directions) and the stress indicators associated with the outrigger system.

Table 3 provides a summary of the results, where lower values of MAE, MSE, and RMSE, along with higher values of  $R^2$ , indicate the model's excellent predictive capability.

Table 3. summary of the results

| Target                      | MAE      | MSE      | RMSE     | $R^2$    |
|-----------------------------|----------|----------|----------|----------|
| Dis(Z)                      | 0.027933 | 0.001178 | 0.034323 | 0.999132 |
| Dis(Y)                      | 0.094614 | 0.015148 | 0.123079 | 0.999855 |
| Dis(X)                      | 0.079317 | 0.010477 | 0.102356 | 0.999811 |
| average sig max outrigger x | 0.169157 | 0.052200 | 0.228474 | 0.990907 |
| average tau max outrigger x | 0.077594 | 0.009098 | 0.095382 | 0.984690 |
| average sig max outrigger y | 0.039730 | 0.002883 | 0.053691 | 0.997130 |

|                             |          |          |          |          |
|-----------------------------|----------|----------|----------|----------|
| average tau max outrigger y | 0.029063 | 0.001275 | 0.035706 | 0.984296 |
|-----------------------------|----------|----------|----------|----------|

From Table 1, it is evident that the model exhibits exceptional performance in predicting displacement across all directions, with  $R^2$  values exceeding 0.999 for the vertical and lateral displacements. The MAE and RMSE values for these displacement targets are consistently low, indicating that the model can effectively predict the displacement under lateral forces.

More notably, the model's performance for the outrigger stress indicators (sig-max and tau-max) also shows remarkable accuracy, with  $R^2$  values above 0.98. This highlights the model's potential to assess stress in critical structural components and detect incipient failures in the outrigger system under lateral loads.

3.2 Prediction of Structural Failure Using Stress Indicators

The model's capability to predict structural failure is underpinned by its ability to monitor stress levels in the outrigger system. As described in the methodology, the average (sig-max) and average (tau-max) values serve as key indicators of the stress imposed on the outrigger system. These indicators are directly tied to the performance and safety of the structure, as excessive stresses may lead to deformation or failure. Figures 3 and 4 depict the residual plots and histograms for the displacement in the X and Y directions. These plots clearly show that the predicted displacements are in close alignment with the actual measured values, suggesting that the model can reliably track structural movements under lateral loads.

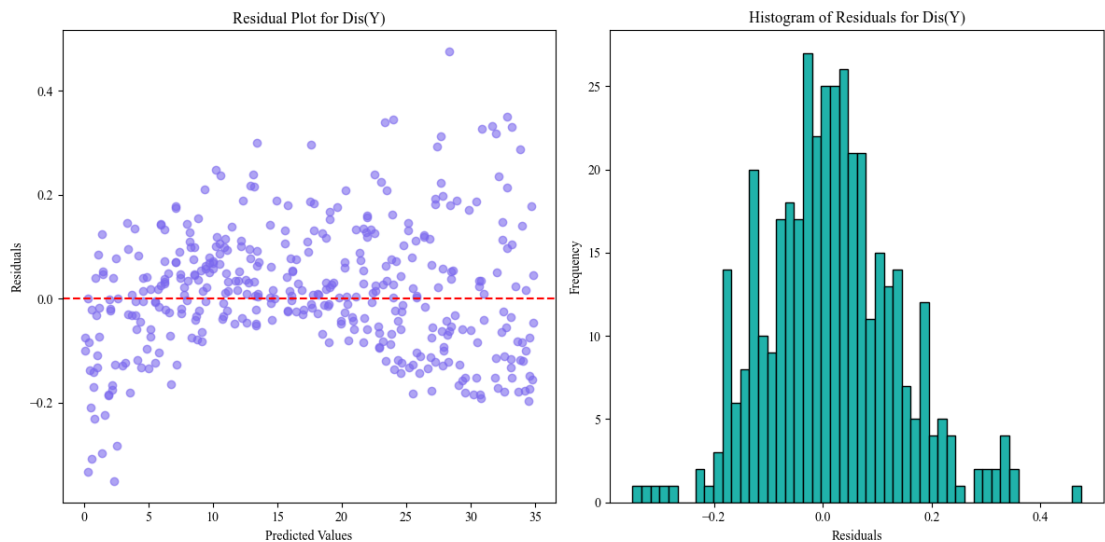


Figure 3. residual plot and histogram of residuals for Dis(Y)

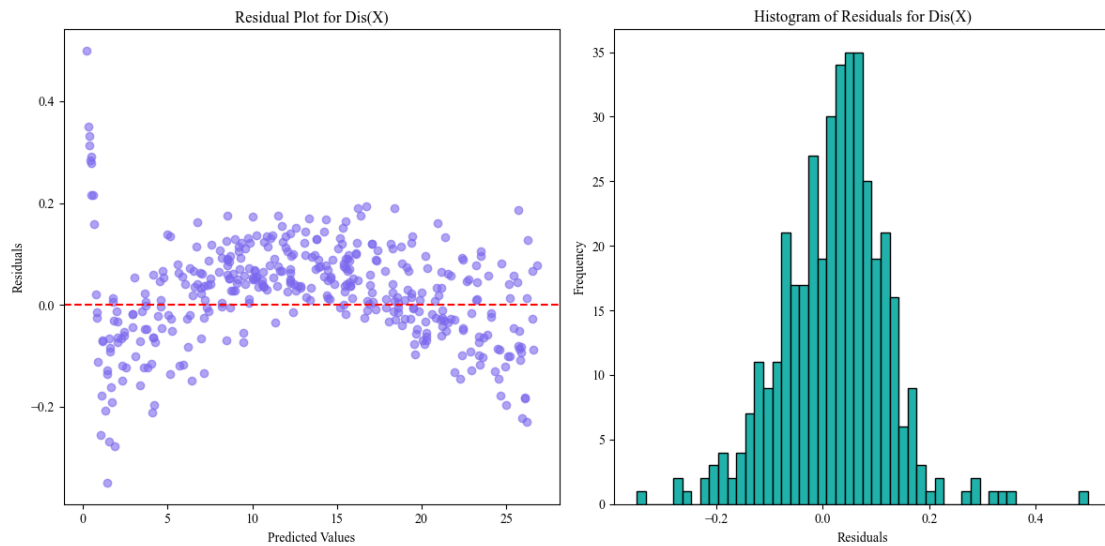


Figure 4. residual plot and histogram of residuals for Dis(X)

- Image 3 shows the residual plot for Dis(Y), where the scatter points are tightly centered around zero, and the histogram of residuals indicates a near-normal distribution, confirming that the model accurately captures the displacement dynamics.
- Image 4 presents a similar analysis for Dis(X), illustrating the model's robustness in predicting lateral displacements along the X-axis.

Next, Figures 5 through 7 display the residual plots and histograms for the stress indicators in the outrigger system. The residuals for the sig-max and tau-max values (Images 3-6) demonstrate that the model not only accurately predicts displacement but also identifies critical stress levels within the outrigger components.

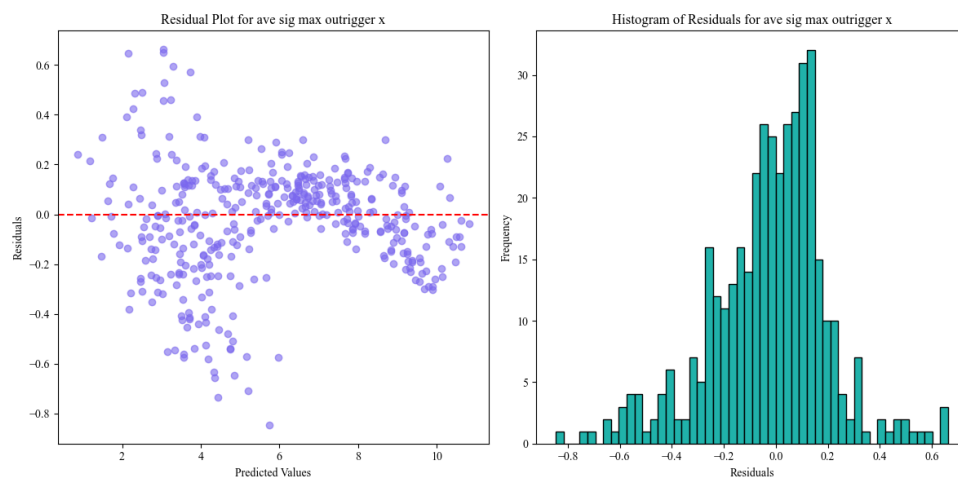


Figure 5. residual plot and histogram of residuals for sig max for (X) direction outrigger

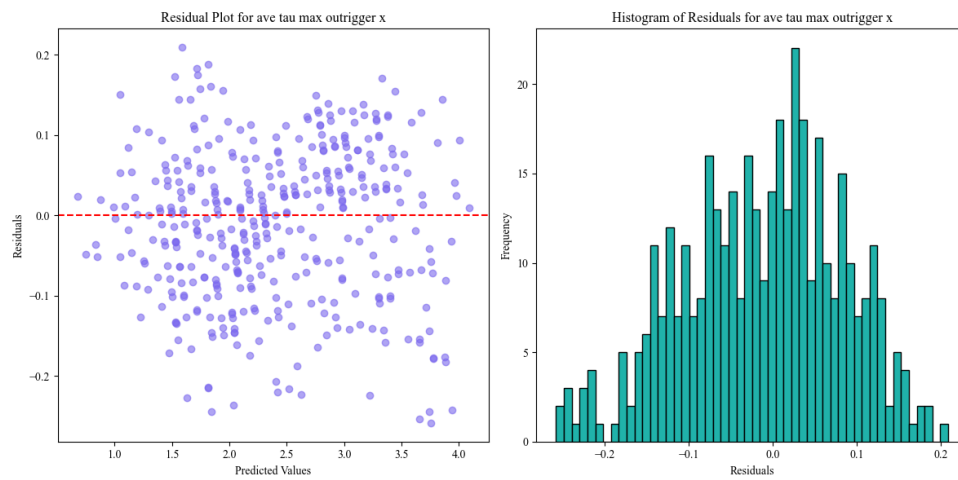


Figure 6. residual plot and histogram of residuals for average tau max for (X) direction outrigger

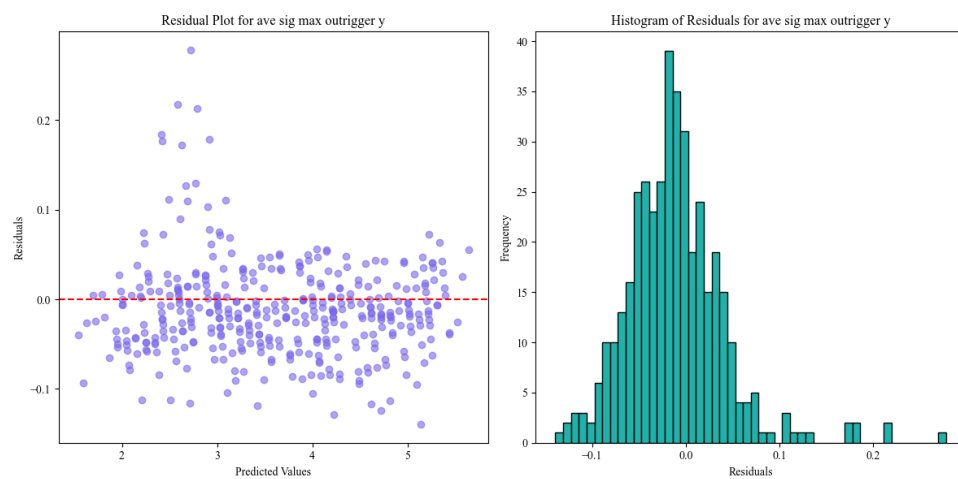


Figure 7. residual plot and histogram of residuals for sig max for (Y) direction outrigger

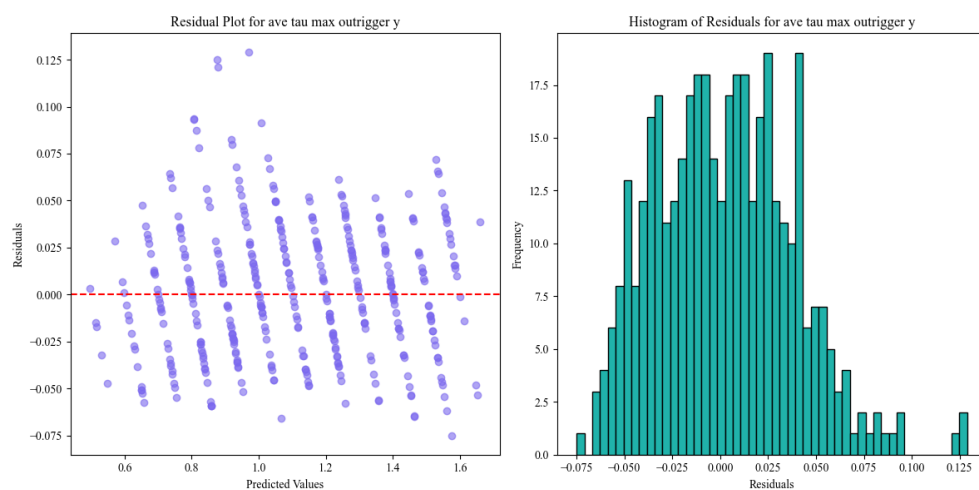


Figure 8. residual plot and histogram of residuals for average tau max for (Y) direction outrigger

- Figure 5 shows the residual plot for average sig max outrigger x, where the predicted stresses closely match the actual values, with a slight concentration around zero residual, indicating minimal error.
- Figure 6 displays the residual plot for average tau max outrigger x, with similar trends, indicating that the model can effectively predict tau-max stress levels.

- Figures 7 and 8 present similar plots for the average signal maximum outrigger  $y$  and average tau maximum outrigger  $y$ , further corroborating the model's ability to predict stress in the outrigger components under lateral forces.

Given the low MAE and RMSE values, combined with high  $R^2$  values, the model can effectively flag when the outrigger system is under significant stress, potentially approaching a critical failure threshold. The model's ability to predict such stress allows for early detection of damage or failure within the outrigger system, providing valuable insights for real-time monitoring and proactive maintenance.

### 3.3 Evaluation of Model's Ability to Detect Failure

A critical aspect of this research is the model's ability to predict failure in the outrigger system. By monitoring stress indicators like sig-max and tau-max, the model can be trained to detect when the system approaches critical failure conditions. The average (sig-max) and average (tau-max) serve as early warning indicators for failure, allowing for preventive actions to be taken before catastrophic failure occurs.

For instance, when the sig-max or tau-max values exceed certain pre-defined thresholds (which can be derived from engineering safety standards), the model can flag these instances as potential failure scenarios, initiating appropriate maintenance protocols. This predictive maintenance capability could significantly enhance the resilience and longevity of tall structures, providing an automated and efficient means of SHM.

### 3.4 Practical Implications

The ability to accurately predict displacement and stress levels in the outrigger system opens up new possibilities for automated monitoring and predictive maintenance in high-rise buildings. The model's high accuracy, as evidenced by the test results, suggests that it can be integrated into real-time Structural Health Monitoring (SHM) systems, where continuous sensor data can be fed into the model to detect any anomalies in structural performance. This enables timely interventions and optimizes maintenance schedules, ultimately improving building safety and reducing the likelihood of failure due to lateral forces. The ML framework developed in this research demonstrates exceptional accuracy in predicting both displacement and stress in high-rise buildings under lateral forces. The ML model's predictive capabilities, especially in detecting stress in the outrigger system, enable early detection of potential failure conditions, providing a proactive approach to structural health monitoring. The results from the model, combined with the low error metrics (MAE, MSE, RMSE) and the high  $R^2$  values, underscore the model's potential for real-world applications in monitoring the health of outrigger systems in tall structures subjected to lateral forces. The successful prediction of failure in critical structural components is a significant step toward ensuring the safety, reliability, and resilience of high-rise buildings under dynamic loading conditions.

## 4 Discussion

The discussion section should begin by interpreting and contextualising the key findings of your study within the broader field of architecture and urbanism. Explain how your results address the research questions or objectives outlined in the introduction, highlighting any significant patterns, trends, or unexpected outcomes that emerge. Compare and contrast your findings with existing literature, demonstrating how your work corroborates, extends, or challenges previous studies. This critical

analysis helps to situate your research within the current academic discourse and underscores its contribution to advancing knowledge in the field.

In addition to interpreting the results, the discussion should explore your study's practical and theoretical implications. Discuss how your findings can inform future research, policy-making, or professional practice in architecture and urban planning. Acknowledge any limitations encountered during your research, such as methodological constraints or data limitations, and explain how these factors may influence the interpretation of your results. Suggest areas for further investigation to address these limitations and build upon your work. Conclude the discussion by summarising the principal insights gained from your study and reiterating their significance, ensuring that your conclusions are well-supported by the evidence presented.

## 5 Conclusions

This study presents a robust Machine Learning framework for Structural Health Monitoring of outrigger systems in tall buildings subjected to lateral forces. The model developed in this research addresses the critical need for efficient, real-time monitoring of structural performance, with a focus on predicting potential failure in outrigger systems under seismic and wind-induced lateral forces. Through the integration of advanced machine learning algorithms, the model is capable of predicting displacements and stress indicators, such as average stress (sig-max) and maximum shear stress (tau-max), which serve as vital metrics for assessing the health of the outrigger system. These stress indicators are particularly crucial in identifying when the system is under excessive stress, allowing for early detection of failure before catastrophic damage occurs.

The model performance was rigorously evaluated using a set of regression metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared ( $R^2$ ), with results demonstrating excellent predictive accuracy. The displacement predictions along the X, Y, and Z axes, as well as the stress predictions for the outrigger system, exhibited minimal error and high  $R^2$  values, confirming the model's reliability in accurately capturing the structural behavior of tall buildings. Specifically, the model's ability to predict displacement with high precision and to monitor stress levels within the outrigger system enables it to function as a real-time predictive maintenance tool. The research emphasizes the importance of monitoring stress indicators like sig-max and tau-max, which provide valuable insights into the structural integrity of the outrigger system. As these indicators approach critical thresholds, the model triggers an alert, signaling the need for preventive maintenance or further investigation into potential failure. This capability is particularly valuable in enhancing the resilience of high-rise buildings, as it enables timely interventions before structural damage becomes irreversible, thus ensuring the safety and longevity of the building.

In conclusion, this study demonstrates the transformative potential of ML in SHM. The proposed framework not only enhances the predictive capabilities for displacement and stress monitoring but also provides an advanced method for detecting failure in structural components, thereby improving the safety, performance, and resilience of tall buildings under lateral forces. As cities continue to grow and the construction of taller buildings becomes more prevalent, this ML-based framework holds promise for revolutionizing SHM practices and enabling more sustainable, safer urban infrastructure.

### Funding

This research received no external funding.

### Data Availability Statement

Data will be made available on request.

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

## References

- Altabay, W. A., & Noori, M. (2022). Artificial-intelligence-based methods for structural health monitoring. In (Vol. 12, pp. 12726): MDPI.
- Armijo, A., & Zamora-ScInchez, D. (2024). Integration of Railway Bridge Structural Health Monitoring into the Internet of Things with a Digital Twin: A Case Study. *Sensors*, 24(7).
- Di Mucci, V. M., Cardellicchio, A., Ruggieri, S., Nettis, A., RenC2, V., & Uva, G. (2024). Artificial intelligence in structural health management of existing bridges. *Automation in Construction*, 167, 105719.
- Shahbazi, Y., Mokhtari Kashavar, M., Ghaffari, A., Fotouhi, M., & Pedrammehr, S. (2025). CISMN: A Chaos-Integrated Synaptic-Memory Network with Multi-Compartment Chaotic Dynamics for Robust Nonlinear Regression. *Mathematics*, 13(9), 1513. <https://doi.org/10.3390/math13091513>
- Fang, C. (2023). Frequency domain-based analytical framework for seismic performance of viscously damped outrigger systems based on continuous Timoshenko beam theory. *Journal of Low Frequency Noise, Vibration and Active Control*, 42(3), 1137-1161. <https://doi.org/10.1177/14613484231166523>
- Ghaffari, A., Shahbazi, Y., Mokhtari Kashavar, M., Fotouhi, M., & Pedrammehr, S. (2024). Advanced Predictive Structural Health Monitoring in High-Rise Buildings Using Recurrent Neural Networks. *Buildings*, 14(10).
- Gomez-Cabrera, A., & Escamilla-Ambrosio, P. J. (2022). Review of Machine-Learning Techniques Applied to Structural Health Monitoring Systems for Building and Bridge Structures. *Applied Sciences*, 12(21).
- Jia, J., & Li, Y. (2023). Deep learning for structural health monitoring: Data, algorithms, applications, challenges, and trends. *Sensors*, 23(21), 8824.
- Langat, R. K., Deng, W., De Luycker, E., Cantarel, A., & Rakotondrabe, M. (2025). In-situ piezoelectric sensors for structural health monitoring with machine learning integration. *Mechatronics*, 106, 103297. <https://doi.org/https://doi.org/10.1016/j.mechatronics.2025.103297>
- Li, X., Bolandi, H., Masmoudi, M., Salem, T., Jha, A., Lajnef, N., & Boddeti, V. N. (2024). Mechanics-informed autoencoder enables automated detection and localization of unforeseen structural damage. *Nature Communications*, 15(1), 9229.
- Lin, P., Ding, F., Hu, G., Li, C., Xiao, Y., Tse, K. T., Kwok, K., & Kareem, A. (2022). Machine learning-enabled estimation of crosswind load effect on tall buildings. *Journal of Wind Engineering and Industrial Aerodynamics*, 220, 104860.
- Liu, Z. (2024). Smart sensors for structural health monitoring and nondestructive evaluation. In (Vol. 24, pp. 603): MDPI.
- Muin, S., & Mosalam, K. M. (2021). Structural Health Monitoring Using Machine Learning and Cumulative Absolute Velocity Features. *Applied Sciences*, 11(12).
- Shahbazi, Y., Abdkarimi, M., Ahmadnejad, F., Mokhtari Kashavar, M., Fotouhi, M., & Pedrammehr, S. (2024). Comparative Study of Optimal Flat Double-Layer Space Structures with Diverse Geometries through Genetic Algorithm. *Buildings*, 14(9), 2816. <https://doi.org/10.3390/buildings14092816>
- Perfetto, D., Rezazadeh, N., Aversano, A., De Luca, A., & Lamanna, G. (2023). Composite Panel Damage Classification Based on Guided Waves and Machine Learning: An Experimental Approach. *Applied Sciences*, 13(18).
- Plevris, V., & Papazafeiropoulos, G. (2024). AI in Structural Health Monitoring for Infrastructure Maintenance and Safety. *Infrastructures*, 9(12).
- Pujari, A. B., & Gunjal, S. P. (2024). Performance Evaluation of the High Rise Steel Building With Outrigger and Belt System.
- Shelake, M. (2025). Analysis of Skyscrapers with K-StyleOutrigger Belt Truss System and ShearWalls Under Lateral Load.

- Tanveer, M., Elahi, M. U., Jung, J., Azad, M. M., Khalid, S., & Kim, H. S. (2024). Recent Advancements in Guided Ultrasonic Waves for Structural Health Monitoring of Composite Structures. *Applied Sciences*, 14(23).
- Tobber, L., Yang, T., & Najam, F. (2025). Seismic performance of reinforced concrete (RC) shear walls with and without damped outriggers and controlled rocking. *Engineering Structures*, 330, 119899.
- Wang, M., Sun, F.-F., Koetaka, Y., Chen, L., Nagarajaiah, S., & Du, X.-L. (2023). Frequency independent damped outrigger systems for multi-mode seismic control of super tall buildings with frequency independent negative stiffness enhancement. *Earthquake Engineering & Structural Dynamics*, 52(9), 2731-2754. <https://doi.org/https://doi.org/10.1002/eqe.3891>
- Yusuf, D. A., Ahmed, A., Sagir, A., Yusuf, A. A., Yakubu, A., Zakari, A. T., Usman, A. M., Nashe, A. S., & Hamma, A. S. (2023). A Review of Conceptual Design and Self Health Monitoring Program in a Vertical City: A Case of Burj Khalifa, U.A.E. *Buildings*, 13(4).
21. Robert McNeel & Associates. Grasshopper3d. Available online: <http://www.grasshopper3d.com> (accessed on 14 March 2025).
22. Ministry of Roads & Urban Development of Iran. Iranian Seismic Code (Standard No. 2800), 4th ed.; Ministry of Roads & Urban Development of Iran: Tehran, Iran, 2014.

### Disclaimer/Publisher's Note

The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and do not reflect the views of the Architecture, Buildings, Construction and Cities (ABC2) Journal and/or its editor(s). DFB Journal and/or its editor(s) disclaim any responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.