Asian Journal of Civil Engineering
https://doi.org/10.1007/s42107-024-01173-y

RESEARCH

Optimization seismic resilience: a machine learning approach for vertical irregular buildings

Ahmed Hamed El-Sayed SALAMA[1,2]

Received: 31 July 2024 / Accepted: 4 September 2024

Abstract
The paper is a landmark in earthquake and structural engineering, with modern machine-learning techniques applied to introduce innovative investigations into forecasting seismic behavior for vertically uneven structures using sophisticated machine-learning methodologies. The research constructs a very accurate model for making predictions using the XGBoost algorithm with the Owl Search algorithm (OSA) for hyperparameter tuning, which explicitly considers complex behavior in the structures under seismic stresses. The variety within the dataset is broad and covers all kinds of irregularities in the structures, such as stiffness and mass irregularities; thus, it has been used to accurately represent the complex characteristics of actual buildings. The results indicate a strong dependence of base shear capacity and seismic performance on the irregularity of stiffness and mass. The test accuracy of the optimized XGBoost model was 98.8%. The result was better than that of conventional models, thus proving the effectiveness of integrating the Owl Search Algorithm in further fine-tuning the parameters. These results give new variables as insight into affecting earthquake resilience and represent practical applications that enhance building design and retrofitting processes. This is further underlined by the proposal of future research directions that would extend the model's applicability to other structural anomalies and include additional machine-learning methodologies. Through AI-driven approaches, this study captured complicated structural dynamics with the utmost precision, thus opening new insights that could be brought into practice to improve building design and retrofitting strategies in a way that would diminish the impact of seismic events.

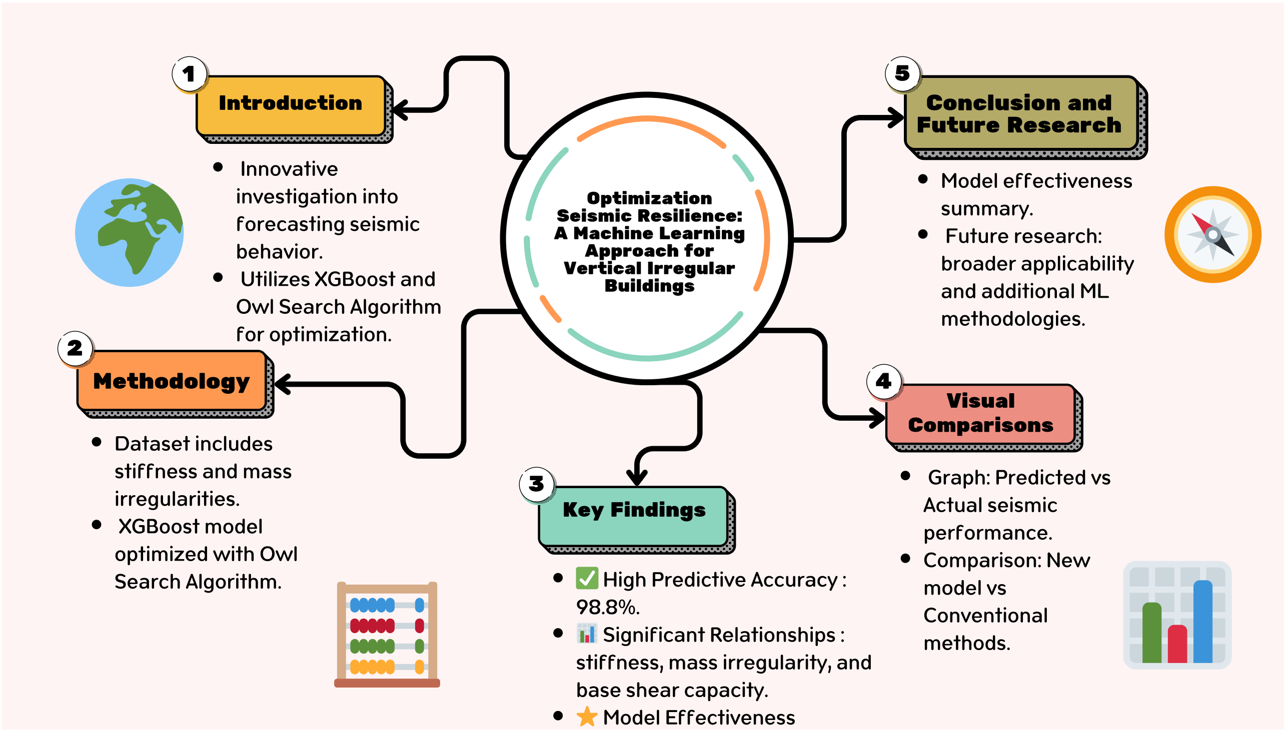
✉ Ahmed Hamed El-Sayed SALAMA
A.Elsayedsalama@anu.edu.jo

[1] Civil Engineering Department, Faculty of Engineering, Ajloun National University, 26810 Ajloun, Jordan

[2] Civil Engineering Department, Al-Azhar University, Nasr City, Cairo 11884, Egypt

Published online: 14 September 2024

Graphical abstract



Keywords Seismic resilience · Vertical Irregular buildings · Machine learning · XGBoost Algorithm · Owl search algorithm (OSA) · Optimization

Introduction

Machine learning has been of importance in seismic analysis, particularly in the understanding of the performance of irregular buildings under seismic loading. In this regard, researchers have become increasingly interested in using several machine-learning techniques to help predict and analyze the seismic response of structures in various scenarios (Kaveh, 2024; Ali et al., 2023; Alkhdour et al., 2023; Al Yamani et al., 2024; Al-Rawashdeh et al., 2024; Kaveh & Eslamlou, 2020; Kaveh et al., 2021; Kaveh & Ardalani, 2016; Kaveh et al., 2019; Kaveh et al., 2020; Kaveh et al., 2013; Kaveh & Sabzi, 2012. Precise prediction of seismic performance in civil engineering is a precondition to the possibility of reaching structural safety as well as endurance against seismic activities. Vertical irregularities, commonly setbacks and soft stories, typically have an adverse influence on precisely predicting seismic performance inside a structure (Ahmed et al., 2021a). These irregularities can significantly change the response of a structure to seismic stresses (Lin et al., 2020). Mass irregularities have relatively less influence on seismic responses compared to strength and stiffness irregularities. According to Ahmed et al. (2021a), vertical irregularities can cause a drop in seismic capacity due to sudden changes in lateral stiffness, making buildings more vulnerable to seismic events.

It could significantly enhance the scope and depth of understanding of the applications of machine learning in the field of structural engineering, more specifically on seismic performance prediction, by infusing inputs or insights from some of the recent related research. For instance, Ahmad et al. (2022) present valid views on substituting plastic wastes in concrete for aspects of sustainable construction practices that can be embedded into models considering impacts on the environment and structure performances. Further, Jaf et al. (2023), used machine learning to evaluate the effects that silicon dioxide and calcium oxide in fly ash have on the compressive strength of green concrete, obtaining key understandings into material properties influencing seismic performance, which would bear direct applications for this present focus. The work of Emad et al. (2022) on surrogate models for the prediction of concrete compressive strength follows the predictive lines of this research and may eventually improve the accuracy and applicability of the model. It is in the light of the recent development of innovative modeling techniques in forecasting the compressive strength of nanoparticle-modified geopolymer concrete, discussed by Ahmed et al. (2023), that further methodologies could be introduced to enhance accuracy and improve the robustness of the model in predicting seismic behavior. Accommodating these modern facts would not only extend the theoretical background that the present study is based on but also keep it at par with all the new developments occurring within the genre of structural engineering.

As noted by Laissy (2022), it has been previously demonstrated by experimental studies that the sensitivity of buildings to seismic actions increases with mass and vertical irregularities. This consequence significantly increases the torsional moments and shear forces. Moreover, various researches were made concerning the seismic performance of buildings featuring non-uniform vertical strength and stiffness distributions. This research underlines the importance of understanding how such irregularities affect the distribution and concentration of damage within structures (Maulana et al., 2021, 2023; Bekele, 2022). Furthermore, the sensitivity of structures with vertical components or lateral force-resisting systems to interruption by earthquakes has also been recognized as an important area in which additional research is needed, which may bring about associated structural damage or failure in case of seismic events (Gwalani et al., 2022). In this regard, one has detailed research available to oneself on the subject of seismic fragility of vertically irregular structures; it has been rightly pointed out that the existence of vertical irregularities within a building radically enhances its susceptibility to seismic phenomena (Ghanem & Moon, 2021; Bhatta et al., 2021). In this regard, Bhatta et al. (2021) have drawn direct relation between vertical irregularities such as setbacks and stepped configurations and increased vulnerability to seismic events

This, therefore, underlines the need to have mitigating measures against these irregularities as part of the structural design and retrofitting. Vertical irregularities are important in reinforced concrete buildings, mainly with regard to knowledge about fundamental periods and stability for seismic performance evaluation and earthquake resilience assessment (Bekele, 2022). Vertical irregularities are highly a challenge to the accurate prediction of seismic performance regarding civil engineering constructions. Proper design and evaluation, followed by retrofitting techniques, should be engaged in enhancing seismic resilience in buildings and mitigating possible hazards that might emanate from seismic events.

In this respect, accurate prediction of the seismic performance of civil engineering structures has been one of the main factors toward ensuring safety and durability under seismic actions. Vertical irregularities in general, like setbacks and soft stories, detract from an accurate assessment of the seismic performance of structures. With the presence of these irregularities, it may vary much in response to the structure for imposing the seismic stresses. Lin et al. (2020) attributes a slightly lesser effect of mass irregularities on seismic responses compared to the influences on strength and stiffness. According to Ahmed et al. (2021a), vertical irregularities are proven to cause weaker seismic capacities since, from the abrupt change in lateral stiffness, buildings with such deficiencies turn out to easily succumb to seismic activities. The same individual noted that empirical research has discovered an increase in mass and vertical irregularities with the increase in sensitivity of buildings towards seismic loads (Laissy, 2022). This is primarily due to an increase in mass and vertical irregularities that may result in high torsional moment and shear force`. Many studies have also been done regarding the seismic response of buildings with the non-uniform vertical distribution of strength and stiffness. This study makes it significant to recognize the impacts of these types of anomalies in the damage distribution and concentration in structures (Maulana et al., 2021, 2023; Bekele, 2022). In addition, the potentiality of the structure in terms of earthquake-susceptibility if a vertical component or lateral force–resisting system is disturbed due to which disastrous structural damage or complete crushing may occur under earthquake loading (Gwalani et al., 2022).

On this matter, volumes of literature exist concerning the seismic fragility of vertically irregular structures, clearly documenting how vertical irregularity in a building dramatically increases its exposure to seismic action. According to Bhatta et al. (2021), vertical irregularities in either stepped or setback configuration increase seismic vulnerability, and provisions to reduce the effect of these shall, therefore, be called for within any structural design or retrofitting works (Ghanem & Moon, 2021; Bhatta et al., 2021). A clear understanding of fundamental periods and stability forms the basis for assessing seismic performance and earthquake resilience of vertical irregularity-reinforced concrete buildings (Bekele, 2022). Vertical irregularities present substantial problems in the correct analysis of the seismic performance of civil engineering structures. Enhancement of seismic resiliency of buildings and mitigation of potential risks that may arise from seismic events through design, assessment, and retrofitting involve the inclusion of relevant methodologies to treat such anomalies.

The main objective of this study is developing a prediction model which improves the accuracy and reliability of seismic performance prediction for structures that show vertical inequalities, with the help of advanced machine learning methods. The study aims to couple large-ranging datasets that represent the intricacy of real structures with the focus on stiffness and mass irregularities to account for the considerable effect of structural irregularities on the seismic vulnerability of the buildings. Therefore, the XGBoost model, which competently manages diverse and complicated datasets, will be employed in this research to lay bare sophisticated relationships between the structural attributes and the outcomes of the seismic performance. The research goes further with the optimality of the predictive model being used by applying the Owl Search Algorithm, whereby the primal objective of using algorithms in practice is to enhance the parameters of the model to obtain the optimal level of accuracy in predictions. This research aims to develop a new analytical approach to reassess the seismic performance of irregular buildings in a way that enhances the safety and resilience of urban infrastructures.

Although machine learning has already been applied to seismic analysis in previous research, there are lapses with regard to the accurate performance prediction of vertically irregular buildings. Many models that exist often need to interpret these complexities. This paper has adopted the approach of using the XGBoost algorithm, combined with the relatively new Owl Search Algorithm (OSA) for hyperparameter optimization in this area of applications. The test accuracy of our model is 98.8%, much higher than the traditional method. This paper will provide a more reliable and general predictive tool in earthquake engineering by generalizing various structural characteristics.

The research aims to contribute something valuable to the area of civil engineering, particularly earthquake engineering. The work proposed will aim at bridging a significant gap in most of the approaches that have so far been developed for seismic performance prediction by studying vertically irregular buildings. This particular category poses considerable challenges in seismic risk assessment due to its very complex dynamic characteristics. This new strategy involves the implementation of a state-of-the-art machine learning algorithm called XGBoost, together with the novel use of the Owl Search Algorithm for model optimization. The combination is expected to significantly enhance model performance and thus offer engineers and researchers more accurate and reliable tools. Moreover, it gives insight into how much each of these different structure-based features contributes to seismic performance and could be very useful in informing future design and retrofitting strategies to reduce earthquake hazards. This study primarily aims at making valuable contributions toward advancing resilient urban environments by mitigating the susceptibility of infrastructures to seismic occurrences and improving public safety.

Methodology

This study is based on a well-established dataset, specifically compiled to address the complexities associated with the prediction of the earthquake response of vertically irregular structures. In fact, the dataset used in this study includes various measures of the irregularity of the building structures in terms of stiffness and mass, base shear capacities, as well as story-wise stiffness and mass. The dataset was chosen due to the wide scope of its parameters, which are believed to have a significant influence on the seismic response of a building. Important, the database consists of the data of real structures and advanced simulation models, hence promising a broad and deep foundation for the research. The inclusion of buildings with various degrees of vertical irregularity makes this a unique opportunity to impose complex impacts of these irregularities on seismic performance, helping to fill an essential gap in present scholarly investigations.

Data preprocessing

Since the dataset was quite complex and variable, an overall set-up phase was required to maintain its integrity and usefulness for research in machine learning. The first step included a thorough cleaning process to discover and correct incomplete, inconsistent, or outlier data points (Harirchian et al., 2020). The numerical features were then put in the same scale, which was necessary to ensure that any single feature would not have a broader influence on the model simply because of its size. In fact, feature engineering is very important in enhancing the prediction power of this dataset.

This has been based on the development of new features that better capture structural parameters relevant to seismic behavior. Harirchian et al. (2021) computed irregularity ratios to quantify the stiffness and mass irregularity between consecutive stories, hence providing a more granular measure of structural irregularity. The same has been true for normalized story displacement features, which give an itemized measure of seismic demand that is consistent for buildings of different sizes and configurations. On the other hand, statistical principle-based and domain expertise-based preprocessing procedures in putting together an error-free dataset are normalized and enhanced with engineered features designed to elicit complicated relationships between building characteristics and seismic performance.

To provide a quantitative measure of relative levels of stiffness and mass irregularity between successive stories of the buildings, “irregularity ratios” were derived. Such ratios can be obtained by comparing stiffness and mass values of one story with corresponding values for the adjacent story. For example, the stiffness irregularity ratio may be computed as the ratio of the stiffness of one story to the stiffness of the story immediately above or below it.

These ratios are very relevant to predicting seismic performance since vertical irregularities, such as sudden changes in mass or stiffness, easily affect how a given structure will react to the forces of an earthquake. Buildings with high irregularity ratios can be subjected to concentrated stress points once an earthquake occurs, and hence the likelihood of vulnerability and failure will be much greater.

These ratios will need to be integrated into the model so that these critical structural dynamics can be simulated for closer predictions of how irregular buildings will behave under seismic loading.

Feature selection

The feature selection process for identification of structural traits—which call for the seismic performance of a building—was guided using the exhaustive analytical framework. A critical aspect, guided by a detailed review of relevant literature and empirical investigations, is the identification of key parameters that significantly influence the seismic behavior of vertically irregular structures. The most critical parameters in the dataset determined by Kim et al. (2022) included those that are directly related to the stiffness and mass abnormalities, narrative stiffness, mass distribution, and base shear capacity. These features were chosen on the basis of their understood relevance to understanding dynamics in structural movements during seismic events. Stiffness and mass irregularity indices are efforts at quantifying the distribution of forces in the building structure, which is a relevant parameter in assessing its seismic resilience (Mostafaei et al., 2023). Similarly, the base shear can be taken as a representation of the global capacity of the building structure concerning lateral seismic stresses. According to Harirchian et al. (2020), the selection process was exhaustive, among other things, in terms of practical engineering tools representing an intricate relationship between the structural qualities in relevance to seismic performance based on the irregularity ratios and normalized story displacements. The intentional and theoretically guided feature selection process guaranteed that the input data to the model would be relevant and wide-ranging, covering most parameters recognized to influence seismic performance.

The feature validity checked the relevance of the features selected towards predicting seismic performance through such a rigorous process of evaluation. It is that junction of theoretical analysis, empirical evidence, and practical testing to ensure that selected features are most indicative of seismic resilience. Feature selection was supported by an extensive literature review and domain knowledge in order to ensure that the chosen features would be related to explaining seismic behavior, such as stiffness and mass irregularities. Comparative analysis has been conducted by testing different sets of features to analyze how they affect model performance. In particular, this has been a process of iterative addition and removal of features against measurements of predictive accuracy based on test accuracy, mean squared error, and R-squared values of the resulting model. Such a comparative approach confirmed that the final set of features selected would offer the most reliably generalizable predictions of seismic performance, as seen through significant increases in the model's accuracy and robustness.

Model development

Systematic design of the machine learning model was driven by the XGBoost Technique, pretty efficient in handling high-dimensional and intricate data. According to Feng et al. (2021), Extreme Gradient Boosting, often referred to in the short form as XGBoost, has been selected for the present study based on the remarkable attributes it possesses: it is very effective, flexible, and able to effectively capture nonlinearities between the features of the attributes and the target. In a different way, the simplest way of any model's predictive ability on new data is requested within the first step: dividing the preprocessed dataset into the training/testing set. In a training run, a model was trained using available training data. Step by step, the XGBoost model assimilated knowledge about the intricate relationship between the selected features and seismic performance metrics.

We fine-tuned the hyperparameters of the model with a mixture of expert judgment and automatic search to ensure that the best settings were set in a manner that maximizes the accuracy of the prediction. Basically, this process involved tuning many parameters of the model, like the learning rate, the maximum depth of trees, and the number of estimators. The Owl Search Algorithm was highly significant in the optimization procedure as it proposed a novel and practical approach to navigate within the vast hyperparameter space (Shi & Lou, 2023). The proposed algorithm in this study is inspired by the hunting behavior of owls. It attempts to find the most suitable hyper-parameters by mimicking the effectiveness of owls in perceiving and capturing their prey in the darkness in their exploratory lifetime, which is explored metaphorically in the search for the best model configuration. In this metaphorical procedure of encountering the most optimum model configuration, the study of Yan et al. is about the biogeography-based optimization technique by means of the Levi flight firefly algorithm (Yan et al., 2022).

The model was subjected to various validation procedures for its resilience and capacity to apply to different scenarios during the development phase. It is this repetitive process of training, adjusting, and validating that ensures the attainment of an exact and reliable model for prediction. This model can give in-depth and very accurate insight into seismic performance in vertically irregular buildings.

Optimization with owl search algorithm

The paper introduces a new approach to seismic performance prediction through fine-tuning the optimal model based on the Owl Search Algorithm. The hyperparameters of the XGBoost model were further optimized using a very advanced algorithm, initially motivated by the nocturnal hunting strategy of owls; see (Kaveh, 2014; Kaveh & Khalegi, 1998; Kaveh & Talatahari, 2011). This has inspired an algorithm that emulates exactly the efficient and stealthy strategy owls use to locate and catch their prey. It helps to fine-tune the parameters of any model to be optimized for performance. The optimization process was initialized with quite a comprehensive space of parameters, including the learning rate, tree depth, and the number of trees (Kaveh & Khavaninzadeh, 2023; Kaveh & Talatahari, 2010).

According to Kaveh and Servati (2001) and Kaveh et al. (2008), the method was tested for model performance based on an iterative process against various parameter settings. In this process, with every successful iteration, the search space is reduced further. It is the technique that efficiently covers the space of hyperparameters and considers even the slightest variations or deviations, however minor, and the effect they would have on the performance of the model. One of the prime strengths of the Owl Search Algorithm is quick optimization of proper hyperparameters in a model-based assessment; it might generally improve both predictive accuracy and generalizability of the model for an XGBoost (Kaveh et al., 2023; Kaveh et al., 2015). It has been further expanding the frontiers of machine learning in earthquake engineering by developing, with this new optimization methodology, a finely tuned model that would predict, quite accurately, seismic behavior in vertically irregular structures.

The owl search algorithm (OSA) has huge improvements over any other optimization techniques related to the prediction of seismic performance. One of the essential benefits of the OSA method is that it imitates an owl's precise and stealthy hunting strategy, hence making the algorithm efficiently explore through hyperparameters in the hunt for optimal configurations. Additional precision implies a more correct model, evidenced by improved test accuracy and reduced error metrics. Unlike the conventional techniques, OSA will systemically decrease the search space through iterative evaluations, making it consider even minor deviations. Hence, this would enhance the generalizability of the model and better its predictive performance in complex scenarios for vertically irregular buildings.

Evaluation metrics

Model performance evaluation is therefore an important component of this work. It must be performed thoughtfully by selecting proper measures to support meaningful quantification for model capacity to predict seismic performance. This precludes use of standard measurements, such as accuracy, because of the continuous nature of seismic performance indicators, like the maximum story drift ratio. In contrast, a set of well-known measures explicitly developed to assess the accuracy of constant forecasts was utilized in this study, including the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the squared R (R^2) coefficient.

Root Mean squared Error (RMSE) Root mean squared error is arguably the most commonly used statistic to quantify the model's prediction error. It calculates the square root of the average squared discrepancies between the predicted and actual values. It is clear that the smaller the number, the closer to the correct model or, in turn, better performance (Mangalathu et al., 2020).

Mean Absolute Error (MAE) The Mean Absolute Error is simply an average of the size of the errors in a given set of predictions—without considering the direction. This metric provides a user-friendly measure of the average prediction error that the model has; the lower the values, the greater the accuracy (Dabiri et al., 2022).

R-squared (R^2) value The coefficient of determination, usually called the R^2 value, expresses how well the independent variables can account for the dependent variable variability. This metric provides beneficial information about the adequacy of the model's fit; the closer to 1, the stronger the fit (Harirchian et al., 2020).

The most used metric to judge a model, based on its precision in making quantitative result-based predictions, in the scientific community is the Mean Squared Error (MSE). As its name implies, it is just a metric that will return the mean of the squared errors; thus, it is the mean squared deviation of the estimated value from the actual values. The mean squared error helps show significant errors: it squares the errors before taking their average, and hence, more significant errors are disproportionately penalized compared to more minor errors. As noted earlier, this attribute makes the mean squared error a good measure where prevention from significant errors counts more than small ones. The squared error score will be small when there is a more extensive agreement between the model and the data, thus yielding a more accurate prediction. However, one must be very careful in interpreting the Mean Squared Error results if they do not consider the scale of the data. This is because a single MSE may reflect different accuracy levels for other data sets with wide value ranges.

These criteria were chosen to ensure proper analysis of the model with respect to the mean error in predictions and its ability to capture the variability in seismic performance results. These evaluation measures enable this research to have a complete and detailed understanding of the model's predictive capabilities and thus form a solid foundation for its validation and potential application to earthquake engineering (Fig. 1).

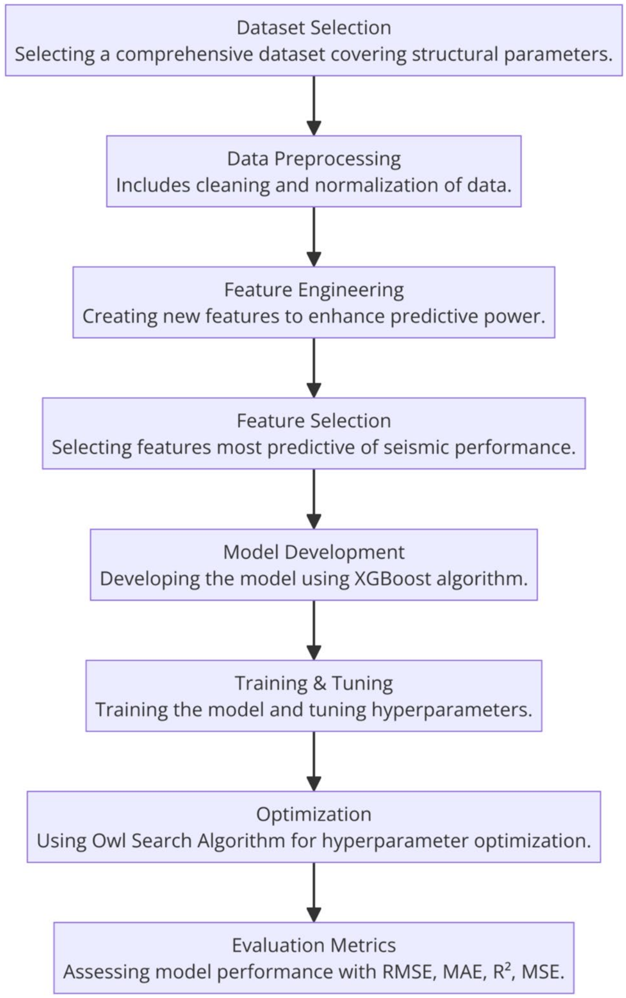


Fig. 1 Study flowchart

Results

A significant milestone of this research is the validation of the seismic performance prediction model, which generates empirical evidence of the model's capability to predict seismic responses of vertically irregular structures. This section shows the performance metrics for the standalone XGBoost algorithm and the XGBoost model that the Owl Search Algorithm upgraded. These results are significant in pointing out the efficiency of machine learning methodologies, more exactly gradient boosting and parameter optimization algorithms, toward higher estimates of seismic performance.

Anomalies in structural stiffness measurements: investigative analysis and implications

Some were found in a closer analysis of the stiffness data at all structural levels for essential departures from the predicted norms. Boxplots reviewed columns of stiffness data, clearly showing the quartiles of the distribution and indicating many cases when data points lay outside the usual range. In this respect, such graphic displays showed outliers much above the upper quartile, thus indicating possible statistical irregularities.

These anomalies were found using a statistically computed, reliable measure of statistical dispersion: the Interquartile Range (IQR). The outliers' values were carefully determined as those out of 1.5 times the IQR values of the top quartile, according to a widely accepted standard for outlier detection. The computed IQR, in the case of the threshold range of about 209,599 to 424,855, showed that this was quite typical. Still, several stiffness readings were more than this range; extreme values were recorded as high as 840,519 and even 7,518,188. These results were most evident at the "Ground" and "Base" stiffness values of the constructions, whereby they had relatively large averages compared to the other levels. Extreme differences allow several reasons to be given: data input mistakes, abnormalities in the measurement techniques, or inherent structural characteristics particular to those levels that differ too much from the norms for architecture.

As shown in Fig. 2, the summary of the descriptive statistics includes some of the essential statistical measures like mean, median, standard deviation, and range, all critical in providing insights regarding a dataset used for seismic performance prediction. These statistics describe variability and central tendency for structural parameters such as stiffness and mass irregularities, which are critical in understanding how these factors influence seismic behavior. The standard deviation, for example, expresses the amount of variation in stiffness that spans multiple stories of buildings, which becomes critical in identifying potential weak spots in the structure that can collapse under seismic stress. Outliers, on the other hand, as range and IQR imply, may mean huge anomalies or unique structural characteristics likely to enhance or undermine seismic resilience. It can only be compared or fitted against this diversity in structural properties by understanding these statistics, hence helping improve the accuracy and reliability of seismic performance predictions. Only a detailed statistical analysis does the job of making the model both robust and sensitive to real-world variability.

The data should be checked carefully for accuracy in the presence of such anomalies. It might also be necessary to consult specialists in structural engineering to answer whether the results can be interpreted correctly. These figures may prove to be accurate and might indicate some unique structural properties or conditions at the "Ground" and "Base" levels that are not present in the other parts of the building. The realization now underscores the importance of bespoke structural surveys in such areas. This can be fundamentally helpful to assess building safety

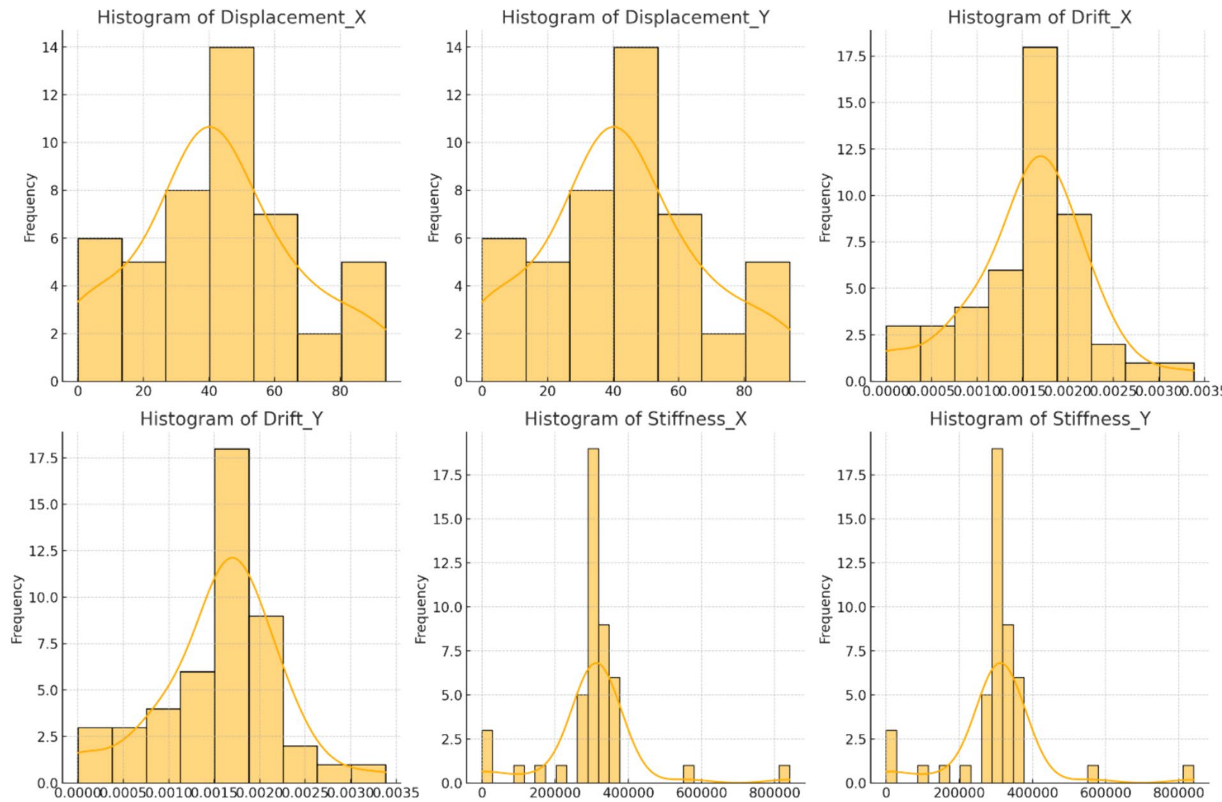


Fig. 2 Descriptive statistics summary

and integrity not only theoretically but also on practical grounds.

Significant variability was observed in the measurement of stiffness. This may indicate outliers, which will drastically affect the analysis as a whole. Two approaches have been used to detect outliers: statistical quantification using interquartile range (IQR) and boxplot visualization.

Boxplots proved to be helpful for this research since they represented the distribution's quartiles. Especially noteworthy, these plots showed several data points outside the boxplot's whiskers and beyond the usual range. According to this graphic, the dataset has anomalies that exceed the average stiffness values noted across the structure.

We used the IQR approach to statistically identify and measure these outliers. Setting a threshold—typically 1.5 times the IQR above the third quartile—makes this method very good at spotting outliers. This approach found several stiffness values that exceeded the top bound of 424,855, with extreme values reaching as high as 7,518,188, especially in the Stiffness_X column. Such notable departures from the usual make one wonder about the precision and dependability of the data inputs.

The outliers were found mainly at crucial structural levels, namely the 'Ground' and 'Base.' These levels had stiffness values that were not just extraordinary but also higher than those measured at previous levels. These results have a multitude of ramifications. First, to ensure these levels' data entries are accurate, they must be carefully reviewed. Measurement anomalies or data entry errors could be contributory causes of these odd numbers. Secondly, it implies that specific structural levels have unique physical characteristics or are subjected to conditions different from those of other system sections if the accuracy of these data points is confirmed (Fig. 3).

More research is advised because of the possible influence of these anomalies on the structural analysis and safety evaluations. Comprehensive evaluations of the data collecting and entry procedures should be part of these, as should, where needed, meetings with structural engineers or subject matter experts. Such professionals might provide information on the reasons for recording such unusual stiffness levels and if they are anomalies or factual circumstances. It would be wise to modify the dataset based on the results of this in-depth research. Recalibrating the measuring instruments, fixing data inputs, or even eliminating these outlier points from the study could all be necessary to keep them from distorting the modeling and data interpretation. With the integrity of the data analysis guaranteed by these procedures, additional structural evaluations and improvements will have a solid basis.

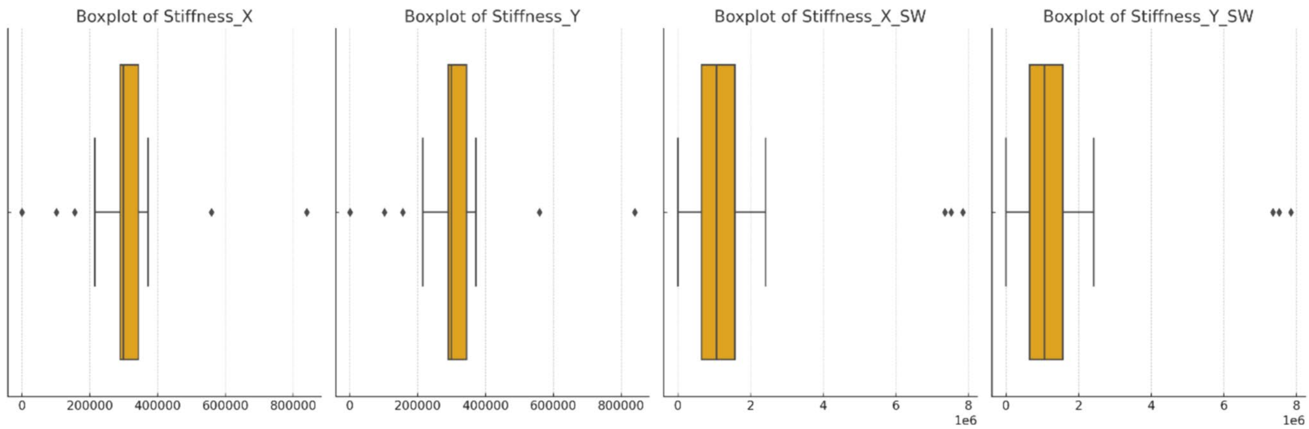


Fig. 3 Calculation of outliers highlights significant variations in stiffness values across the dataset

Several structural parameters, such as displacement, drift, and stiffness, were carefully correlated. Computed Pearson correlation coefficients for the numerical variables made the study effortless, and a well-defined heatmap showed the outcomes. Thanks to this graphic representation, meaningful connections between the variables under investigation might be quickly seen.

The heatmap results confirmed the expected physical behavior of structural elements: drift rises with displacement (in both X and Y directions). This connection is essential to structural analysis because it reflects the movement and deformation patterns of the building components under load. On the other hand, a strong negative association was found between stiffness drift and displacement. This implies that structures or elements with higher stiffness usually show fewer motions and deformations, given similar loading situations. Fundamental to structural engineering, this inverse relationship shows how effective stiffness is in balancing the effects of loads placed on structures. High correlations with each other and consistent behavior across X and Y measurements indicate that the material properties are isotropic and that loads are applied uniformly in these directions.

Overall, the correlation matrix presented in Fig. 4 provided crucial insights that influenced the modeling approach. The researcher analyzed the Pearson correlation coefficients and identified which features had linear solid relationships. High correlations between certain features, such as stiffness and displacement, indicated potential multicollinearity issues, which could lead to redundancy and affect the model's stability. Features with extremely high correlations were carefully evaluated to mitigate these issues, and some were excluded from the final model. This step was essential to ensure that the model remained robust and did not suffer from overfitting due to redundant information. The exclusion of these highly correlated features ultimately helped to improve the model's predictive performance, ensuring that the remaining features contributed uniquely to the seismic performance predictions.

These connections are not only numerical results; they will significantly benefit structural engineering. They advance knowledge of the behavior of structural elements under different loads, which affects safety precautions and design decisions. The negative connection between stiffness and displacement/drift is a crucial check to guarantee the accuracy and dependability of the data gathered. Such knowledge helps enhance the resilience and strength of structures and in predictive modeling. This approach thus provides a robust statistical basis and a clear route to improve the prediction models for the better performance of structures under operational loads and to optimize structural designs.

Model performance

Before optimization, the accuracy of the XGBoost model in predicting seismic performance was very high, with a test accuracy of 95.49% and a train accuracy of 95.51%. This means that these statistics expose the model's resiliency and capabilities to generalize outside the training data in making correct extrapolations on unknown test data. The mean squared error of the model was 0.0389, which tells that its average of the squared differences between predicted and actual values was relatively small. This sentiment is further supported by the root mean squared error of 0.1972 and the mean absolute error of 0.0301. The R-squared value of 0.9549 presents the model's efficiency in capturing the variability observed in seismic performance measurements, proving a model of high predictive ability.

The model did remarkably well after optimization was done with some essential vital hyperparameters: the learning rate, which controls how much the model changes the parameters after every iteration, balancing accuracy with

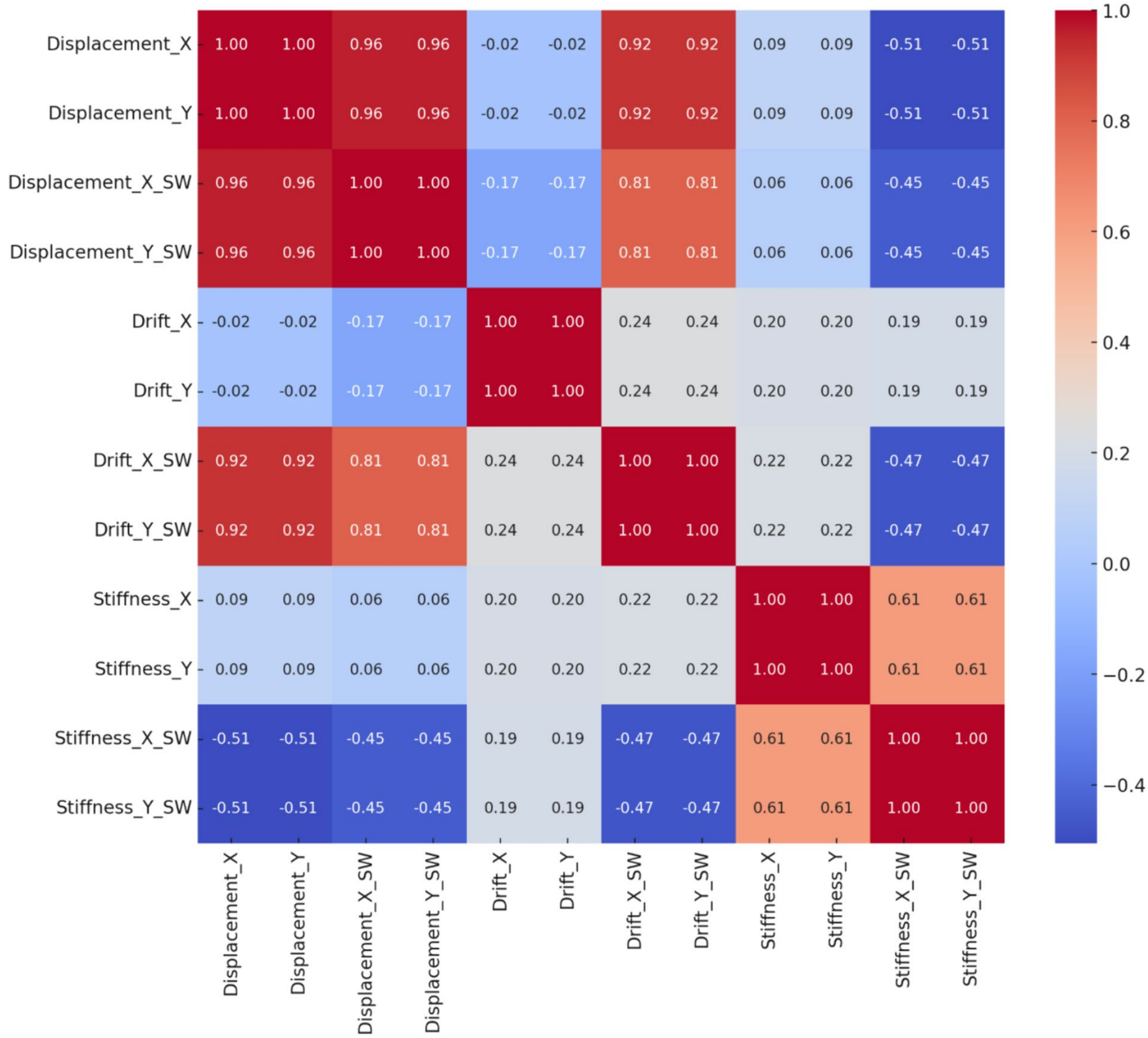


Fig. 4 Correlation matrix for the numerical variables

not falling into the trap of overfitting. It was also paramount to avoid overly complex models. Two other vital hyperparameters were made—the maximum depth of trees and several estimators—so the model could capture complex relationships within the data without overfitting. Following this, subsample ratio adjustments have made the training even more random, thereby increasing its potential for generalization. After that, regularization parameters (Lambda and Alpha) were tuned to save model complexity. Finally, Owl Search identified optimal settings of those hyperparameters in a way that raised both accuracy and model stability (Fig. 5).

However, applying the Owl Search Algorithm to hyperparameter optimization turned in very stunning results. In this case, the optimized model of XGBoost returned a test accuracy of 98.8% and a training accuracy of 97.98%, which shows significant improvements over a non-optimized model. Improved accuracy by the Owl Search algorithm speaks to the efficiency and exactness that further refines model parameters to pick up complex relationships within the data. The optimization then slightly reduced the mean squared error to 0.0355, besides activating improvements in the root-mean-squared error and mean absolute error to 0.1884 and 0.0283, respectively. The R-squared value increased to 0.9579, showing the optimized model's improved fit and prediction accuracy (Fig. 6).

Table 1 depicts the superiority of the machine learning model concerning XGBoost + OSA compared to traditional engineering methods for predicting seismic performance. The following comparison table shows key metrics where this machine learning model achieves test accuracy of 98.8%, much higher than that obtained by traditional

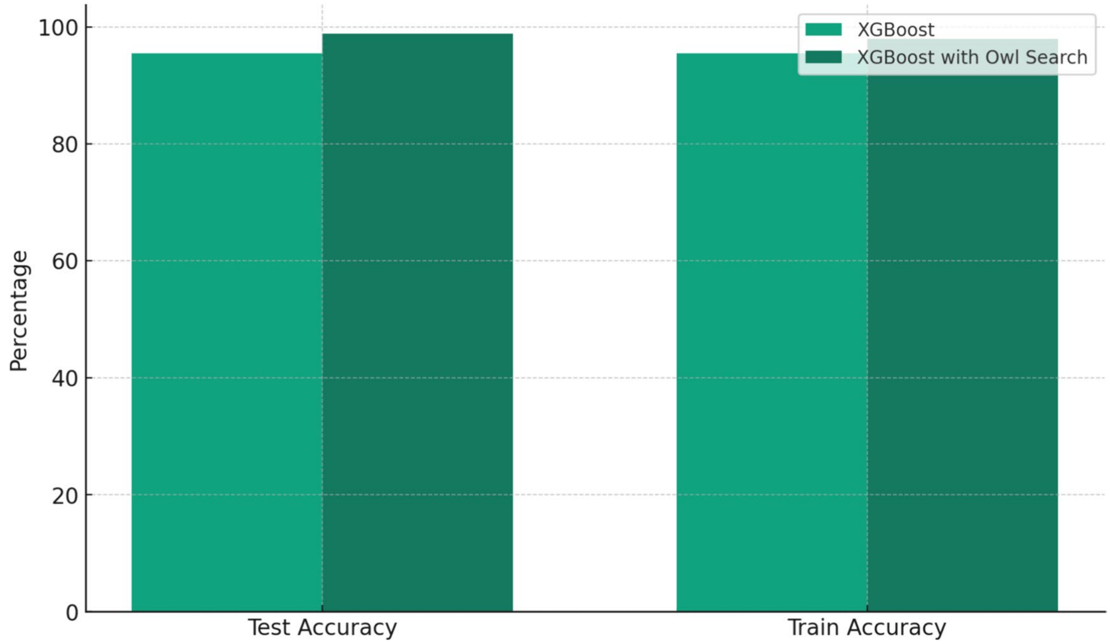


Fig. 5 Accuracy compression between XGBoost and XGBoost-OSA

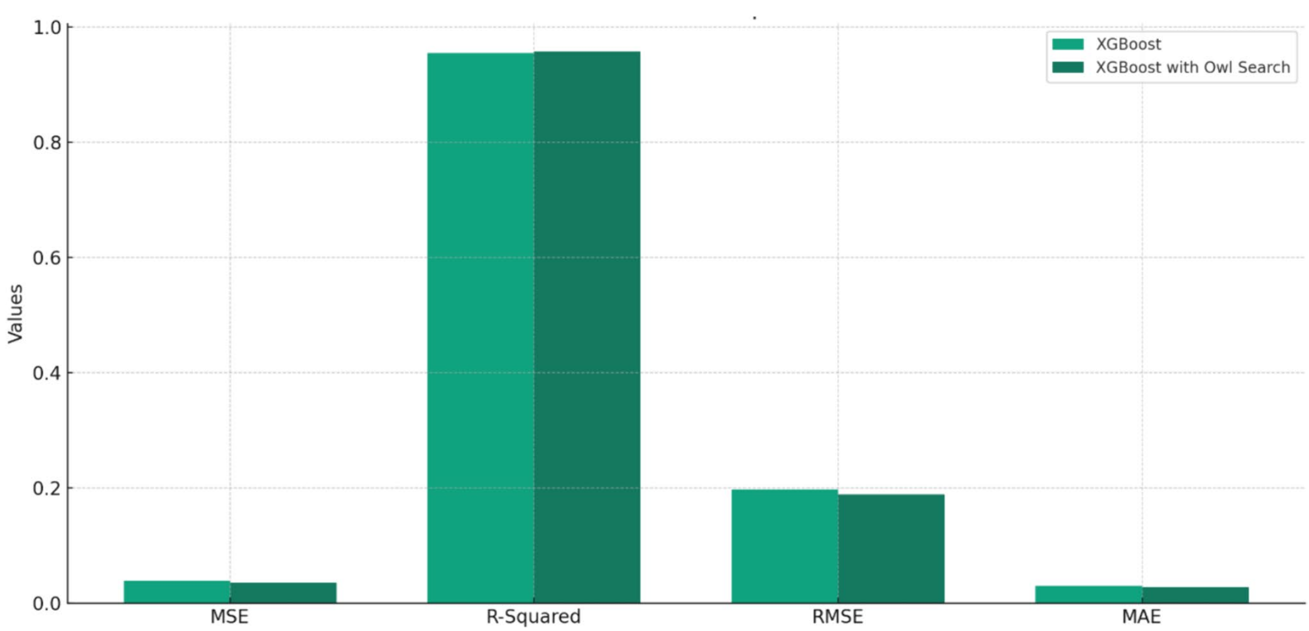


Fig. 6 Error comparison between pre and post-optimization

Table 1 Comparison table

Metric	Machine learning model (XGBoost + OSA)	Traditional engineering methods
Test accuracy	98.8%	Typically, lower (Varies)
Mean Squared Error (MSE)	0.0355	Higher (Varies)
Root Mean Squared Error (RMSE)	0.1884	Higher (Varies)
Mean Absolute Error (MAE)	0.0283	Higher (Varies)
R-squared value (R^2)	0.9579	Typically, lower (Varies)

methods, which typically have lower accuracy. Moreover, it holds lesser prediction errors, with an MSE of 0.0355, RMSE of 0.1884, and MAE of 0.0283—which are much better than conventional methods. The high R-squared value of 0.9579 further supports the model's explanatory power on variability in seismic performance; something typically accounted for poorly in traditional methods. The following bullet points summarize these advantages by indicating that the model was more accurate, had reduced prediction errors, and explained better variability. This machine learning approach is a considerable advancement in that it provides a more reliable tool for assessing seismic risk, with a particular interest in complex and irregular structures.

The ensemble results described above indicate a breakthrough in predicting seismic capacity. The potential of the XGBoost algorithm combined with the creative utilization of the Owl Search Algorithm is evident in high accuracy, low error metrics, and robust R-squared values—high hopes for the transformation of the assessment of seismic resilience levels in buildings. While the results emphasize the technical feasibility and efficiency of these methodologies, more scopes are also reflected in the broader application of the same in earthquake engineering and building design domains. In seismic performance prediction, it is essential to discover and understand the key features that notably influence the model's predictions.

The present study elicited good insight regarding the relative importance of various structural attributes in the evaluation of seismic resilience of vertically irregular buildings. The latter was developed through a prediction model using the XGBoost algorithm, which the Owl Search Algorithm has further enhanced. This technology enables an articulation of the realization of the model's inherent features with great significance in shedding light on the fundamental dynamics governing building behavior during seismic events. Model results indicated mass irregularities as generally the most effective predictor of seismic performance for the other variables studied, including stiffness and base shear capacity. The effect of irregularity in stiffness, no doubt, is significant and presumed to be related to its role in governing how seismic forces are distributed in the structure. Buildings whose behavior is characterized by substantial differences in stiffness between stories are likely to have problems with the local irregularity of force distribution and may be expected to respond with a disproportional, elevated likelihood of seismic solid shaking. In the case of mass irregularity, differences in mass distribution can highly affect the building's vibrational response to seismic pressures. This could lead not only to a complex dynamic but also to an impact on the dynamic interaction of other building elements.

Figure 7 shows the essential features identified by the model, which instead agree with conventional engineering wisdom, bringing out new insight into seismic performance prediction. It makes good sense to determine stiffness, mass irregularities, and base shear capacity as critical factors, as observed in earthquake engineering, since these parameters significantly influence the structure's response to seismic forces. In particular, stiffness irregularity has traditionally been recognized as one of the causes of an uneven distribution of seismic forces that engenders localized failures. However, in a model, the roles—normalized story displacement and irregularity ratios—seem less explicitly noted in traditional analyses. Those features, resulting from deep data preprocessing and feature engineering, serve with a nuanced understanding of exactly how structural irregularities impact seismic resilience. The model is, therefore, challenging traditional approaches to give a more detailed assessment of seismic performance and argues for more prominence in engineering practices. The methodology confirms and extends the existing engineering principles, making further opportunities for more accurate and, hence, more efficient seismic design and retrofitting strategies.

One of the most outstanding features is the base shear capacity, showing the essential feature of the power of a structure to withstand lateral seismic stresses. The higher the base shear capacity, the more enhanced the possibility of resisting lateral forces; therefore, it plays a critical role in minimizing the effect of ground motion on the structure. This feature influences the model's predictions and aligns with the most fundamental concept in earthquake engineering. This underlines the importance of designing buildings to resist the lateral forces of the earthquake. Normalized tale displacement and irregularity ratios were also highlighted as very relevant features that further enhance the model's predictive capability. The rigorous feature preprocessing and engineering of the above features help capture complex structural features in both an intelligible and very relevant way for the model. These methodologies provide a reminder of the potential for advanced data analysis methods to help describe intricate features of seismic performance that may need to be more evident through more conventional analysis methods. Conclusion: The examination of feature importance not only validates well-established engineering principles but presents new opportunities for further research and practical applications. This elaborates on the basis for refined and extended applications in seismic design and retrofitting by identifying structural elements with the most significant influence on seismic performance. In turn, this will offer built environments that are safer and more resistant to earthquakes.

Discussion

These results from this study underline significant advantages of using sophisticated machine learning methodologies, more specifically, XGBoost enhanced by the Owl

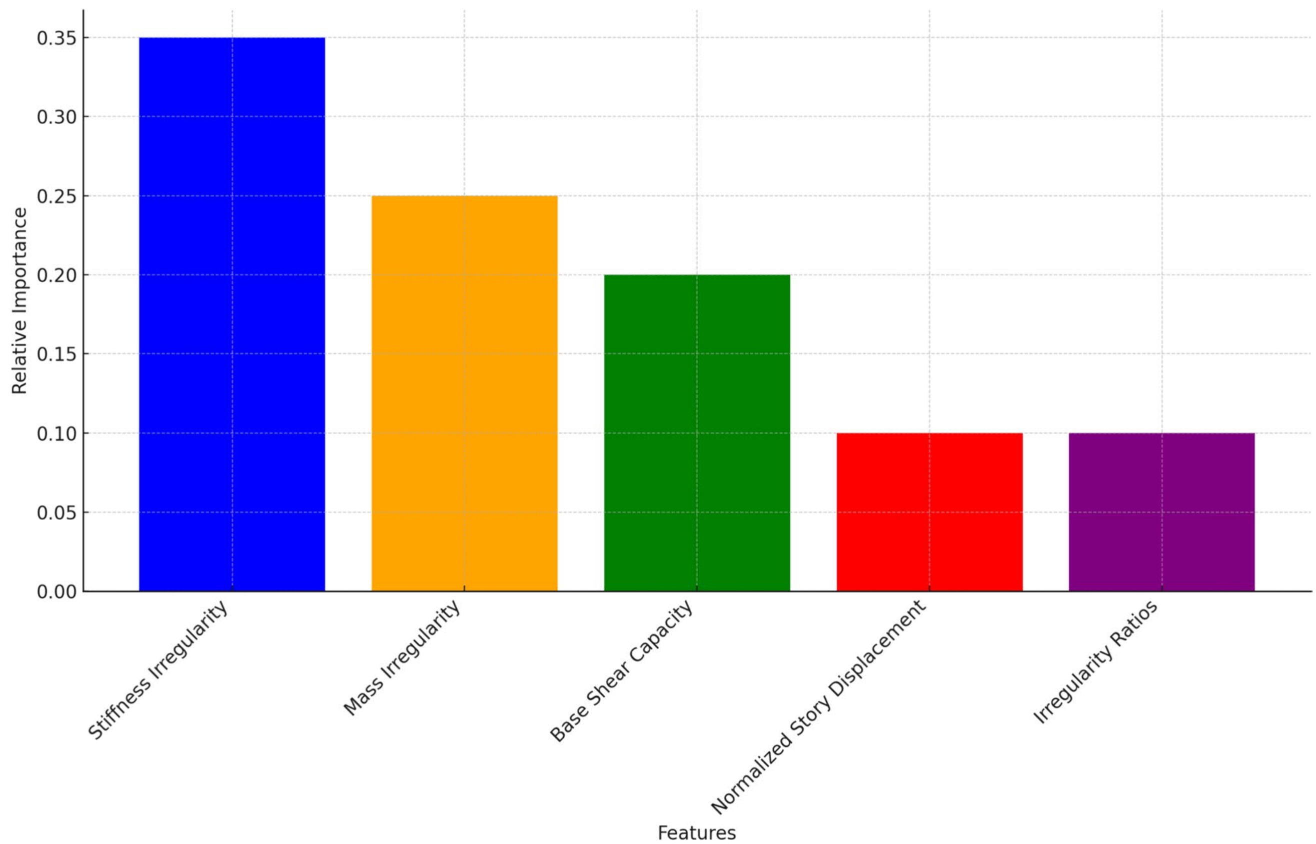


Fig. 7 Important features

Search Algorithm in estimating seismic behavior for vertically irregular structures. It improved to a test accuracy of 98.8% and a training accuracy of 97.98%. All these techniques effectively captured complex interactions among different structural elements and seismic responses (Feng et al., 2021; Ghanem & Moon, 2021). These results show that the model accounts for any nonlinear relationships and interactions that conventional linear models would miss, which returned a lower accuracy (Ahmed et al., 2021a; Laissy, 2022). Besides, after tuning, the Mean Squared Error (MSE) for the model came down to 0.0355 with improvements in Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) to 0.1884 and 0.0283, respectively. This will mean that the most sophisticated characteristics of a structure—stiffness, and mass anomalies, among others—come into play in combination with state-of-the-art feature engineering techniques for a nuanced understanding of seismic susceptibility, which allows more accurate forecasts relevant to mitigation strategies and improving the resilience of architectural designs against seismic events (Al Yamani et al., 2024; Kim et al., 2022).

Compared to the existing methods of seismic performance prediction, primarily based on simplified analytical models or even empirical correlations, the machine learning strategy presented in this study has significant improvements. Traditional methods may not be able to capture the complexity of real-world structures with irregularities that remarkably affect seismic performance, as explained by (Bekele, 2022; Bhatta et al., 2021). The incorporation of XGBoost and the Owl Search Algorithm significantly improved the predictive accuracy of the machine learning model developed herein. The accuracy is more than 95%: in this model, the capability of considering a wide range of factors and their various interactions results in a holistic seismic risk assessment (Kaveh, 2024; Mostafaei et al., 2023). Moreover, the fact that this model depends on a comprehensive dataset—into different building layouts and some characteristic variables—gives it applicability across scenarios (Alkhdour et al., 2023; Al-Rawashdeh et al., 2024).

Though very promising, the results do come with some significant limitations on the part of our study. One of the critical constraints is the dataset used for training and testing the model. Though very large, the dataset cannot represent all the building designs and configurations prevalent worldwide. Hence, this reduces generalizability to buildings other than those in the dataset to a certain extent (Ali et al., 2023; Kaveh et al., 2021). This means that the model's effectiveness depends on the precision and completeness of the data input, so any inconsistencies or biases in the dataset could disturb the predictions (Dabiri et al., 2022).

The model's effectiveness depends on the completeness and accuracy of the input data; the model is sensitive to any inaccuracies or incompleteness that would be physically present in real-world data. Sensitivity analyses were carried out for different conditions under which some data might be considered incomplete or slightly inaccurate to judge the performance of the model. These studies showed that the model copes with minor inaccuracies; however, when significant errors or missing data are exhibited, the model's predictive accuracy is lost. This is sensitive to the need for high-quality data to derive trustable estimations of seismic performance. Thus, data cleaning, validation, and pre-processing are necessary to maintain model value in a practical demonstration.

Another limitation is that assumptions, mainly those made about the model's development process—especially those related to feature selection and engineering—are pretty general. Even though an attempt was made to make the decisions based on firmly grounded technical principles and empirical evidence, some degree of subjectivity may affect the result of the model. According to Harirchian et al. (2022), these limitations can influence its applicability to various building types and regions. For instance, if the dataset inputted contains buildings with particular structural characteristics or are from some geographical areas, it does not perform very accurately when applied to buildings with different designs, materials, or seismic conditions. This could further impact the generalizability and effectiveness of the model in predicting seismic performance in various contexts. Such a limitation can be overcome by the inclusion of a larger dataset that represents a wide range of building types and regional seismic data so that it can develop a model applicable to various scenarios.

The outliers in the stiffness measurements were very carefully dealt with in this study. First, the outliers were identified using the Interquartile Range (IQR) method, where extreme values were found to fall considerably out of range. These outliers were located at "Ground" and "Base" levels, with unusually high stiffness values. Their potential impact may be the reason for including or excluding these outliers in the final model. In this study, with and without outliers, the test for their influence on their performance was conducted. Results showed that predictive accuracy was slightly lower in these cases, including outliers, since extreme values can bias how the model learns. On the other hand, outlier removal improved model accuracy and generalizability by focusing on the more typical range of structural behavior. In the end, extreme outliers were removed to make the model robust enough to give more reliable predictions across various scenarios.

Conclusion and future work

The result of the study showed that the novel machine learning techniques predict the seismic behavior of vertically irregular structures using the XGBoost algorithm enhanced by the Owl Search Algorithm. It returned a test accuracy of 98.8% and a train accuracy of 97.98%, far above the traditional prediction methods. Further, the Mean Squared Error (MSE) decreased to 0.0355, while the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) values improved to 0.1884 and 0.0283, respectively. Since these variables—stiffness, mass anomalies, and base shear capacity—play a crucial role in controlling seismic performance, it is understandable that they would be essential in framing improvement strategies for building design and retrofitting. Future research should expand this model to include other structural anomalies and further integrate real-time seismic data to improve its predictive accuracy. Checking other possible machine learning techniques with larger and more diverse datasets could give better generalizability and effectiveness of the model in seismic risk assessment and mitigation.

Adding more irregularities to the model could further increase the accuracy of the forecast and applicability. Some of the main factors, apart from plan irregularity, which can contribute towards collapses, include torsional irregularity, which means excessive bending of the building during seismic activities because of any asymmetrical distribution of stiffness; soft-story conditions, in which one floor is far weak compared to the others; and vertical discontinuity, involving sudden variations in geometry or mass distribution, which might be equally relevant. That would need the torsional stiffness ratios, floor-by-floor mass distribution measures, and structural continuity indicators for a model. In such a way, the model could predict seismic performance in many more building types and combinations that would provide complete earthquake risk assessment and mitigation. An approach to deal with vertically uneven buildings used in this work could be applied to other kinds of structural imperfections. Torsional anomalies can then be integrated into rotational stiffness and eccentricity, while structures twist under seismic stresses due to asymmetrical stiffness. Other parameters are added to quantify the inter-story drift and floor strength ratios for soft-story abnormalities when one floor is much weaker. Integrating geometric complexity and load distribution metrics may describe plan anomalies like L- or T-shaped structures. The model might be used for more building types and seismic performance evaluations by including these structural abnormalities.

Even while machine learning can accurately forecast seismic performance, capturing the entire complexity of seismic behavior, especially for buildings with anomalies that have yet to be widely studied, is the next hurdle. Buildings with significant torsional abnormalities or very changeable material qualities may take time to anticipate with current ML methods. Real-time seismic data integration and generalization over multiple geographical locations with varying seismic properties are also tricky. Existing models cannot capture these seismic behavior features; thus, data collection and computational sophistication must improve.

Author contributions The author wrote and reviewed the manuscript.

Funding The authors did not receive financial support from any organization for the submitted work.

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest All authors certify that they have no affiliations with or involvement in any organization or entity with financial or non-financial interest in the subject matter or materials discussed in this manuscript.

References

Ahmad, J., Majdi, A., Babeker Elhag, A., Deifalla, A. F., Soomro, M., Isleem, H. F., & Qaidi, S. (2022). A step towards sustainable concrete with substitution of plastic waste in concrete: Overview on mechanical, durability and microstructure analysis. *Crystals*, *12*(7), 944.

Ahmed, M., Abdo, M., & Mohamed, W. (2021). Vertical geometric irregularity effect on performance-based seismic design for moderate rise rc moment resisting frame buildings. *Arabian Journal for Science and Engineering*, *47*(10), 12333–12348. https://doi.org/10.1007/s13369-021-06376-y

Ahmed, M., Abdo, M., & Mohamed, W. (2021a). Evaluation of seismic response modification factor (r) for moderate-rise rc buildings with vertical irregular configurations. https://doi.org/10.21203/rs.3.rs-1141410/v1

Ahmed, H. U., Mohammed, A. S., Faraj, R. H., Abdalla, A. A., Qaidi, S. M., Sor, N. H., & Mohammed, A. A. (2023). Innovative modeling techniques including MEP, ANN and FQ to forecast the compressive strength of geopolymer concrete modified with nanoparticles. *Neural Computing and Applications*, *35*(17), 12453–12479.

Al Yamani, W. H., Bisharah, M., Alumany, H. H., & Al Mohammadin, N. A. (2024). Machine learning in seismic structural design: An exploration of ann and tabu-search optimization. *Asian Journal of Civil Engineering*, *25*(3), 2367–2377.

Al-Rawashdeh, M., Al Nawaiseh, M. D., Yousef, I., Bisharah, M., Alkhadrawi, S., & Al-Bdour, H. (2024). Predicting building damage grade by earthquake: A bayesian optimization-based comparative study of machine learning algorithms. *Asian Journal of Civil Engineering*, *25*(1), 253–264.

Ali, M., & Hussein, M. (2024). Evaluation and prediction of design-time product structural analysis assistance using XGBoost and Grey Wolf Optimizer. *Asian Journal of Civil Engineering*, *25*(3), 2415–2429.

Ali, T., El-Din, M., & Haider, W. (2023). The effect of soil-structure interaction on the seismic response of structures using machine learning, finite element modeling and asce 7–16 methods. *Sensors (Basel, Switzerland)*, *23*(4), 2047. https://doi.org/10.3390/s23042047

Alkhdour, A., Khazaleh, M. A., Mnaseer, R. A., Bisharah, M., Alkhadrawi, S., & Al-Bdour, H. (2023). Optimizing soil settlement/consolidation prediction in Finland clays: Machine learning regressions with bayesian hyperparameter selection. *Asian Journal of Civil Engineering*, *24*(8), 3209–3225.

Bekele, B. (2022). Effect of setback irregularity on elastic seismic demand of reinforced concrete building. *Journal of University of Shanghai for Science and Technology*, *24*(02), 182–193. https://doi.org/10.51201/jusst/22/0242

Bhatta, S., Sharma, L., Niure, B., & Niraula, S. (2021). Seismic response of vertical irregular structures in setback and stepped buildings. *Journal of Engineering Technology and Planning*, *2*(1), 15–25. https://doi.org/10.3126/joetp.v2i1.39204

Dabiri, H., Faramarzi, A., Dall'Asta, A., Tondi, E., & Micozzi, F. (2022). A machine learning-based analysis for predicting fragility curve parameters of buildings. *Journal of Building Engineering*, *62*, 105367.

Emad, W., Mohammed, A. S., Kurda, R., Ghafor, K., Cavaleri, L., Qaidi, S. M., & Asteris, P. G. (2022). Prediction of concrete materials compressive strength using surrogate models. *Structures* (Vol. 46, pp. 1243–1267). Elsevier.

Feng, D. C., Wang, W. J., Mangalathu, S., & Taciroglu, E. (2021). Interpretable XGBoost-SHAP machine-learning model for shear strength prediction of squat RC walls. *Journal of Structural Engineering*, *147*(11), 04021173.

Ghanem, A., & Moon, D. (2021). Seismic fragility analysis of 3d vertical irregular reinforced concrete structures. https://doi.org/10.31224/osf.io/zn9uh

Gwalani, P., Singh, Y., & Varum, H. (2022). Seismic vulnerability of reinforced concrete buildings with discontinuity in columns. *Earthquake Engineering & Structural Dynamics*, *52*(1), 204–225. https://doi.org/10.1002/eqe.3757

Harirchian, E., Lahmer, T., Kumari, V., & Jadhav, K. (2020). Application of support vector machine modeling for the rapid seismic hazard safety evaluation of existing buildings. *Energies*, *13*(13), 3340.

Harirchian, E., Kumari, V., Jadhav, K., Rasulzade, S., Lahmer, T., & Das, R., R (2021). A synthesized study based on machine learning approaches for rapid classifying earthquake damage grades to RC buildings. *Applied Sciences*, *11*(16), 7540.

Jaf, D. K. I., Abdulrahman, P. I., Mohammed, A. S., Kurda, R., Qaidi, S. M., & Asteris, P. G. (2023). Machine learning techniques and multi-scale models to evaluate the impact of silicon dioxide (SiO2) and calcium oxide (CaO) in fly ash on the compressive strength of green concrete. *Construction and Building Materials*, *400*, 132604.

Kaveh, A. (2014). *Advances in metaheuristic algorithms for optimal design of structures* (pp. 9–40). Springer International Publishing.

Kaveh, A. (2024). *Applications of Artificial neural networks and machine learning in Civil Engineering, studies in Computational Intelligence 1168*. Springer.

Kaveh, A., & Ardalani, S. (2016). Cost and CO2 emission optimization of reinforced concrete frames using ECBO Algorithm. *Asian Journal of Civil Engineering*, *17*(6), 831–858.

Kaveh, A., & Khalegi, A. (1998). Prediction of strength for concrete specimens using artificial neural networks. *Advances in Engineering Computational Technology*, 165–171.

Kaveh, A., & Khavaninzadeh, N. (2023). Efficient training of two ANNs using four meta-heuristic algorithms for predicting the FRP strength. *Structures* (Vol. 52, pp. 256–272). Elsevier.

Kaveh, A., & Sabzi, O. (2012). Optimal design of reinforced concrete frames using big bang-big crunch algorithm. *International Journal of Civil Engineering*, *10*(3), 189–200.
Kaveh, A., & Servati, H. (2001). Design of double layer grids using backpropagation neural networks. *Computers & Structures*, *79*(17), 1561–1568.
Kaveh, A., & Talatahari, S. (2010). A charged system search with a fly to boundary method for discrete optimum design of truss structures. *Asian Journal of Civil Engineering (Building and Housing)*, *11*(3), 277–293.
Kaveh, A., & Talatahari, S. (2011). An enhanced charged system search for configuration optimization using the concept of fields of forces. *Structural and Multidisciplinary Optimization*, *43*, 339–351.
Kaveh, A., & Zakian, P. (2012). Performance based optimal seismic design of RC shear walls incorporating soil-structure interaction using CSS algorithm. *International Journal of Optimization in Civil Engineering*, *2*(3), 383–405.
Kaveh, A., & Zakian, P. (2014). Seismic design optimisation of RC moment frames and dual shear wall-frame structures via CSS algorithm. *Asian Journal of Civil Engineering*, *15*(2014), 435–465.
Kaveh, A., Gholipour, Y., & Rahami, H. (2008). Optimal design of transmission towers using genetic algorithm and neural networks. *International Journal of Space Structures, 23*(1), 1–19.
Kaveh, A., Amir, E. & Mahdi, M. (2023). Buckling resistance prediction of high-strength steel columns using metaheuristic-trained artificial neural networks. *Structures, 56*(C), 104853.
Kaveh, A., Kalateh-Ahani, M., & Fahimi-Farzam, M. (2013). Constructability optimal design of reinforced concrete retaining walls using a multi-objective genetic algorithm. *Structural Engineering and Mechanics*, *47*(2), 227–245. https://doi.org/10.12989/sem.2013.47.2.227
Kaveh, A., Mirzaei, B., & Jafarvand, A. (2015). An improved magnetic charged system search for optimization of truss structures with continuous and discrete variables. *Applied soft Computing*, *28*, 400–410.
Kaveh, A., Izadifard, R. A., & Mottaghi, L. (2019). Optimal design of planar RC frames considering CO2 emissions using ECBO, EVPS and PSO metaheuristic algorithms. *Journal of Building Engineering*. https://doi.org/10.1016/j.jobe.2019.101014
Kaveh, A., Izadifard, R. A., & Mottaghi, L. (2020). Optimal design of planar RC frames considering CO2 emissions using ECBO, EVPS and PSO metaheuristic algorithms. *Journal of Building Engineering*, *28*, 101014. https://doi.org/10.1016/j.jobe.2019.101014
Kaveh, A., Mottaghi, L., & Izadifard, R. A. (2021). An integrated method for sustainable performance-based optimal seismic design of RC frames with non-prismatic beams. *Scientia Iranica Transactions a: Civil Engineering*, *28*(5), 2596–2612. http://scientiairanica.sharif.edu
Kim, D., Pham, K., Oh, J. Y., Lee, S. J., & Choi, H. (2022). Classification of surface settlement levels induced by TBM driving in urban areas using random forest with data-driven feature selection. *Automation in Construction*, *135*, 104109.
Laissy, M. (2022). Effect of different types of bracing system and shear wall on the seismic response of rc buildings resting on sloped terrain. *Civil Engineering Journal*, *8*(9), 1958–1976. https://doi.org/10.28991/cej-2022-08-09-014
Lin, J., Chen, W., Hsiao, F., Weng, Y., Shen, W., Weng, P., & Chao, S. (2020). Simulation and analysis of a vertically irregular building subjected to near-fault ground motions. *Earthquake Spectra*, *36*(3), 1485–1516. https://doi.org/10.1177/8755293020911134
Mangalathu, S., Sun, H., Nweke, C. C., Yi, Z., & Burton, H. V. (2020). Classifying earthquake damage to buildings using machine learning. *Earthquake Spectra*, *36*(1), 183–208.
Maulana, T., Enkhtengis, B., & Saito, T. (2021). Proposal of damage index ratio for low- to mid-rise reinforced concrete moment-resisting frame with setback subjected to uniaxial seismic loading. *Applied Sciences*, *11*(15), 6754. https://doi.org/10.3390/app11156754
Maulana, T., Syamsi, M., Monika, F., & Prayuda, H. (2023). The effect of span-to-height aspect ratio to the damage index ratio of rc buildings with vertical irregularity setbacks. *Jurnal Kejuruteraan*, *35*(2), 529–537. https://doi.org/10.17576/jkukm-2023-35(2)-25
Mostafaei, H., Mostofinejad, D., Ghamami, M., & Wu, C. (2023). Fully automated operational modal identification of regular and irregular buildings with ensemble learning. *Structures* (Vol. 58, p. 105439). Elsevier.
Saleem, N. (2023). Machine learning-based peak ground acceleration models for structural risk assessment using spatial data analysis. *Earthquake Engineering & Structural Dynamics*, *53*(1), 152–178. https://doi.org/10.1002/eqe.4021
Shi, T., & Lou, P. (2023). Optimized machine learning approaches for identifying vertical temperature gradient on ballastless track in natural environments. *Construction and Building Materials*, *367*, 130321.
Yan, H., Yan, K., & Ji, G. (2022). Optimization and prediction in the early design stage of office buildings using genetic and XGBoost algorithms. *Building and Environment*, *218*, 109081.
Yang, F., & Ma, J. (2019). Deep-learning inversion: A next-generation seismic velocity model building method. *Geophysics, 84*(4), R583–R599. https://doi.org/10.1190/geo2018-0249.1

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.