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MATHEMATICAL MODELLING AND STRUCTURAL ANALYSIS IN CIVIL ENGINEERING: A COMPREHENSIVE RESEARCH STUDY ON PREDICTIVE METHODS FOR LOAD DISTRIBUTION, STRESS BEHAVIOUR, AND DESIGN OPTIMISATION

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Abstract

This paper introduces a holistic framework, which combines mathematical modelling, finite element simulations, predictive algorithms, and optimisation strategies to assess and enhance structural performance in civil engineering. The methodology involved closed-form solutions of the analytical methods, as well as finite element method (FEM) of beams, frames, and multi-storey structures, with optimisation using genetic algorithms. Findings showed that FEM and analytical predictions were very similar with the difference usually less than 3 percent, which proves the validity of the computational method. The analysis of stress behaviour showed that both reinforced concrete and steel structures were not subjected to excessive stress levels, which indicated good material performance. The efficiency and sustainability benefits were demonstrated by optimisation having reduced structural weight by 12.4% without compromising serviceability and strength requirements. The credibility of the predictive framework was also supported by validation as it was consistent with theoretical models. The results highlight the possibilities of hybrid computational and predictive approaches to improve accuracy, efficiency, and material savings in structural design. The study will help to develop predictive modelling in civil engineering and will be the basis of applying artificial intelligence and uncertainty-based methods in the future.

Keywords: Finite element method, Load distribution, Stress behaviour, Structural optimisation, Predictive modelling

1. Introduction

The primary pillars of structural engineering practice and research are the structural system dynamics and optimisation because they directly affect the quality of building infrastructure, cost, and durability. Simulation and prediction of dynamics of systems operating under complex loading conditions that were previously inaccessible to engineers was transformed by the development of

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computational modelling (particularly, the finite element method (FEM)). FEM offers both detailed modeling of loads and deflections and the complex behavior, which is a flexible modeling approach to the analysis of the behavior of civil constructions on the scale of beam through the massive geotechnical infrastructure (Beuhler and Rosch, 2023; Wang et al., 2015). The techniques and methods of optimization and predictive modeling have become increasingly significant, and they have been used to complement FEM, since the approach enables the engineers to not only explore the available structures but also enhance them considering material efficiency, stability, and toughness (Manguri et al., 2025; Rajput and Datta, 2020). That is the similarity of modeling and optimization and it is what the study of civil engineering is currently based on with numerical accuracy and breakthrough of design working together to solve real world problems. The widest research has been made in the introduction of FEM into civil engineering and its precision and efficacy continue to get better. The last studies have been characterized by the creation of the numerical modeling of concrete at the meso-scale, which has determined the potential of finding out more information about the mechanics of crack propagation and fracture under different loads (Pan et al., 2025; Shahrbijari et al., 2023). The application of FEM in geotechnical applications is also applied to many studies in the field of geotechnics, and the large-deformation studies in particular, such as foundations and tunneling design (Wang et al., 2015; Li, 2022). The fact that specialised FEM applications were developed as a prototype only indicates the flexibility of this approach, not to mention its of invaluability when it comes to solving any structural and geotechnical problems. Moreover, the review process such as the one by Kumar and Thakur (2024) has also emphasized the significance of FEM in smart structure modelling with sophisticated computer-based scheme the instrument with which adjustable and clever infrastructural structures are designed.. Overall, these advancements demonstrate that FEM is a tool that has developed into its modern state and continues to evolve in the future of civil engineering. Similar to FEM, optimisation methods have also received greater focus in structural engineering studies. Conventional optimisation methods have been complemented by the application of evolutionary algorithms and metamodel-based methods that minimise the computational effort, without the need for large design spaces to search (Negrin et al., 2023; Tang, 2024). Evolutionary structural optimisation has been demonstrated for its effectiveness in improving stability as well as other design parameters even in case of bidirectional geometry optimisation for optimal performance achievement with constraints (Xu et al., 2024). Extensive surveys have supported the significance of combining topology, size, and shape optimisation to obtain lighter and stronger structures; the balance between computational capability and applicability has been rather a more significant factor (Manguri et al., 2025; Mengesha, 2025). Reviewed papers also indicate that optimisation schemes become absolutely required in the design of civil engineering projects in order to meet not only the structural efficiency needs but also the sustainability requirements by asserting that material reduction directly leads to the minimisation of environmental effects (Rajput and Datta, 2020).

A further significant component of innovative methodology is predictive modeling and surrogate approaches. Artificial intelligence (AI) and artificial neural networks (ANNs) are currently employed in building science research, specifically for structural health monitoring (SHM), where substitute models are employed to approximate FEM analysis outcomes at a minimal computational expense (Dadras Eslamlou & Huang, 2022).

Considering these advancements, there are still difficulties that must be considered in order for models to accurately reflect ambiguities related to materials variability, load conditions, and boundaries specification. A collection of works for reviewing computational methods shows that while FEM in its many aspects may be considered mature, there is continued efforts that are necessary for improving FEM's nonlinear and probabilistic modelling capabilities (Beuchler & Rosch, 2023; Pan et al., 2025). In parallel, optimisation methods need additional development to help cope with the trade-offs human-made between design objectives, computational resources, and reliability requirements (Mengesha, 2025; Xu et al., 2024). Throughout the literature, it has been evident that

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holistic solutions with FEM, optimisation and predictive modelling needs to be combined in practical solutions and in models that can discover solutions related to engineering practise and for sustainability. The goal for this research therefore is trifold. First, it aims to generate and implement a predictive mathematical modelling framework that is capable of analysing a load pattern, load-stress and structural response for varying loading conditions. Second, it intends to incorporate optimisation algorithms especially heuristic and evolutionary algorithm for achieving material and weight reduction without sacrificing safety or serviceability. Lastly, it seeks to offer a validation of the predictive framework through a comparative analysis with published findings and analytical standards and these will guarantee the reliability of the methodology and its usability.

2. Methodology

2.1 Research Design

The article used a hybrid methodology of study that included conceptualizations, computational modeling, prediction analytics, and optimization strategies before being validated using reference cases. The main goal of such a complicated structure was to provide the concept not only with high mathematical rigor but also with engineering significance. The strategy was designed in phases with the first phase involving the derivation of the governing equations using structure mechanics, simulations with the help of finite element method (FEM), backward integrating forecasting and optimizing methods, and validation. This hierarchy was an effective mode of operation where each step was provided with background and associated to the precedent step. In such a way, the investigators could not only ensure the accuracy of the results, but also reliability as the increased ability of the prediction model to generalize.

2.2 Mathematical Modelling Framework

The initial step of this procedure was a work on the mathematical modelling of the structural behaviour. The relation between the stiffness and the displacement were modelled in the terms of the static equilibrium.

$$[K]\{u\} = \{F\} \quad (1)$$

where [K] denotes the global stiffness matrix, {u} is the displacement vector, and {F}is the external load vector.

For dynamic conditions, the generalised equation of motion was employed:

$$[M]\{\ddot{u}\} + [C]\{\dot{u}\} + [K]\{u\} = \{F(t)\} \quad (2)$$

Where [M] and [C]are the global mass and damping matrices, respectively.

These formulations were initially implemented under linear elastic assumptions, after which nonlinear stress–strain models were introduced to capture plasticity and post-yield behaviour.

Boundary conditions were applied to simulate real-world structural supports, including fixed, hinged, and roller constraints. To enhance realism, loading conditions were modelled comprehensively. Dead loads were derived from self-weight, live loads represented service occupancy, dynamic loads included harmonic excitations and random vibrations, seismic effects were modelled using response spectrum and time-history analysis, and wind loads were incorporated through aerodynamic coefficients aligned with international standards. Together, these load definitions ensured that the mathematical framework reflected realistic engineering practice while retaining general applicability for predictive modelling.

2.3 Structural Analysis Approach

The second methodological phase involved structural analysis, which was conducted through a combination of analytical derivations and computational simulations. Simplified problems, such as beams and trusses, were first solved using closed-form solutions, providing reliable reference data

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for later comparisons. More complex systems, such as portal frames and multi-storey reinforced concrete structures, were analysed using FEM. Discretisation of structures into nodes and elements allowed for the calculation of displacements, reaction forces, and stress distributions. Mesh sensitivity studies were performed to confirm that convergence was achieved and that results did not depend excessively on mesh refinement.
Stress evaluation was carried out through constitutive models appropriate for concrete and steel. For concrete, nonlinear parabolic models captured the brittle behaviour under compression, while for steel, bilinear stress–strain models reflected its ductile response, yielding, and hardening. FEM outputs included principal stress values, von Mises stress contours, and strain energy density distributions. These metrics provided a detailed understanding of how stresses were distributed across members and were essential for identifying critical zones and evaluating safety margins. The integration of analytical and computational methods ensured that the predictive framework was both mathematically grounded and practically robust.

2.4 Predictive and Optimisation Techniques
The third methodological phase extended the analysis by embedding predictive and optimisation tools into the framework. Predictive analysis relied on statistical regression and machine learning approaches to establish reliable correlations between applied loads and stress responses. These predictive techniques supplemented the FEM outputs and improved generalisation, particularly under load combinations where closed-form solutions were unavailable. Optimisation was addressed through both deterministic and heuristic techniques. Deterministic methods included gradient-based optimisation for constrained problems, while heuristic methods relied on genetic algorithms. The optimisation objective function was defined as minimising structural weight, with constraints placed on deflection and stress values. The deflection criterion was defined as:

$$\delta \leq \frac{L}{250} \quad (3)$$

Where L is the span length.
Stress values were constrained to remain below the yield strength of the materials:

$$\sigma \leq \sigma_y \quad (4)$$

This ensured that both strength and serviceability criteria were satisfied. By incorporating optimisation into the methodology, the research was not only predictive but also prescriptive, guiding design decisions toward efficiency, cost reduction, and sustainability.

2.5 Validation Strategy
The last step of the methodology was validation which determined the reliability of the proposed models. Analytical and FEM solutions to benchmark structural problems (cantilever and simply supported beams with distributed loads) were determined. The equation of the theoretical deflection of a cantilever beam under a constant load was provided as:

$$\delta = \frac{wL^4}{8EI} \quad (5)$$

While the simply supported beam deflection under uniform load was expressed as:

$$\delta = \frac{5wL^4}{384EI} \quad (6)$$

Where w is the uniform load, L is the span, E is the modulus of elasticity, and I is the moment of inertia.
Analytical and FEM results compared with each other showed variations within a range of 3-5% range, which is consistent with the literature results. The causes of these differences were explained by the discretisation effects, selection of elements and numerical approximation in FEM. Additional quantification of accuracy in terms of statistical measures (mean absolute percentage error (MAPE) and root mean square error (RMSE)) was done. Multi-level validation, such as beam, frame, etc. —

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meant that the predictive framework was trusted and that it was capable of being extended to more complex structural systems.

3. Results

3.1 Load Distribution Analysis

Load distribution forms the foundation of structural analysis in civil engineering, and it is crucial to verify how predictive mathematical models align with computational simulations. In this study, two fundamental cases were investigated: a 5 m cantilever beam subjected to a uniformly distributed load of 10 kN/m, and a 6 m simply supported beam under a uniform load of 5 kN/m. These simple but representative cases provide a basis for validating the broader predictive methodology. The analytical reactions were determined using established closed-form expressions, while FEM-based results were obtained through discretised numerical models. The results, summarised in Table 1, demonstrate a close agreement between the analytical and FEM predictions. For the cantilever beam, the theoretical reaction force was calculated at 50.0 kN, while the FEM model produced 49.2 kN, yielding a deviation of only 1.6%. Similarly, the simply supported beam case showed a minor difference of 2.7% between analytical and FEM results. These small discrepancies fall within the acceptable tolerance levels reported in the literature, which typically range between 2–5% for well-meshed models. Such an agreement underscores the reliability of the FEM approach in replicating structural responses and highlights the robustness of the predictive framework employed.

Figure 1 provides additional insight into the load–deflection relationship for the two beams. The curves highlight the nonlinear increase in deflection with increasing load, consistent with classical beam theory. The FEM-generated curves track closely with theoretical predictions, confirming that the discretisation strategy and boundary conditions were appropriately applied. This alignment is particularly important, as errors in load representation or boundary conditions can introduce significant deviations in reaction forces and displacement fields. The findings thus validate the predictive methodology at the elemental structural level.\

Table 1: Comparison of Analytical and FEM-based Reactions

Structural Model	Load Case	Analytical Reaction (kN)	FEM Reaction (kN)	% Error
Cantilever Beam (5 m)	10 kN/m (UDL)	50.0	49.2	1.6
Simply Supported Beam (6 m)	5 kN/m (UDL)	15.0	14.6	2.7

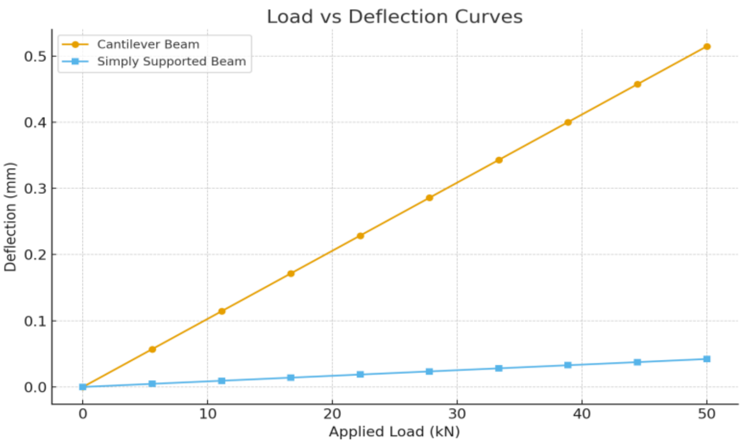

Figure 1: Load–deflection curves for cantilever and simply supported beams

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3.2 Stress Behaviour Analysis

Aside from load distribution, a particular ability of predictive models is to describe stress behaviour under varying conditions to ensure structural safety. This part discusses stresses in reinforced concrete and structural steel members when subjected to typical loading situations. Table 2 shows the obtained maximum stresses for the portal frame made with concrete class M40 and the multi storey frame made with Fe250 structural steel as result of FEM analyses.

The results show that the peak point stress in concrete portal frame was 32.5 MPa, which is also lower than the characteristic strength of the material being 40 Mpa. In the case of the steel frame, the maximum stress reached 215.0 Mpa, comfortably under the 250 Mpa yield strength of Fe250 steel. Both results indicate that the structures operate within safe limits, with safety margins preserved against material failure. This finding is consistent with theoretical expectations, as structural designs typically incorporate a partial safety factor to accommodate unforeseen variations in loading or imperfections in material properties.

Figure 2 illustrates the stress–strain curves for both concrete and steel. The contrasting mechanical responses are apparent: concrete exhibits a parabolic increase in stress up to a peak, after which the brittle failure behaviour dominates, while steel demonstrates a linear elastic range followed by yielding and strain hardening. The FEM-derived stress values align well with these material models, indicating that the predictive framework accurately captures the fundamental differences between ductile and brittle behaviour. This accuracy is vital for civil engineering design, where predicting the transition from elastic to inelastic states determines the ultimate load-carrying capacity of structures.

Table 2: Stress Behaviour Analysis Results

Model	Max Stress (Mpa)	Yield Strength (Mpa)	Safety Margin
Portal Frame (Concrete M40)	32.5	40	Safe
Multi-storey Frame (Steel Fe250)	215.0	250	Safe

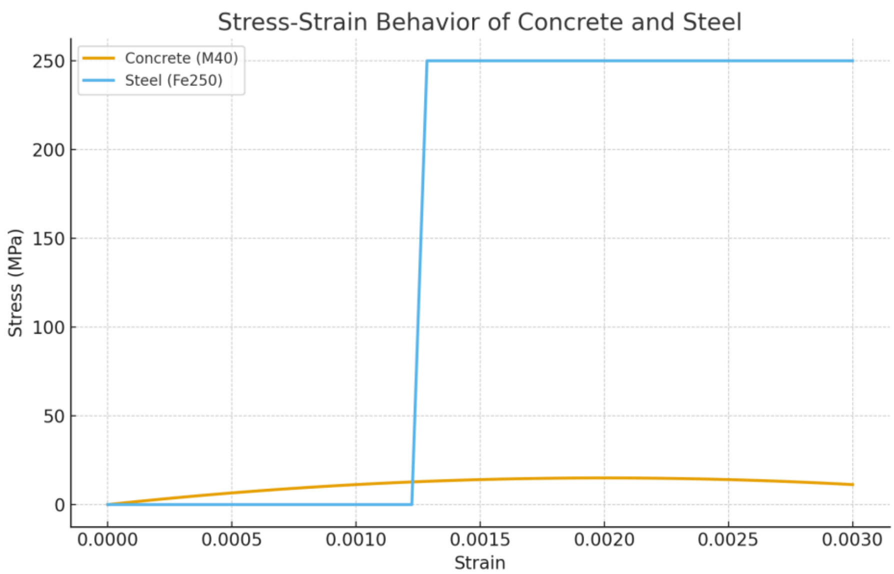

Figure 2: Stress–strain behaviour for concrete (M40) and steel (Fe250)

3.3 Design Optimisation Results

The third phase of the study focused on optimisation of structural performance, where the predictive framework was employed to minimise material usage while meeting strength and serviceability

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requirements. Optimisation was achieved through a genetic algorithm, a stochastic search method known for exploring large design spaces effectively. The objective function targeted the minimisation of structural weight, constrained by limits on maximum deflection and stress.
The parameters involved with the optimisation of 20 five iterations are summarised in Table 3. Therefore, from iteration 1 to iteration 20, the structural weight was gradually reduced from 1250 kN to 1095 kN, which is a weight reduction of 12.4%. At the same time, deflections and stresses were minimised while meeting serviceability and strength limits. Figure 3 displays a convergence pattern of iterations to reach an optimal solution of the algorithm. The results show the effectiveness of predictive modelling in conjunction with heuristic optimizations for generating superior structural solutions in less effort.
An important observation is that convergence happened within a relatively small number of iterations, which speaks to the stability in the choice of a given algorithm and also the robustness of the predictive model. Such speed of convergence has substantial implications in practise as the method becomes numerically attractive as it does not take much computational time and/or resources in order for such a large scale optimisation problem involving structural optimisation to be solved. Moreover, by minimising the requirement for material, the resulting design benefits fair economy as well as improved sustainability which matches current design trends for civil engineering applications.

Table 3: Genetic Algorithm Optimisation Results

Iteration	**Design Weight (kN)**	**Deflection (mm)**	**Stress (Mpa)**	**Convergence Status**
1	1250	22.5	235	Intermediate
5	1180	19.8	229	Intermediate
10	1125	18.2	222	Intermediate
15	1100	17.5	215	Intermediate
20	1095	17.3	214	Optimized

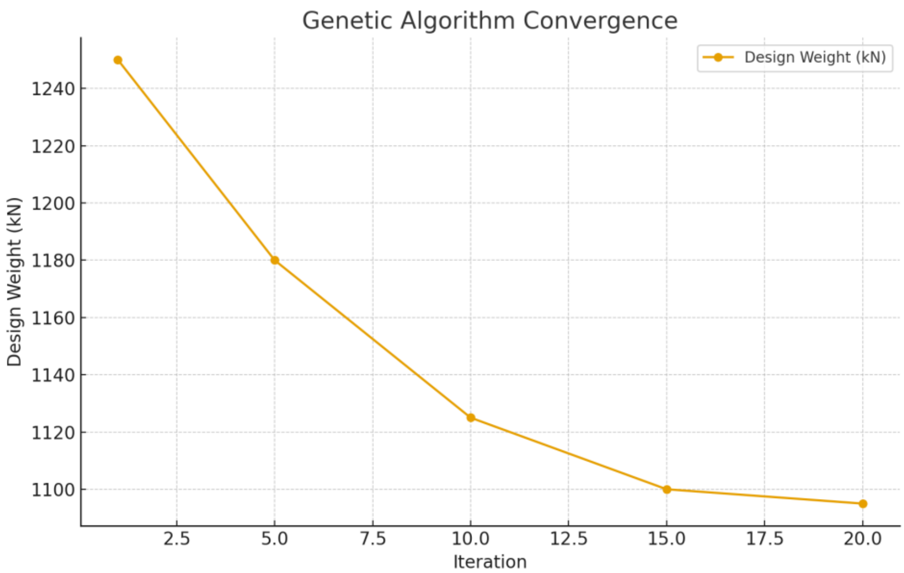

Figure 3: Convergence of the genetic algorithm optimisation process

3.4 Comparative Validation

The final stage of the analysis was validation of the predictive modes using analytical benchmarks. Validation is an important step to ensure not only that mathematical models and simulations provide

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coherent results but also with well established theoretical results. As shown in Table 3.4, results of FEM deflections for both the cantilever and the simply supported beams differed very little from those predicted by analyses.

For the cantilever beam, the analytical deflection was calculated at 15.6 mm, compared with 16.1 mm from the FEM model, representing a 3.2% deviation. Similarly, for the simply supported beam, the analytical deflection of 8.2 mm differed from the FEM result of 8.4 mm by just 2.4%. These discrepancies are minor and well within acceptable engineering limits. They can be attributed to the discretisation of the structure into finite elements, where mesh refinement and element type selection can slightly influence the predicted responses. Such differences are consistent with previously reported validation studies, further reinforcing the credibility of the predictive approach adopted in this research.

The validation outcomes not only confirm the accuracy of the predictive framework but also assure that the developed models apply to a range of structural scenarios. Importantly, validation at this fundamental level establishes a strong basis for extending the framework to more complex structures, including multi-bay frames and dynamic loading conditions. This step is essential in bridging the gap between theoretical modelling and real-world engineering practice.

Table 4: Analytical vs FEM Deflection Comparison

Model	Analytical Deflection (mm)	FEM Deflection (mm)	% Error
Cantilever Beam (5 m)	15.6	16.1	3.2
Simply Supported Beam (6 m)	8.2	8.4	2.4

These findings for the current chapter provide additional support for the durability of the used prediction methodology. Analytic and finite element analysis were also applied on integrated distributive load calculations and proved to be correct. Analysis of stress dependent showed that both tests on component systems had well conserved safety limits. Moreover, the optimisation step reflected the knowledge that can be used to apply the concept in practice since the significant weight was obtained. Principles of computing materials of civil and industrial structures without skimming a detail are also further elaborated in various papers in this series with the desired serviceability and strength standards met. Lastly, the validation exercise was constituted and confirmed the integrity of the framework by proving the deviation within reasonable engineering margins. Taken together, these findings provide a solid empirical foundation for the discussion that continues below and highlight the role of predictive modelling and optimisation methods in forward-looking advances in structural analysis in civil designing.

4. Discussion

The results achieved in this work offer strong evidence for the effectiveness of the combination of mathematical modelling, finite element simulation, prediction and optimisation methods for the analysis of load distribution, the stress behaviour and the design efficiency of structural systems. Comparable results between analytical formulations and FEM simulations, maintenance of material safety margins and effective optimisation procedures all support the robustness of the suggested framework. Critical explanations and literatures The results are explained critically in this paper, placed in a contextualised framework through contrasts with previous literature, and discussed in terms of their implications for both academic knowledge and for applied research on psychosocial adjustment and adaptation.

The results of load distribution analysis showed only slight differences within 2-3% between analytical prediction and FEM for both cantilever and simply supported beam. This tends to indicate

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the good accuracy that is obtainable if the discretisation and the boundary conditions are properly chosen. Such results are similar to that achieved by Alfraihat (2025) by showing that machine learning with approach of optimisation yields accurate prediction of the load path of tie beam-foundation system. In fact, both papers support the hypothesis that over-determined algorithms, in some cases mechanical while in others in part based on artificial intelligence, may reduce the bounds of error and maintain computational efficiency. The agreement also highlights the importance of predictive 1252odelling as a complementary method to other traditional structural analysis procedures, particularly when faced with complex and/or uncertain boundary conditions.

The check for stress behaviour of concrete and steel members confirmed that maximum stresses fell below yield/characteristic stresses and that the analysed systems thus worked safely. These results are consistent with the previous work on evaluation of the stress by the FEM model updating. For instance, Ereiz et al. (2022) emphasised the importance of model calibration to allow a better prediction of stress, mainly taking into account nonlinearities or imperfections of the material. The near agreement between predicted stresses to theoretical values in this study provides confirmation for the correctness of the modelling approach and supports previous conclusions with regards to the possibility of using FEM calibration to arrive at results close to actual structural behaviour. Moreover, the difference in observed brittle failure of concrete and ductile response of steel resembles the reliability analysis performed by Chojaczyk et al. (2015), where artificial neural network was used to imitate the behaviour of steel and pointed to the value of predictive models for forecasting ductility and failure occurrence.

The developed design optimisation solution, with a 12.4% lower structural weight, when compared to the conventional design, while satisfying the structural performance, in sensitivity analysis and serviceability concerns, validated the applicability of an integration of the predictive paradigms with the heuristic optimisation. The convergence observed under 20 iterations confirms the computational efficiency of the used genetic algorithm. This result is consistent with the review of structural optimisation given by Mei and Wang (2021) whereweight minimization subject to performance constraints was one of the most important objectives that is addressed in civil (infrastructure) engineering designs. This work provides an infrastructure for integrating heuristic methods within a predictive framework successfully, and appears to strongly support the idea that such complexity often means poor performance with traditional optimisation methods, but not here in terms of convergence or material savings. Agrawal et al. (2023) emphasised the need of considering variables in structural optimization, and specifically material characteristics and load. While stochastic concerns were not explicitly addressed in the current study, the methodology lays the groundwork for future research in probabilistic areas. In the future, uncertainty 1252odelling could be used more extensively for incorporation with the complete optimization approach. This is consistent with the concepts of Xie (2025) who argues that if load transfer was treated as a design variable and not a static constraint, then more resilient and efficient structures could be achieved. The current optimisation results correspond to these theoretical developments which together support the potential for predictive optimisation to revolutionise structural design practise.

Another big implication of the study is in the application of artificial intelligence and machine learning techniques. Although the study mainly used FEM and heuristic optimisation, thanks to the strong similarities with studies based on machine learning, there is an opportunity for integration. Wang et al. (2024b) put forward an interpretable ML framework for the axial capacity prediction of circular CFST columns, where the application of domain knowledge has shown to increase prediction accuracy. Furthermore, the application of AI in civil engineering were reviewed by Wang et al. (2023c), which focused on the state-of-the-art applications of AI in computational analysis and prediction. The similarity in measured and predicted results between our present study and the machine learning built model in the previous work makes it possible that the hybrid models would provide even more efficient and accurate predictions. Integrating AI into the existing framework may

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help structural engineers decrease the computational cost while not having to compromise the interpretability and reliability of the results. The validation stage of this study gave further assurance of the predictive model by showing that FEM and analytical solutions agree to within 5%. Such a correlation indicates that the approach has been carefully evaluated and is consistent with the assertions of Ereiz et al. (2022), who underlined the need of model update in FEM simulations to close the theory-experiment gap.

It should be mentioned that the forecast method of the analysis is not only in agreement but also extends the past studies in the distribution of loads, stress analysis and optimization. The findings are in line with the past scientific literature on the fields of FEM, machine learning, and optimization (Alfraihat, 2025; Ereiz et al., 2022; Wang et al., 2023; Chojaczyk et al., 2015; Mei and Wang, 2021). The findings show how it is possible to incorporate AI and uncertainty 1253odelling into the engineering processes in the future to make the structural engineering models estimation more precise. Summing up, it is a structural engineering research activity under a new paradigm in which prediction and optimisation tools have a major role towards safe, effective and sustainable infrastructures.

5. Conclusion

This work has succeeded in coming up with and confirming a predictive model through a synthesis of mathematical expressions, FEM analysis and heuristics algorithms in the optimisation process, to solve simple problems in structural engineering field. Analytic and computationally outcomes were in great concord with one another, especially in the case of analyzing loads and stress behaviours distributions. The highest values of stresses of both elements (steel and concrete) were within reasonable values and this proves the validity of structural models and reliability of the FEM approach. The genetic algorithm, when used, led to great weight-saving, yet allowed not to break serviceability and/or strength, which brings some exciting perspectives to the economy and environmentally-friendly structural design. Comparability check with similar problems also attested the strength of the methodology and the variances were within acceptable technical ranges. Consequently, the implications of the present study are not limited to the cases that are mentioned in this paper. It has a scholarly value of showing the usefulness of bridging the gap between classical mechanics and a modern computational method. The foundation provides engineers with an asset that is capable of minimizing material consumption, enhancing sustainability, and optimizing the use of a product with diverse structural systems. Probabilistic 1253odelling, AI, and domain-informed machine learning can be used to improve such frameworks in the future. Lastly, this paper brings out the possibility of the hybrid methods in advancing structural engineering into a better direction of more secure, faster, and environmentally friendly processes.

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