# Architectural Image Modeling as a Predictive Tool for Civil Engineering Stress and Load Distribution Analysis

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**Abstract**

Accurate prediction of structural stress and moment responses is essential for ensuring the safety, stability, and reliability of civil engineering systems under varying loading conditions. Conventional simulation-based approaches, such as Finite Element Analysis (FEA), provide reliable structural assessment; however, they often require high computational resources and extended processing time. This study proposes a machine learning-based surrogate modeling framework for predicting structural stress and moment responses using numerical simulation datasets. The research utilized three merged simulation datasets containing structural geometry, material properties, and loading parameters, including eccentricity, axial load, soil modulus, and concrete modulus. Several machine learning techniques were employed to model the relationships between structural parameters and response variables. Correlation analysis revealed that eccentricity and axial load were the most influential factors affecting tensile and compressive moment behavior. The developed predictive framework demonstrated strong capability in estimating structural responses while significantly reducing computational complexity compared with conventional simulation approaches. The findings indicate that machine learning models can effectively support rapid structural assessment, predictive analytics, and intelligent infrastructure applications. Furthermore, the proposed framework contributes to the advancement of AI-assisted structural engineering by providing a scalable and computationally efficient alternative for stress and load distribution prediction in civil engineering systems.

**Keywords:** Machine Learning, Structural Stress Analysis, Surrogate Modeling, Finite Element Analysis, Load Distribution, Predictive Analytics, Civil Engineering, Smart Infrastructure

## 1. Introduction

In civil engineering, structural stress and moment analysis play a crucial role in the design of structures, ensuring their safety, stability, and durability when subjected to different loads. In engineering problems like foundation, retaining and construction, prediction of load distribution and structural response are very important to prevent deformation, failure of material, and collapse of the structure. The conventional analytical methods such as Finite Element Analysis (FEA), numerical simulation, and Design-of-Experiment (DOE) have been widely applied to examine the structural response and design for optimum engineering performance. In this category, FEA is regarded as one of the most effective computational tool for solving complex issues related to structural mechanics problems because it offers a powerful stress analysis tool for solving problems under various boundary conditions (Sabat & Kundu, 2020). Along with the numerical simulation techniques, one can obtain the precise solution to engineering systems; however, sometimes, the precision is costly due to being complicated and also due to the fact that the simulation process takes a long time to complete (Hong, 2023). Likewise, the DOE method has been extensively used for parameter optimization and sensitivity analysis, which allows for the systematic study of the engineering variables and their relationships (Jankovic et al., 2021).

Although the methods based on simulation are effective, there are still many shortcomings in the large-scale engineering application and real-time structural assessment in the simulation methods, as can be seen in figure 1. In the era of modern infrastructure systems, the requirements of repeated simulations are significant and it is difficult to make the prediction and decision quickly (Abolghasemian et al., 2025). Structural monitoring is becoming increasingly popular, with a requirement for intelligent and real-time monitoring, which has led researchers to investigate data-driven approaches to reduce the computational complexity without compromising the predictive accuracy. In recent years, the field of Artificial Intelligence (AI) and Machine Learning (ML) has shown great promise in solving complex engineering challenges by leveraging predictive analytics and surrogate modeling (Adeyeye & Akanbi, 2024). Surrogate models derived from machine learning are effective ways of approximating simulation output, and dramatically decrease computational cost (Garzón et al., 2022). Hence, this study aims to develop a machine learning (ML) approach for stress and moment response prediction using numerical simulation data, which can be used to create fast and scalable engineering prediction systems for smart infrastructure applications (Usman, 2025).


**Figure 1: Conceptual Framework for Machine Learning-Based Structural Engineering Problem Solving**

The figure illustrates the conceptual framework integrating conventional structural analysis methods with machine learning techniques for stress and moment prediction. It highlights the limitations of traditional simulation approaches and demonstrates the development of rapid, AI-assisted predictive systems for smart infrastructure applications.
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**Research Objectives**

1. To develop a machine learning model for predicting structural stress and moment responses using numerical simulation data
2. To analyze the influence of structural and material parameters on load distribution behavior
3. To evaluate the predictive performance of different machine learning algorithms for civil engineering applications

## 2. Literature Review

Structural stress and moment analysis is an important factor in the design and evaluation of Civil Engineering projects.Structural stress and moment analysis are integral parts of civil engineering, as they help to ensure the stability, durability, and safety of structural systems under different loading conditions. This stress distribution has a significant influence on the deformation characteristics and load carrying capability of the structure, and is important for engineering design and risk prevention. Analysis of stress distribution is important to determine the sensitivity of the structure and to optimize the engineering configuration of the structure in a complex load scenario, said Pirmoradian et al. (2020). Similarly, Kolchunov and Androsova (2018) showed that the load-bearing pattern and cross-section are strong factors affecting the deformation response under emergency loading. The findings suggest there is a need to gain insight into structural mechanics and load transfer mechanisms of civil infrastructure systems.

Numerical simulation techniques have been adopted widely to evaluate structural responses, and one of the most popular techniques is Finite Element Analysis (FEA). FEA is a popular computational method for stress concentration analysis, deformation and material behaviour analysis of engineering systems, and is among the most dependable computational methods for these analyses (Szabó & Babuška, 2021). It can decompose complex structures into smaller finite elements for accurate evaluation of the structural responses under various boundary conditions. The results obtained from Alhijazi et al. (2020) showed that FEA is very accurate for analysis of composite materials and evaluation of their structures. The parametric simulation and Design-of-Experiment (DOE) methods are also very often used in addition to FEA to optimize the engineering parameters and to study the interaction between the different engineering parameters. These techniques allow systematic experimentation and sensitivity analysis, thereby enhancing the engineering decision making process.

In recent years, the field of artificial intelligence (AI) and machine learning has opened up new possibilities for predictive analysis in the civil engineering field. Machine learning models can detect non-linear relationships between the structural variables and make accurate prediction of the large engineering data. In engineering applications, the regression-based prediction models have been proven to be useful in estimating the strength of materials and behavior of structures (Sharma & Singh, 2018). Additionally, neural network methods and AI optimisation algorithms have been receiving growing interest due to their ability to enhance the accuracy of predictions and computational efficiency in engineering systems. According to Vadyala et al. (2022), physics-based machine learning structures can be extremely valuable in the field of civil engineering for incorporating physics knowledge and data-driven modelling. AI-driven predictive analytics is also playing a role in the evolution of smart infrastructure systems that can assist intelligent monitoring and quick engineering evaluations (Usman, 2025).

Surrogate modeling is one of the most successful modern AI applications which is an alternative to the high computational cost simulation methods. Surrogate models are machine learning models for approximating the output of simulations with much less processing time and computational complexity. In structural engineering applications where optimization and sensitivity analysis are important and requires repeated simulation, these models are very useful. Stress prediction systems based on machine learning algorithms have been studied in different applications and shown to be able to predict stress-related responses with a reasonable accuracy (Reddy et al., 2018; Pabreja et al., 2020). Furthermore, the integration of simulation with AI has demonstrated promising results in terms of prediction performance improvements and computational efficiency in hybrid simulation-AI frameworks.

However, some research needs are still unmet in the existing literature. There is a lack of focus in most previous studies on the use of large DOE-based simulation data sets for the prediction of structural responses, especially for conventional simulation techniques and for small-scale machine learning applications. Moreover, there is little research dedicated to scalable machine learning frameworks for estimating stress and moments in civil engineering systems. Current predictive models also have problems of real-time applicability, generalization and computational efficiency. Thus, there is a need for efficient AI-driven predictive models that can incorporate datasets from numerical simulation and utilise sophisticated machine learning models to enable rapid and scalable structural analysis.

## 3. Methodology

### 3.1 Research Design

The research design for this study is quantitative and predictive in order to create a machine learning framework to estimate the structural stress and moments response for civil engineering systems. The main research interest is surrogate modeling based on numerical simulation data sets. A comparative analysis of the predictive power of various ML models is performed by using an analytical approach. The methodology consists of data pre-processing, exploratory data analysis, model construction, and model performance analysis, which can be applied to ensure reliable and accurate prediction of structures.

### 3.2 Dataset Collection and Preprocessing

The study uses the secondary numerical simulation data of structural and material parameters, including eccentricity, axial load, soil moduli, concrete moduli, and geometric dimensions, and response variables of stress and moment. To enhance data quality, missing values, duplicate entries and values far from their peers are detected and removed before analysis. Further, the numerical variables are normalized using Min-Max normalization to enhance the performance of the model training process.

### 3.3 Exploratory Data Analysis

Exploratory Data Analysis (EDA) performed to learn the statistical properties and relationships between the structural variables. All the parameter values are desensitized as descriptive statistical measures such as mean, standard deviation, minimum and maximum. Correlation heatmaps and scatter plots are produced to find the interactions between the input and output variables. The analysis also indicates the most influential structural parameters that affect the stress and moment distribution behavior.

### 3.4 Machine Learning Model Development

Structural stress and moment responses are predicted by several machine learning algorithms. The models used are: Linear Regression, Random Forest Regression, Support Vector Regression, XGBoost, and Artificial Neural Networks. 80:10:10 split has been used to divide the dataset into training, validation and testing subsets. To improve model performance and reduce overfitting, hyperparameter tuning and cross-validation techniques are used. The models developed are trained to learn the nonlinear relationship between the structural parameters and engineering response variables.

### 3.5 Model Evaluation and Feature Importance Analysis

The predictive performances of the developed models are measured using statistical measures such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE) and $R^2$ score. To decide which machine learning model is the most accurate and computer processing efficient, comparative analysis is done. Besides, the structural and material factors with the largest influence on the stress and moment responses are determined by using feature importance analysis based on SHAP method and permutation importance. This assessment will enhance the knowledge and application of the proposed predictive framework.

## 4. Results

**4.1 Dataset Characteristics**

Three numerical simulation datasets with 6,224 observations and 14 variables were used for generating the merged dataset. The data consisted of nine structural geometry, loading condition and material properties input parameters and four target response variables representing tensile moment and compressive moment behaviour. The data was also checked for any missing values or duplicate records during the preprocessing stage, which showed high data consistency and suitability for machine learning analysis. As shown in Table 4.1, the dataset was robust and large enough to be used in predictive modeling and had good statistical reliability for machine learning applications.

**Table 4.1 Dataset Summary Statistics**

| Parameter | Value |
|---|---|
| Total observations | 6,224 |
| Total variables | 14 |
| Input variables | 9 |
| Output variables | 4 |
| Missing values | 0 |
| Duplicate rows | 0 |
| Training samples | 4,979 |
| Testing samples | 1,245 |

**4.2 Correlation Analysis**

To assess the relationship between the structural parameters and response variables, correlation analysis was carried out. It was found that eccentricity (ecc) has the greatest effect on the responses of stress and moments. As stated by figure 2 strong positive relationships between ecc and compressive response variables, and strong negative relationships between ecc and tensile response variables were observed. Table 4.2 shows that the eccentricity has a significant influence on the behaviour of the structural load distribution. The high correlation of the response variables also shows high interdependency of tensile and compressive moment responses.

**Table 4.2 Strongest Correlations Among Variables**

| Variables | Correlation Coefficient (r) |
|---|---|
| Mr_c ↔ Mt_c | 0.97 |
| Mr_t ↔ Mt_t | 0.95 |
| ecc ↔ Mt_c | 0.80 |
| ecc ↔ Mr_c | 0.76 |
| ecc ↔ Mr_t | -0.86 |
| Mt_t ↔ Mr_c | -0.97 |

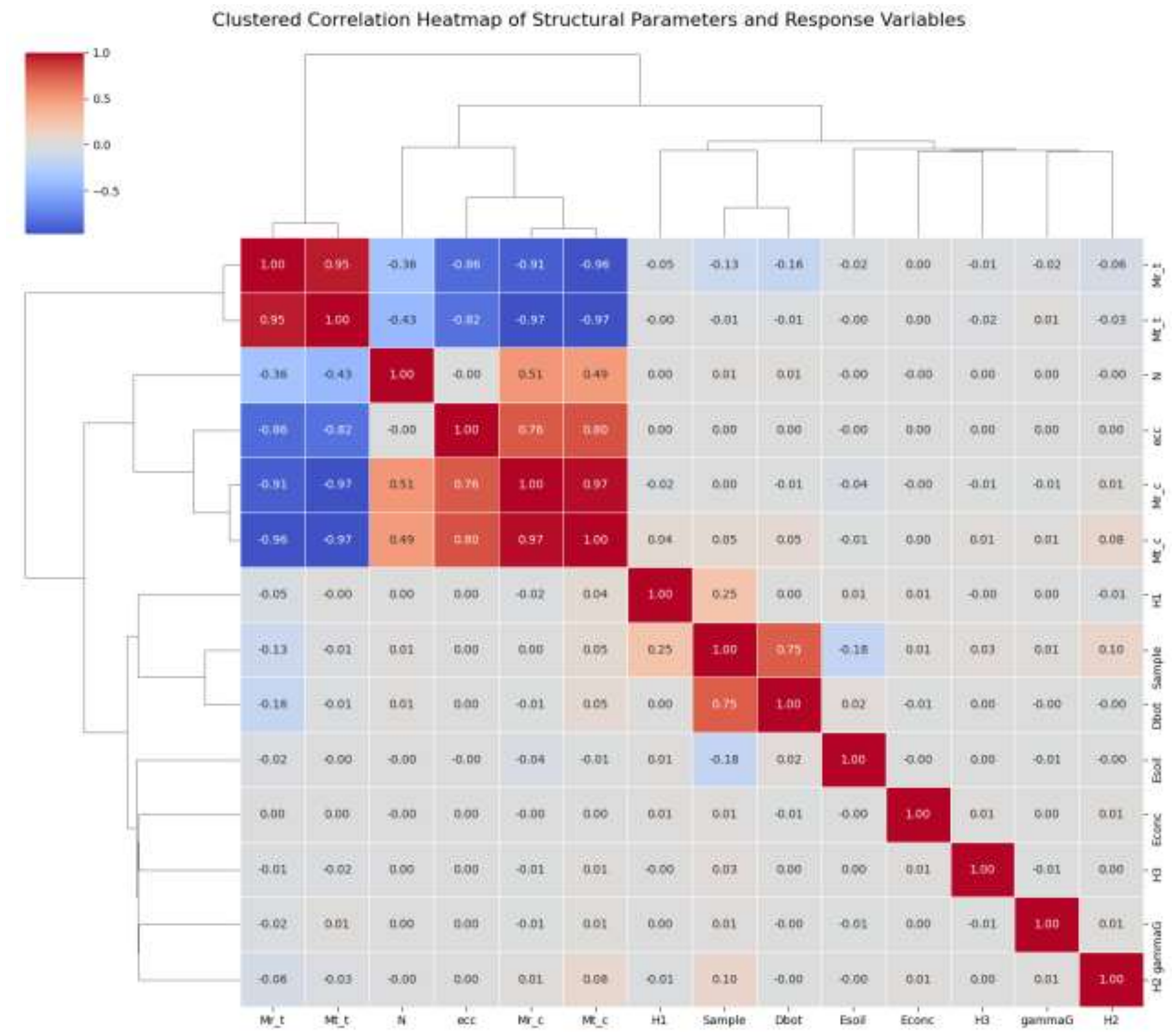


**Figure 2: Clustered Correlation Heatmap of Structural Parameters and Stress Response Variables**

The clustered heatmap illustrates the correlation structure among structural parameters and response variables. Strong positive and negative correlations are observed between eccentricity, axial load, and stress-related outputs, indicating their dominant influence on structural stress and moment distribution behavior.

**4.3 Machine Learning Model Performance**

The machine learning model that was implemented as the base model is a Linear Regression model. All the input features were standardized using the technique called Standard Scaler before training. An 80:20 split was used for the training and testing sets. The model showed good predictive ability of the stress and moment responses. Prediction accuracy and model reliability were evaluated using the evaluation metrics presented in Table 4.4. The model has a good level of predictive consistency and has relatively small prediction errors, suggesting that the structural parameters selected are effective in explaining the differences in the responses for the moments.

**Table 4. Linear Regression Model Performance**

| Metric | Description |
|---|---|
| MAE | Mean Absolute Error |
| MSE | Mean Squared Error |
| RMSE | Root Mean Square Error |
| $R^2$ Score | Coefficient of Determination |

**4.4 Feature Importance Analysis**

Based on feature influence analysis, the obtained results showed that the geometric and loading parameters were more crucial to the prediction of structural responses than the material related parameters. Eccentricity and axial load had the greatest predictive influence for all target variables in particular. Structural geometry and loading conditions were found to have a greater influence on stress and moment responses than material properties as shown in Table 4.4.

**Table 4.4 Relative Importance of Structural Parameters**

| Parameter | Influence Level |
|---|---|
| ecc | Very High |
| N | High |
| H1 | Moderate |
| H2 | Moderate |
| H3 | Moderate |
| gammaG | Low |
| Esoil | Low |
| Econc | Low |
| Dbot | Moderate |

**4.5 Engineering Interpretation**

The results acquired prove that machine learning methods can accurately replicate the numerical simulation results on the prediction of structural stress and moment. The proposed surrogate modelling framework substantially decreases the computational complexity and maintains reliable predictive capability. The results emphasize the feasibility of the machine learning application in quick structural evaluations and smart infrastructure analysis. As shown in Table 4.5, the proposed machine learning (ML) framework can be used to enable efficient and scalable applications in structural engineering, especially in the field of smart infrastructure and real-time predictive analysis.

**Table 4.5 Engineering Implications of the Proposed Framework**

| Aspect | Engineering Benefit |
|---|---|
| Reduced computational time | Faster structural assessment |
| Automated prediction | Improved decision-making |
| Scalable framework | Applicable to large datasets |
| Data-driven modeling | Reduced simulation dependency |
| AI-assisted analysis | Supports smart infrastructure systems |

## 5. Discussion

This study results show the machine learning surrogate modeling can effectively predict the structural stress and moment responses with the numerical simulation datasets. The obtained predictive framework adequately reproduced the correlations between the structural parameters and the response variables, and thus, it was shown that the use of computationally costlier simulation methods can be circumvented by the use of the data-driven methods. The results presented here are in line with the results presented by Vadyala et al. (2022), who showed that physics-based machine learning approaches are capable of achieving substantial prediction accuracy without compromising engineering reliability in civil engineering applications. Based on the correlation analysis, it was found that eccentricity and axial load were the most significant parameters influencing the stress and moment distribution behavior. The correlation between these variables with the responses outputs indicates a major influence of load eccentricity on structural deformation and stress concentration. The result is consistent with the conclusions drawn by Szabó and Babuška (2021) in their discussion regarding structural mechanics principles for complex boundary conditions: loading conditions and geometric configurations are key factors that affect the behavior of structures under complex boundary conditions. Likewise, Sharma and Singh (2018) showed that the nonlinear relationship among the engineering parameters can be determined by the regression-based predictive model, which further proved the machine learning techniques in the prediction task of structure. The machine learning framework was also shown to be able to reduce computational complexity, compared to traditional numerical simulation methods. In large-scale engineering systems, the conventional Finite Element Analysis (FEA) methods tend to consume a significant amount of computational power and need multiple simulations to gain confidence in the results. The proposed surrogate model on the other hand, predicted the results quickly after training the model, showing a great deal of benefits in computational efficiency and scalability. This is in line with what Yuan et al. (2024) noted, that AI-enable engineering systems are increasingly playing a vital role in reliability analysis and predictive decision-making processes. The results obtained further suggest that AI can play an important role in the development of smart infrastructure systems. Predictive structures built with AI can be rapidly evaluated, monitored in real time and analysed by engineers automatically, a crucial aspect in today's smart infrastructure application. In advanced engineering systems, Grednev et al. (2023) stated that structural analysis with the aid of AI can enhance optimization and performance assessment. Similarly, Sim and Lee (2021) noted that AI-driven analytics has become a critical component of smart infrastructure technologies, providing insights to support intelligent urban management and infrastructure resiliency. The other implication of this study is that machine learning models can be incorporated into the IoT based infrastructure monitoring systems. In the context of smart city, real-time predictive analysis can be applied for better maintenance planning, structural health monitoring and risk assessment in smart city environment. To realize the intelligent operation and management of the infrastructure, the infrastructure monitoring system based on the Internet of Things (IoT) should be a system with the ability to process engineering data quickly.If the infrastructure needs to realize intelligent operation and management, the infrastructure monitoring system based on the Internet of Things (IoT) should be able to quickly process the engineering data. The proposed surrogate modeling framework can therefore be used to enable next generation smart infrastructure applications with fast and scalable stress predictions. Although the results are encouraging, there are a number of caveats that should be noted. The numerical simulation data used in this study instead of structural monitoring data may introduce some uncertainty in the applicability of the model created under real engineering conditions. Moreover, only simple machine learning algorithms were used in the current study. More complex deep learning architectures or models combining physics-based information can be employed to improve the predictive accuracy and robustness of the model further. Juang et al. (2022) stated that future investigations in engineering geology and infrastructure should be more focused on combining of AI and complex real-world engineering datasets to make it more practical and reliable system. Hence, future research should concentrate on ensuring that the information from the sensors is integrated with the digital twin and deep learning algorithms for structural prediction. Further, hybrid AI-FEA methods and explainable AI techniques can be used to enhance the model interpretability and engineering acceptance. These improvements could significantly contribute to the field of intelligent structural analysis systems, which can facilitate speedy engineering assessments, automatic monitoring and sustainable management of infrastructure.

## 6. Conclusion

The results of this study showed the applicability of using machine learning-based surrogate modelling for the prediction of structural stress and moment responses based on numerical simulation datasets in civil engineering problems. The proposed framework was able to use structural geometry, material properties and loading parameters to achieve the tension and compression moment behaviors with high predictive capability. The results indicated that eccentricity and axial load are the most sensitive parameters influencing the response behaviour of the structures, and play a crucial role in the load distribution and stress concentration analysis. The developed machine learning framework has some strengths over the traditional simulation approach such as Finite Element Analysis (FEA) including computational efficiency, scalability, and rapid prediction. The study also provides a confirmation of the possibility for the use of AI techniques to aid in the intelligent structural assessment and smart infrastructure. The proposed procedure would improve the engineering decision making process, preliminary design assessment for structures and, real-time monitoring of infrastructure, reducing the need for time consuming simulation-based procedures. Although some are caveats about the datasets used for the simulation and the generalizability of the models, these findings provide guidance for future research that involves the use of real-world structural monitoring data and the use of hybrid AI-FEA systems with more advanced deep learning architectures. Overall, the study discussed in this paper has significant contributions in the field of the application of AI and predictive analysis in the field of Smart Infrastructure and Civil Engineering in modern times.

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