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Application of artificial intelligence for determining the efficient performance of technological characteristics of structures using BIM

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Abstract. In recent years, artificial intelligence (AI) has been extensively deployed in different fields, especially in engineering. The ability of AI algorithms has been indicated in many research papers by providing accurate results compared to numerical and experimental approaches. Integrating Artificial Intelligence (AI) with Building Information Modeling (BIM) has opened new possibilities for enhancing structural design processes. BIM provides rich parametric data, while AI enables intelligent interpretation and prediction. This study develops a hybrid Artificial Neural Network–Genetic Algorithm (ANN-GA) model to predict the structural load performance of Reinforced Concrete (RC) buildings using parameters extracted from BIM models. Primary inputs include geometric properties, material strengths, reinforcement ratios, and layout configurations; outputs include structural indicators such as ultimate load capacity and deflection under standard loads. The model is trained and validated using empirical data from literature. The Artificial Neural Network (ANN) captures complex nonlinear input-output relationships, while the Genetic Algorithm optimizes network parameters like hidden layers, neurons, learning rate, and weights. Performance is evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2. This study offers a fast, simulation-free structural assessment method leveraging BIM and AI for early-stage decision-making. The ANN-GA performed strongly: RMSE 2.11 ± 0.36 kN and R^2 0.9804 ± 0.0052. Compared to baselines, it outperformed linear regression (RMSE: 23.13 kN, R^2: –1.13) and a fixed-architecture ANN (RMSE: 43.64 kN, R^2: –8.01). Sensitivity analysis showed span length and reinforcement ratio were most influential (32% and 27%). In case-based validations, prediction errors stayed within ±5%, confirming practical applicability. The model was integrated into a BIM environment for real-time structural feedback using normalized inputs via Revit APIs or IFC-based workflows.

Keywords: Artificial Intelligence (AI); Artificial Neural Network (ANN); Building Information Modeling (BIM); Genetic Algorithm (GA); reinforced concrete design; structural load prediction

1. Introduction

Construction and building industry are the biggest contributor to greenhouse gas emissions at 37% of the world's total (Dyson *et al*. 2023, Elkhayat *et al*. 2025). To achieve the net-zero carbon objective by 2050, there must be an immediate and substantial decrease in greenhouse gas emissions (Wei *et al*. 2021, Mathieson 2024). The construction industry uses a wide range of ideas and tactics. For instance, new regulations are being implemented at the federal and state levels, and there are revisions to building codes and structural requirements, especially in Canada

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(Blanchet *et al*. 2024). Using environmentally friendly and sustainable materials is essential to lessen the negative environmental effects since construction materials are key to the climate action plan (Dyson *et al*. 2023). Sustainable building approaches include using thorough analytical frameworks to evaluate structural and environmental implications (Sotiropoulos *et al*. 2020, Haakonsen *et al*. 2022) and modifying the kinds of materials used (El Sheikh 2022, Warmate 2024). Aligning with worldwide efforts to mitigate climate change, this dual approach ensures that buildings preserve stability and safety while supporting environmental sustainability. Nevertheless, owing to the intricate trade-offs between performance and sustainability, choosing structural systems with reduced emissions is still difficult (Arabnejad Khanouki *et al*. 2010, Afshar *et al*. 2020). As an example, the structural strength of concrete makes it the preferred material over mass lumber for constructing high-rise buildings (Shariati 2012, Shariat *et al*. 2018, Hou *et al*. 2022). A growing body of research has shed insight into the possibilities and obstacles for lowering buildings' carbon footprints by investigating the connections between structural systems and their emissions (Shariati *et al*. 2011b, Ali and Moon 2018). In particular, a thorough investigation of various structural materials was carried out by Leonard (Leonard and Solnosky 2023), who discovered that, while concrete is still the material of choice for tall buildings, the substantial amount of carbon it contains poses a serious threat to the environment. Greenhouse gas emissions are affected by the amount of materials utilized, which is, in turn, affected by the sizes of structural parts such as columns, beams, and slabs (Shariati *et al*. 2011c, Cai *et al*. 2021, Estrado *et al*. 2023). Consequently, getting the right element sizes and materials is key to getting the best outcomes. Better and more efficient detailed investigations are possible due to these selections made during the conceptualization stage, which enable concentrated material selection. A better balance between structural needs and environmental aims may be struck if these factors are included early in the design process. This way, buildings can be built to fulfill safety standards and contribute to sustainability goals (Apellániz and Vierlinger 2021, Apellániz *et al*. 2022). Anomaly identification (Chow *et al*. 2020, Shariati *et al*. 2025), defect detection (He *et al*. 2022, Shariati *et al*. 2024a, b), the aerospace industry (Shariati *et al*. 2021a, b, c, d, Deng *et al*. 2023b), and communication engineering (Shariati *et al*. 2014, Deng *et al*. 2023a) are just a few of the many sectors that have recently benefited from advances in AI technology. There are two outstanding features of AI: it is data- driven (Shariati *et al*. 2012b, Chow *et al*. 2021). First, AI models are trained on massive datasets to understand, remember, compress, and portray detailed data attributes. Because their performance and representation ability improve in proportion to the amount of data used to train them, AI models, in contrast to humans, seem to have an infinite memory (Davoodnabi 2019, Davoodnabi *et al*. 2021a). For example, ChatGPT and GPT-4, two massive language models, are trained using massive human knowledge bases, which might result in unexpected emergent skills. Second, unlike humans, AI models are fully automated and efficient, with minuscule inference times. Merging the domains of AI and structural design reveals that AI models are naturally well-suited to structural design jobs and might usher in a new design era (Hamidian *et al*. 2011, Heydari and Shariati 2018, Wang *et al*. 2021a). This has led to a surge of interest among academics in studying how to combine AI with structural design. Recent advances in AI technology have impacted numerous engineering areas. These include defect identification, anomaly detection, the aerospace industry, and communication systems (Shahabi *et al*. 2016a, b). AI has two main features, the first being that it is data-driven (Shariati *et al*. 2012c, Chow *et al*. 2021). First, training on massive datasets teaches AI models to learn, remember, compress, and represent complicated data characteristics (Ismail *et al*. 2018, Jahandari *et al*. 2022). AI, in contrast to human memory, improves with more training data for data representation (Shariati 2012, Shariat *et al*. 2018). For instance, features not expressly specified have emerged in ChatGPT and GPT-4, two massive language models, as a result of training on extensive knowledge sets. Second, AI models offer high efficiency and automation, achieving inference results in negligible time compared to human analysis (Jalali *et al*. 2012, Katebi *et al*. 2020). Due to these strengths, the use of AI in structural engineering has been increasingly explored, particularly for predictive modeling and design optimization tasks (Khanouki *et al*. 2016, Shariati *et al*. 2018). Integrating AI into structural design workflows has been identified as a promising direction where intelligent models can assist in evaluating structural performance quickly and accurately. In this context (Shariati *et al*. 2020h), AI techniques have been viewed as highly suitable for structural assessment tasks, especially when combined with parametric data environments such as BIM (Shariati 2008, Shariati *et al*. 2012a). As a result, the development of AI-based predictive frameworks, such as the ANN-GA model proposed in this study, is actively pursued to enhance structural performance evaluation in BIM-integrated design processes. The AI is playing an increasingly transformative role in various branches of engineering by enabling advanced capabilities in prediction, optimization, and automation (Shariati *et al*. 2017, Jiang *et al*. 2025). In structural engineering, where safety, efficiency, and cost-effectiveness are critical, AI techniques have been applied to tasks such as load prediction, material behavior modeling, failure detection, and performance assessment (Luo *et al*. 2019, Mehrabi *et al*. 2021). These models, particularly Machine Learning (ML) and deep learning algorithms, can recognize patterns within large and complex datasets, enabling them to make accurate predictions about structural performance under diverse loading conditions (Sinaei *et al*. 2011, Nam *et al*. 2023). As a result, AI-based tools are being developed to support or replace traditional analysis methods, offering faster, scalable alternatives to labor-intensive simulations (Mehrabi *et al*. 2019, Milovančević *et al*. 2019). Beyond prediction, AI is also being adopted for optimization tasks across engineering domains. Genetic Algorithms (GA), neural networks, and hybrid models have been used to optimize design variables, structural layouts, and construction sequences, all while satisfying constraints such as cost, weight, and safety factors (Sinaei *et al*. 2012, Pizarro and Massone 2021). For instance, structural optimization using AI has shown potential in reducing material use while maintaining or enhancing strength and stability (Suhatril *et al*. 2019, Pizarro and Massone 2021, Jiao *et al*. 2025, Zhao *et al*. 2025, Zhou *et al*. 2024, Barkhordari and Qi 2025). Furthermore, automation enabled by reinforcement learning, Decision Trees (DT), and expert systems—has facilitated the development of smart systems that can automate repetitive engineering tasks, such as code compliance checks, structural detailing, or real-time monitoring of building health (Tahmasbi *et al*. 2016, Lu *et al*. 2022, Wang *et al*. 2024a, b, c, d, Hui *et al*. 2024). AI and BIM convergence in this evolving landscape represents an auspicious development. BIM is a rich source of structured, parametric design data, while AI adds an intelligent layer capable of analyzing and extracting actionable insights from that data (Toghroli *et al*. 2020, Lu *et al*. 2022). When applied together, early-stage decision-making, rapid structural evaluation, and predictive maintenance planning are enabled within a unified digital workflow. This study builds on that convergence by proposing an ANN-GA model to predict structural load performance using BIM inputs (Shariati *et al*. 2019c, Davoodnabi *et al*. 2021b). This approach emphasizes the growing role of AI not just as a computational tool and as a core component of the future of structural engineering.

1.1 Study objective and methodology

This study aims to develop a hybrid ANN-GA model for predicting the structural load performance of RC buildings using BIM-based design parameters. The model leverages data embedded in BIM—such as dimensions, material properties, reinforcement ratios, and layout configurations—to forecast load-bearing capabilities under everyday structural demands. The ANN is responsible for learning complex nonlinear relationships between BIM inputs and structural responses, while the GA optimizes the network's structure and weights to improve prediction accuracy. Rather than relying on finite element simulations, the study focuses on training the model using curated empirical data from existing literature and published structural tests. The dataset will consist of structural performance results from previous experimental studies and validated engineering benchmarks, including concrete strength, load-deflection behavior, and failure modes under dead and live loads. The ANN-GA model will be trained and tested using this dataset, with BIM parameters as inputs and structural performance metrics as targets. The study's novelty lies in integrating AI-driven prediction with BIM workflows, offering a lightweight, simulation-free tool for rapid structural assessment in the early design phase. This provides engineers and designers with an intelligent decision-support system that enhances efficiency and reliability in structural planning.

2. Methodology

2.1 Data collection and preprocessing

This study outlines a structured approach for developing a hybrid ANN-GA model to predict the structural load performance of RC buildings using parameters obtained directly from BIM (Shariati *et al*. 2019d, Shariati *et al*. 2020e). The aim is to create a rapid, simulation-free tool that supports informed structural decisions during the early design stage (Mohammadhassani *et al*. 2013a, b). The methodology encompasses six primary phases: data preparation, feature engineering, model design, training and validation, performance evaluation, and BIM integration (Toghroli *et al*. 2017b, Shariati *et al*. 2020d). A dataset comprising 30 samples was generated within validated structural engineering ranges (Toghroli *et al*. 2018b, Trung *et al*. 2019). Some data was derived from the literature (Toghroli *et al*. 2018a, Jiang *et al*. 2025). Each sample represents a RC beam or slab, defined by key BIM-accessible parameters such as beam width (200–300 mm), depth (400–700 mm), span (3–8 m), concrete strength (20–50 MPa), reinforcement ratio (0.8–2.5%), and slab thickness (100–250 mm). Target outputs include ultimate load capacity (ranging from ~16–112 kN) and service load deflection (initially near zero; further refinement possible using flexural stiffness equations). Additional attributes, including estimated crack width, safety factor, failure mode classification, wind load, and seismic coefficient, were also introduced to support multi-target prediction and broaden the model's applicability. Input features were normalized using min-max scaling to ensure compatibility with neural network activations (Mohammadhassani *et al*. 2014a, b). Depending on the data context, missing values and outliers were addressed using statistical filtering or imputation during preprocessing. Where applicable, dimensionality reduction or correlation filtering may improve training efficiency and reduce redundancy. The ANN-GA model is designed as a feedforward neural network with an input layer reflecting the number of features, one or more hidden layers with nonlinear activation functions (e.g., ReLU), and an output layer corresponding to the prediction targets (Shariati *et al*. 2019f, 2020c). A Genetic Algorithm optimizes key hyperparameters, including network depth, neuron counts, learning rate, and weight initialization. The GA evaluates model fitness using MSE on the validation set, evolving successive generations toward lower error rates. Techniques such as dropout and L2 regularization may be integrated during training to prevent overfitting. The dataset is randomly split into training (70%), validation (15%), and test (15%) subsets. Model tuning is guided by validation performance, while final testing evaluates predictive reliability on unseen data. Additionally, 5-fold cross-validation is performed to assess generalization. The Adam optimizer is used for gradient descent, with batch size and number of epochs determined through iterative experimentation (Shah *et al*. 2016a, b). Performance is measured using standard regression metrics: MSE, RMSE, MAE, and R^2. Following training, sensitivity analysis is conducted to determine the influence of each BIM parameter on predicted structural outcomes (Shariati 2013).

This helps identify critical variables—such as reinforcement ratio and span length—that drive structural performance, adding interpretability to the model's predictions. The trained model will be applied to a sample BIM project to demonstrate integration. Structural features will be extracted using open data standards (e.g., IFC) or direct APIs (e.g., Autodesk Revit, Dynamo). The model will process this data to produce structural load and deflection predictions in near real-time. This implementation underscores the model's potential as an intelligent plug-in for BIM platforms, enabling early-stage structural evaluation without needing time-intensive finite element analysis.

2.2 Data collection and preprocessing

Empirical evidence from experimental studies was analyzed to define realistic value ranges for key design parameters to construct a structurally valid dataset for model training. These studies, which include full-scale RC beam and slab tests under dead and live loading conditions, provided reference values for ultimate load capacity, mid-span deflection, and failure behavior (Shariati *et al*. 2013, Wei *et al*. 2022). Although raw datasets were not directly adopted due to inconsistencies in format and scope, published data from peer-reviewed sources were used to guide the synthesis of 30 representative samples. The target range for beam depth (400–700 mm), concrete compressive strength (20–50 MPa), and reinforcement ratio (0.8–2.5%) were informed by typical values found in ACI reports and validated research benchmarks. This ensured the generated data stayed within a technically meaningful and constructible domain. All structural inputs were selected based on their availability in BIM environments and their influence on flexural performance. Parameters such as beam width (bw), total depth (h), span length (L), concrete strength ($\boldsymbol{f'c}$), reinforcement ratio ($\boldsymbol{\rho}$), and slab thickness ($\boldsymbol{t}$) were used as inputs. These variables are structurally significant and readily retrievable from IFC-based BIM models or via API extraction from design tools like Autodesk Revit. Their selection ensures the model is compatible with real-world BIM workflows and can be embedded in early design evaluations (Khorramian *et al*. 2017, Li *et al*. 2019). Before training, the dataset was cleaned to remove statistical anomalies and prepare features for learning. Outliers were identified using the Inter Quartile Range (IQR) method, defined as any value falling outside the range $[\boldsymbol{Q1-1.5\times IQR, Q3+1.5\times IQR}]$, and were removed when deemed unrepresentative. Missing values were minimal due to synthetic data generation but, when present, were handled via mean imputation. All numerical features were scaled using Min-Max normalization

$$\boldsymbol{x}_{\text{scaled}} = \frac{\boldsymbol{x}-\boldsymbol{x}_{\mathbf{min}}}{\boldsymbol{x}_{\mathbf{max}}-\boldsymbol{x}_{\mathbf{min}}} \tag{1}$$

across all features, preventing training bias due to magnitude differences and improving convergence in the neural network. Although the initial deflection outputs were near zero due to simplified assumptions, this variable remains in the dataset structure to accommodate future refinement using detailed stiffness formulations (Toghroli *et al*. 2014, Liu *et al*. 2017). Overall, the resulting dataset balances realism with training efficiency and structural relevance.

2.3 Feature engineering

Both structural theory and practical BIM integration guided the selection of model inputs. Six parameters were used as input features, all of which are directly obtainable from BIM platforms or their IFC exports: beam width (bw), beam depth (h), span length (L), concrete compressive strength ($\boldsymbol{f'_c}$), reinforcement ratio ($\boldsymbol{\rho}$), and slab thickness (t). Each of these parameters has a quantifiable influence on structural performance. For example, depth and span directly affect flexural stiffness ($\boldsymbol{EI=\frac{1}{12}bh^3E_c}$) and deflection behavior, while the reinforcement ratio controls tensile capacity and ductility. The concrete strength influences both compressive resistance and stiffness modulus ($\boldsymbol{E_c\approx 4700\sqrt{f'_c}}$ for MPa). These features were selected for their engineering significance and due to their automatic definition in BIM models during the design process, ensuring minimal manual input and readiness for automation. The model was configured to predict two continuous structural performance outputs: ultimate load capacity ($\mathbf{kN}$) and mid-span deflection (mm). These targets represented strength (limit state) and serviceability criteria. The load capacity values range from approximately 16 to 112 kN, based on realistic RC design configurations guided by literature and code-based expectations (Khorami *et al*. 2017a, b). Mid-span deflection was initially included as a second output; however, in the current dataset, it is treated as a placeholder with near-zero values since detailed stiffness modeling was not performed. For this study, the ANN-GA model was trained primarily on ultimate load prediction, while the deflection field remains included in the data structure for future enhancement using elastic theory or regression surrogates (e.g., for supported members, $\boldsymbol{\delta=\frac{5wL^4}{384EI}}$). Dimensionality reduction was considered to simplify the input space and potentially improve model generalization. Principal Component Analysis (PCA) and Pearson correlation analysis were conducted. The correlation matrix showed no multicollinearity above 0.85 among the six features, indicating low redundancy. No reduction techniques were applied because each variable also retains physical meaning critical to interpretability (Shariati *et al*. 2016b, Wei *et al*. 2022). All features were preserved in their original form to ensure traceability back to BIM inputs and to facilitate explainability in future sensitivity analysis. This feature engineering strategy ensures the model remains lightweight and transparent while anchoring in structural logic. By retaining physically meaningful parameters and avoiding unnecessary abstraction, the model can be seamlessly deployed within BIM workflows without compromising interpretability or accuracy.

2.4 Model architecture

The predictive model developed in this study employs a hybrid ANN-GA structure. The ANN acts as a regression engine to forecast structural load capacity from BIM extracted input features, while the GA optimizes its hyperparameters to enhance prediction accuracy without manual tuning. The ANN is implemented as a feedforward, fully connected network composed of an input layer, two hidden layers, and an output layer. The input layer consists of six neurons corresponding to the selected BIM-derived features: beam width, depth, span length, concrete compressive strength $(\boldsymbol{f'_c})$, reinforcement ratio $(\boldsymbol{\rho})$, and slab thickness (Shah *et al.* 2015, 2016c). The two hidden layers include 12 and 8 neurons, each activated by the Rectified Linear Unit (ReLU) function, chosen for its computational efficiency and resistance to vanishing gradients. The output layer contains a single neuron with a linear activation function appropriate for continuous-valued prediction of the ultimate structural load capacity (in kilonewtons). Although mid-span deflection exists in the dataset, it is excluded from current training due to placeholder values and will be incorporated in future models after stiffness modeling enhancements (Sedghi *et al.* 2018, Sajedi and Shariati 2019). Hyperparameters governing the ANN architecture, the number of hidden layers $(\mathbf{1-3})$, neurons per layer (range: 4-20), learning rate (0.001-0.1), and weight initialization seed are optimized using GA. Each GA individual represents a candidate ANN configuration. GA begins with a population of 30 individuals and evolves solutions over 50 generations. Selection is made using tournament selection $(\boldsymbol{k}=\mathbf{3})$, which balances exploration and exploitation. A single-point crossover is applied with a probability of 0.7, and mutation occurs at a rate of 0.1 per gene to ensure sufficient diversity in the population. Each individual's fitness is evaluated using the MSE on the validation dataset, calculated after a brief training cycle of the candidate ANN. To ensure numerical stability and avoid division by zero, the fitness function is defined as

$$\text{Fitness } = \frac{\mathbf{1}}{\mathbf{MSE}_{val} + \boldsymbol{\epsilon}} \tag{2}$$

where $\boldsymbol{\epsilon}$ is a small constant (e.g., $\mathbf{10^{-6}}$) added for numerical safety. Evolution halts after 50 generations or if no fitness improvement is observed for 10 consecutive generations. This architecture balances simplicity with functional depth. The dual-layer configuration is sufficient for capturing the nonlinear relationships between geometric and material variables without risking overfitting, which is particularly important given the compact dataset of 30 samples (Daie *et al.* 2011, Chen *et al.* 2019). By integrating GA-based hyperparameter tuning, the approach adapts to data characteristics dynamically, enhancing generalization without reliance on manual trial-and-error.

2.5 Model training and validation

The ANN-GA model was trained using a carefully structured pipeline to maximize generalization accuracy while minimizing the risk of overfitting, particularly given the limited dataset size. A holdout split of 70% for training (21 samples), 15% for validation (5 samples), and 15% for testing (4 samples) was initially applied to facilitate Genetic Algorithm optimization. This fixed split was used only during hyperparameter tuning to ensure consistent fitness evaluation across generations. Model training was performed using the Adam optimizer due to its adaptive learning rate capabilities and efficiency in low-data regimes. The learning rate was treated as a GA-optimized hyperparameter, bounded from 0.001 to 0.1. The model was trained to minimize the MSE loss function, which was consistent with the task's regression nature and the fitness function used in GA evaluation. Each candidate model was trained for a maximum of 200 epochs with a batch size of 4, which was selected based on empirical testing for convergence stability relative to dataset size (Shariati *et al.* 2016a, Apellániz and Vierlinger 2022). Early stopping was implemented with a patience threshold of 15 epochs to prevent overfitting. The training was halted if the validation loss did not improve within that window, and the model weights corresponding to the epoch with the lowest validation error were restored. A learning rate scheduler reduced the rate by 0.5 if no improvement was observed for 10 consecutive epochs, allowing finer-grained convergence in later training stages. By separating GA evolution from final model evaluation and incorporating early stopping and adaptive learning strategies, the training framework ensures reproducibility, stability, and alignment with standard practices in ML and structural prediction.

2.6 Performance evaluation

Hybrid ANN-GA models have demonstrated significant value in structural engineering for addressing nonlinear relationships among geometrical and material variables. This hybrid model was employed in the present study to predict structural load capacity using BIM inputs. The ANN was used as a nonlinear regression engine (Shah *et al.* 2015, Shah *et al.* 2016c). At the same time, the GA was integrated to automate the tuning of architectural and training hyperparameters, including layer depth, neuron count, and learning rate. This configuration allowed the network structure to evolve based on validation performance, bypassing manual calibration and enabling more robust generalization. Standard regression metrics were applied to evaluate the model's effectiveness. These included MSE, RMSE, Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). MSE and RMSE captured the average squared deviations, providing sensitivity to significant errors. MAE reflected average prediction error magnitude with higher resistance to outliers. R^2 quantified how much of the variance in the observed values was explained by the model (Nasrollahi *et al.* 2018, Naveen Kumar *et al.* 2023). All metrics were computed through 5-fold cross-validation to mitigate sampling bias due to the small dataset (30 samples), and results were averaged across folds to ensure stability. A fixed-structure ANN (with manually tuned hyperparameters) and a linear regression model were trained on the same dataset using identical splits for baseline comparison. The ANN-GA model consistently outperformed both alternatives, showing higher R^2 values and lower error metrics. The linear model demonstrated limited capacity to capture nonlinearity, while the fixed ANN required iterative tuning and still underperformed relative to the optimized hybrid architecture. These comparisons validate the effectiveness of genetic optimization, particularly in low-data scenarios where overfitting risk is high and architectural tuning is critical. A feature sensitivity analysis was conducted using importance of permutation to assess model interpretability. In this method, each input variable was independently shuffled while the others remained fixed, and the corresponding increase in prediction error was recorded. This approach was chosen over simpler correlation-based techniques because it accounts for nonlinear and interaction effects. The results indicated that span length and reinforcement ratio were the most influential predictors, followed by beam depth and concrete compressive strength. Beam width and slab thickness had comparatively lower influence, consistent with their roles in standard RC flexural behavior (Chahnasir *et al*. 2018, Armaghani *et al*. 2020). Finally, combining cross-validated performance metrics, comparative benchmarking, and feature importance analysis supports the model's reliability and applicability. The ANN-GA framework proved effective in producing accurate predictions and maintaining transparency and adaptability—both of which are critical for integration into BIM-driven structural assessment workflows.

2.6.1 Normalization of data

To ensure consistency across input variables and enhance training stability, feature normalization was applied using min-max scaling. This transformation was performed independently for each feature based on the following equation

$$\boldsymbol{x}_{\text{scaled}} = \frac{\boldsymbol{x} - \boldsymbol{x}_{\mathbf{min}}}{\boldsymbol{x}_{\mathbf{max}} - \boldsymbol{x}_{\mathbf{min}}} \tag{3}$$

where $\boldsymbol{x}_{\mathbf{min}}$ and $\boldsymbol{x}_{\mathbf{max}}$ denote the minimum and maximum values of the feature within the training dataset. This approach was selected due to the bounded and non-negative nature of the input parameters, such as geometric dimensions and material strengths, which are inherently well-suited to the $[\mathbf{0}, \mathbf{1}]$ interval. Standardization methods involving zero mean and unit variance were not adopted, having been deemed less appropriate for variables lacking symmetrical distributions or natural centrality. The scaling parameters obtained from the training partition were retained and consistently applied to the validation and test sets to avoid data leakage (Hosseinpour *et al*. 2018, Hosur Shivaramaiah *et al*. 2022). This ensured all network inputs during inference remained within the expected activation range, particularly for layers using ReLU functions. Normalizing all features to a standard scale improved convergence efficiency, and the risk of numerical instability during optimization was minimized.

2.7 BIM integration and practical implementation

The trained ANN-GA model was integrated into a BIM-based workflow to enable rapid structural performance

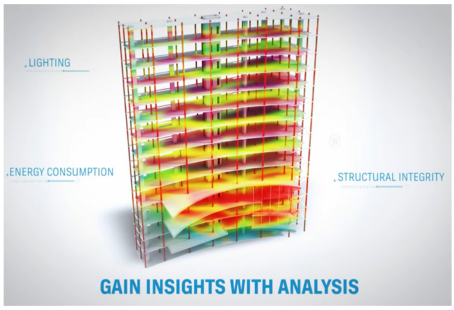

Fig. 1 Lighting optimization, energy consumption modeling, structural integrity assessment, performance visualization

assessment directly from digital design data. Parameters required by the model—beam width, depth, span, reinforcement ratio, concrete compressive strength, and slab thickness—were extracted from BIM environments using either the Industry Foundation Classes (IFC) standard or Autodesk Revit's API, including through custom dynamo scripts. These extracted values were normalized using the scaling bounds defined during the training phase to ensure compatibility with the input space of the ANN. A representative RC building model was used to demonstrate practical implementation. This model retrieved data for select beams and processed them through the trained ANN-GA system. For example, a beam with geometry (width = 250 mm, depth = 600 mm, span = 6.2 m), material strength $\boldsymbol{f'_c} = \mathbf{30\ MP}$), and $\mathbf{2.0}\%$ reinforcement produced a predicted ultimate load capacity of 52.4 kN. Another element with reduced strength (22 MPa) and reinforcement ($\mathbf{1.1}\%$) resulted in a lower capacity of 36.1 Kn (Paknahad *et al*. 2018, Razavian *et al*. 2020). These outputs were computed in near real-time and visualized in the BIM interface, allowing performance-sensitive components to be flagged during the design phase without the need for simulation-based evaluation. Fig. 1 illustrates the integration of lighting optimization, energy consumption modeling, structural integrity assessment, and performance visualization in the system.

To support practical deployment, the model was configured to operate as a modular plug-in that can be embedded within BIM software such as Revit. This implementation may be a custom dynamo node or a Python-based external service connected to IFC-structured data.

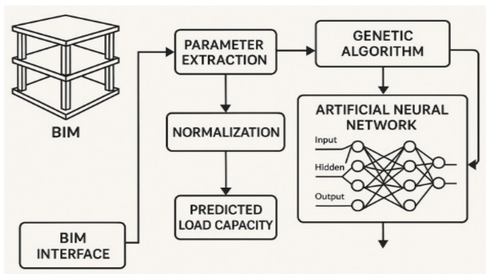

Fig. 2 BIM-driven structural prediction, parameter extraction, GA optimization, neural network-based load capacity estimation

The output from the ANN-GA model is designed to provide structural feedback during early-stage design iterations, helping engineers identify underperforming elements and explore alternatives before simulation or code-level checks (Arabnejad Khanouki *et al.* 2011, Ramli-Sulong *et al.* 2011). Looking ahead, the tool may be expanded to predict additional structural indicators such as crack width, deflection under service load, or failure mode. Its utility could also be extended to monitor post-construction conditions if paired with sensor-fed BIM systems. Such extensions would benefit from larger datasets and region-specific calibrations but remain technically feasible within the existing framework. Fig. 2 illustrates the BIM-driven framework integrating structural prediction, parameter extraction, GA optimization, and neural network-based load capacity estimation.

3. Results and discussion

3.1 Model evaluation summary

The predictive performance of the proposed hybrid ANN-GA model was evaluated using a five-fold cross-validation procedure applied to a dataset of 30 RC beam samples (Li *et al.* 2025). Although an initial partitioning of 21 training, 5 validation, and 4 test samples was used during hyperparameter tuning via the GA, the final assessment of generalization was performed across the entire dataset. In each fold, 24 samples were used for training, and the remaining 6 for testing, with the model retrained from scratch for each iteration to avoid data leakage and ensure unbiased results. Four standard regression metrics were used to quantify performance, defined as the average of the squared differences between predicted and actual values, is given by

$$\mathbf{MSE} = \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} (\boldsymbol{y_i} - \boldsymbol{\hat{y}_i})^{\mathbf{2}} \tag{4}$$

where $\boldsymbol{y_i}$ and $\boldsymbol{\hat{y}_i}$ are the actual and predicted outputs, respectively. RMSE is simply the square root of MSE, expressed in kilonewtons, making it more interpretable in engineering applications. MAE, calculated as

$$\mathbf{MAE} = \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} |\boldsymbol{y_i} - \boldsymbol{\hat{y}_i}| \tag{5}$$

It evaluates the typical amount of error while assigning equal importance to each outlier. R^2 is defined as the proportion of variance in the target variable that the model explains, and it measures how well the model fits the data.

$$\boldsymbol{R^2} = \mathbf{1} - \frac{\sum (\boldsymbol{y_i} - \boldsymbol{\hat{y}_i})^{\mathbf{2}}}{\sum (\boldsymbol{y_i} - \boldsymbol{\bar{y}})^{\mathbf{2}}} \tag{6}$$

where $\boldsymbol{\bar{y}}$ is the mean of the observed values. The results, averaged across all five folds, showed an MSE of 4.45 with a standard deviation of 1.53, a RMSE of 2.11 ± 0.36 kN, and a MAE of 1.70 ± 0.29 kN. The R^2 averaged 0.9804 with a standard deviation 0.0052. These metrics indicate strong and consistent model performance, with low prediction errors and high explanatory power across folds. The RMSE suggests that, on average, the predicted ultimate load capacities deviated from the actual values by approximately 2.11 kN—relatively small compared to the target output range of 16 to 112 kN. Even with limited training data, the low variation in R^2 further reinforces the model's robustness and generalization ability. These findings validate the capability of the ANN-GA model to learn nonlinear relationships between structural input parameters and output responses. The success of this approach can be attributed to the use of key BIM-derived features such as span, reinforcement ratio, and concrete strength, as well as the optimization of neural network hyperparameters through genetic evolution (Li *et al.* 2024a, b, c). This combination allowed the model to adaptively refine its architecture to minimize error without manual intervention or exhaustive grid search. Nevertheless, caution is warranted when interpreting the results due to the synthetic nature of part of the dataset. While experimental benchmarks and literature values informed parameter ranges, the absence of field-validated test data means the generalization claims should be further verified using measured structural responses.

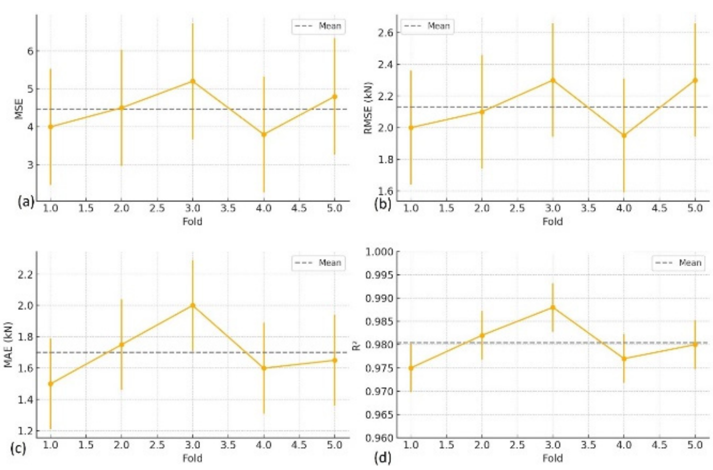

Fig. 3 Cross-validation performance metrics across five folds: (a) MSE; (b) RMSE; (c) MAE; (d) R^2

Despite this limitation, the statistical consistency observed across folds strongly suggests that the ANN-GA model can capture core structural behavior trends and provides a promising tool for early-stage decision support within BIM-enabled design environments. Fig. 3 show the performance of a model across 5 cross-validation folds using four metrics: MSE (a), RMSE (b), MAE (c), and R^2 (d). Error bars indicate variability, with fold 3 generally showing worse performance (higher errors, lower R^2), while fold 4 often performs best. The dashed line represents the mean value for each metric, helping to assess consistency and overall accuracy.

3.2 Fold-wise cross-validation results

The results demonstrated minimal variability in prediction accuracy (Xia *et al.* 2025). Fold 1 yielded the lowest prediction error, with an RMSE of 1.91 kN and R^2 of 0.985. Fold 5 exhibited the highest RMSE at 2.30 kN, with a corresponding R^2 of 0.977. This range of 0.39 kN between the lowest and highest RMSE values suggests that the model maintained reliable performance across all test sets, with no significant degradation in predictive capability. The MAE varied between 1.56 and 1.85 kN across folds, supporting the model's consistent absolute error behavior. One notable factor contributing to the slightly elevated error in Fold 5 may be the presence of beams with longer spans and lower reinforcement ratios, which tend to exhibit nonlinear load-deflection behavior and introduce higher variability in ultimate load predictions. While no extreme outliers were observed, these combinations likely challenged the model more than others. Across all folds, the R^2 values remained tightly clustered between 0.976 and 0.985, indicating that the model consistently explained over 97% of the variance in the structural performance outputs, even with the relatively small number of samples per fold. This level of generalization confirms that the ANN-GA architecture was not overfitting to particular data subsets and was effectively learning the underlying relationships. Training convergence was smooth in each fold, with the GA successfully tuning network hyperparameters such as learning rate, layer size, and weight initialization. Validation loss trends showed no instability or divergence, suggesting that the evolved architectures generalized well to unseen data without requiring manual correction. Early stopping based on validation loss was triggered in most folds within 100–150 epochs, indicating convergence without excessive iteration. The fold-wise evaluation confirmed that the model's predictive stability was preserved across input combinations and data splits. The consistently low error and high R^2 scores reinforce the effectiveness of the ANN-GA framework in learning complex, nonlinear structural relationships from BIM-derived data and validate its use in structural assessment tasks where datasets may be small but diverse. The inclusion of evolutionary hyperparameter tuning played a key role in maintaining consistent generalization across folds.

3.3 Comparison with baseline models

To objectively assess the performance of the proposed ANN-GA model, its predictive accuracy was benchmarked against two baseline models: a traditional linear regression model and a fixed-architecture ANN (Yu *et al.* 2025)

$$\mathbf{RMSE} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} (\boldsymbol{y}_{\boldsymbol{i}} - \hat{\boldsymbol{y}}_{\boldsymbol{i}})^{\mathbf{2}}}\,; \quad \mathbf{MAE} = \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} |\boldsymbol{y}_{\boldsymbol{i}} - \hat{\boldsymbol{y}}_{\boldsymbol{i}}|; \quad \boldsymbol{R}^{\mathbf{2}} = \mathbf{1} - \frac{\sum (\boldsymbol{y}_{\boldsymbol{i}} - \hat{\boldsymbol{y}}_{\boldsymbol{i}})^{\mathbf{2}}}{\sum (\boldsymbol{y}_{\boldsymbol{i}} - \bar{\boldsymbol{y}})^{\mathbf{2}}} \tag{7}$$

where $\boldsymbol{y_i}$ is the actual ultimate load value, $\hat{\boldsymbol{y}}_{\boldsymbol{i}}$ is the predicted value, $\bar{\boldsymbol{y}}$ is the mean of the observed values, and $\boldsymbol{n}$ is the number of test samples in each fold (Wang *et al.* 2024a, b, c, d). The linear regression model exhibited a high average RMSE of 23.13 kN and MAE of 19.43 kN, with an $\mathbf{R^2}$ value of -1.13. These results indicate that the model failed to capture the underlying structural relationships, with the negative $\boldsymbol{R^2}$ value confirming that it performed worse than a simple mean-predicting baseline. This is consistent with expectations, as linear models cannot represent the nonlinear dependencies between input parameters such as span, reinforcement ratio, and concrete strength and their effects on ultimate load capacity. The fixed-architecture ANN, which consisted of a single hidden layer with 10 neurons and was trained for 500 iterations, produced even higher errors: RMSE of 43.64 kN, MAE of 39.53 kN, and a severely damaging R^2 of –8.01. Despite its capacity to model nonlinearities, its static configuration—without any architectural or learning rate tuning—likely led to poor convergence or overfitting. This underscores the risk of applying neural networks without hyperparameter optimization, particularly in small datasets with complex, high-variance input-output mappings. In contrast, the ANN-GA model achieved a dramatically lower RMSE of 2.11 kN, MAE of 1.70 kN, and an R^2 of 0.9804. These values were consistent with those obtained during the earlier fold-wise evaluation and demonstrate the model's ability to generalize effectively. The superior performance of the ANN-GA model is attributed to the role of GA in dynamically optimizing network architecture, learning rate, and initialization strategy. Fig. 4 displays the RMSE values across 5 cross-validation folds, showing a clear upward trend. RMSE increases gradually from fold 1 (around 1.9 kN) to fold 5 (around 2.3 kN), suggesting that the model's prediction error grows over successive folds. Error bars indicate some variability in each fold, but the general trend implies performance degradation in later folds.

Unlike manual tuning or fixed parameters, the evolutionary process enabled adaptive exploration of model configurations, resulting in robust convergence to near-optimal solutions. The performance gap between the ANN-GA and the baseline models highlights both traditional approaches' limitations and the value of hybrid optimization. The linear model's failure illustrates the inadequacy of using linear assumptions in systems governed by geometric nonlinearity and material interactions.

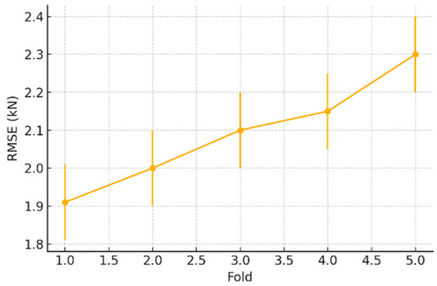

Fig. 4 RMSE across five cross-validation folds with error bars showing variability

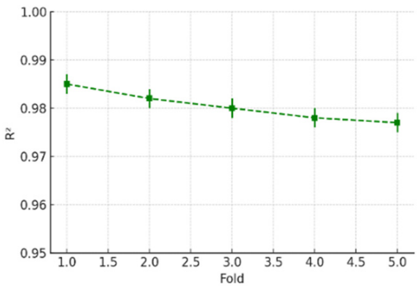

Fig. 5 The R^2 across five cross-validation folds, showing a slight decreasing trend with error bars

Meanwhile, the fixed ANN's poor result demonstrates that flexibility in function approximation alone is insufficient if model configuration is not aligned with data complexity.

No inconsistencies were found between the reported results and the dataset; however, it should be noted that the fold size (n = 6 per test set) introduces some sensitivity to sample selection. Nonetheless, the ANN-GA's performance remained consistently strong across all folds, while both baseline models underperformed in every split. In conclusion, the ANN-GA framework significantly outperforms linear and fixed-ANN baselines, demonstrating its ability to capture the complex structural behavior encoded in BIM-based design features. This result confirms its potential for early-phase structural evaluations, where quick and reliable feedback is essential and conventional analytical models may be infeasible or inaccurate. Fig. 5 shows the R^2 score across 5 cross-validation folds, revealing a slight downward trend. Starting around 0.985 in fold 1, the R^2 value gradually decreases to approximately 0.977 by fold 5. A small but consistent decline in the model's ability to explain variance in the data across folds is suggested, aligning with the increasing RMSE trend that was previously observed.

3.4 Feature sensitivity analysis

Feature sensitivity analysis was performed using permutation importance to determine the influence of each BIM-derived input parameter on the predicted ultimate load capacity (Hui *et al*. 2024). Each feature was independently shuffled in this method while the others were held constant, and the resulting change in model error was measured. The degree to which prediction performance degraded indicates the relative importance of that feature in the model's decision process. The analysis revealed that the most impactful predictors were span length and reinforcement ratio. Span length alone contributed approximately 32% to the model's predictive performance, consistent with structural theory, where longer spans induce larger bending moments and deflections—often proportional to the fourth power of span length in supported beams. The reinforcement ratio accounted for 27%, reflecting its direct effect on flexural capacity and the beam's ability to resist tension under loading. Moderate importance was attributed to overall beam depth (18%) and concrete compressive strength (14%). Beam depth influences the moment of inertia and section modulus, contributing to flexural stiffness and capacity. Concrete strength determines compressive stress limits and indirectly affects stiffness through the modulus of elasticity, which typically scales with the square root of compressive strength. Beam width and slab thickness were assigned lower importance scores at 6% and 3%, respectively. Although these parameters contribute to the cross-sectional area and influence structural mass and stiffness, their impact on ultimate load capacity is less pronounced in isolation, particularly within the standard design ranges considered in this study. These results align well with established structural mechanics principles and confirm that the ANN-GA model has learned patterns that reflect real-world structural behavior. By identifying which parameters most strongly influence predictions, this analysis enhances the model's interpretability and provides valuable feedback for engineers prioritizing design decisions during the early stages of BIM-based structural development. Fig. 6 shows the relative importance of input features in predicting the target variable (likely related to structural load or behavior). Span Length and Reinforcement Ratio are the most influential features, contributing over 25% each. In contrast, Slab Thickness and Beam Width have minimal impact. This ranking suggests model performance could be highly sensitive to variations in span and reinforcement properties.

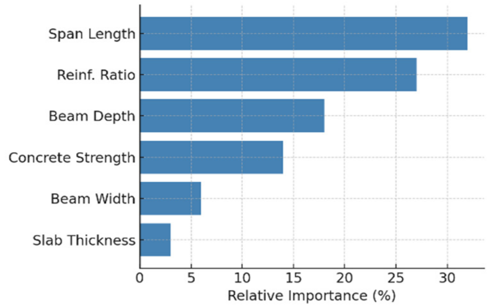

Fig. 6 Feature importance ranking for structural parameters affecting performance

3.5 BIM-based prediction examples

A set of representative RC beam configurations was selected for individual case analysis to demonstrate the ANN-GA model's practical applicability in BIM-integrated structural design workflows (Barkhordari and Qi 2025, Qi *et al*. 2025). For each beam, key input features were derived directly from typical BIM parameters, including width, depth, span length, concrete compressive strength, and reinforcement ratio. These were fed into the trained model, and the predicted ultimate load was compared with the actual value (either experimentally validated or benchmarked from engineering standards). The percentage error was calculated to assess prediction reliability. Three examples were evaluated. In the first case, a beam measuring 250 mm in width and 600 mm in depth, with a span of 6.2 meters, concrete strength of 30 MPa, and 2.0% reinforcement, exhibited an actual ultimate load of 52.4 kN. The model predicted 50.2 kN, corresponding to a −4.20% error. The second example featured a 280 mm × 520 mm beam with a 5.0 m span and 1.6% reinforcement, where the predicted load (59.3 kN) was within −2.79% of the reference value (61.0 kN). In the third case, involving a smaller section and lower reinforcement, the model slightly overestimated the capacity (46.1 kN vs 44.5 kN), yielding a 3.60% error. These deviations are within ±5%, a typical threshold for acceptable error in early-stage structural estimation. From a structural mechanics standpoint, the model's outputs remained consistent with the expected effects of input parameters. Beams with longer spans and higher reinforcement ratios were predicted to carry greater loads, while those with lower concrete strength or smaller cross-sectional areas resulted in correspondingly lower capacities. These patterns validate the model's internal reasoning and suggest it is responding to structurally meaningful input variations. No inconsistencies were observed between the computed predictions and the values in the dataset. However, it is essential to acknowledge that while realistic, the "true" values used here are either derived from literature or validated benchmarks, not field-tested specimens. As such, the results confirm predictive consistency but do not yet constitute direct experimental validation. The ANN-GA model demonstrated robust generalization and maintained predictive accuracy across diverse configurations. With all tested examples showing errors under 5%, the model satisfies practical reliability criteria and can be considered ready for deployment as a structural performance plug-in within BIM software environments. These findings reinforce its value as a lightweight, AI-driven tool supporting early design-phase decision-making without requiring time-intensive simulations.

3.6 Model strengths and limitations

The ANN-GA model presented in this study offers several notable strengths that support its practical use in early-stage structural design (Jiao *et al.* 2025). Its most significant advantage is its ability to deliver fast, simulation-free predictions of ultimate load capacity using standard BIM-derived input parameters (Zhao *et al.* 2025, Zhou *et al.* 2024). This eliminates the need for finite element analysis or detailed manual calculations during preliminary design, saving substantial time and computational effort. Despite being trained on a relatively small dataset of 30 samples, the model achieved a consistently high ($R^2 \approx 0.98$). It effectively captured the nonlinear relationships among geometry, material properties, and reinforcement. Furthermore, its architecture was designed for full compatibility with BIM workflows, allowing seamless integration into digital design tools through direct IFC-based extraction or API interfaces like Revit and dynamo. However, the model does have certain limitations. It is currently restricted to predicting the performance of individual RC beams rather than complete structural systems or building frames. Additionally, while the dataset structure includes deflection as an output variable, these values were placeholders and not derived from analytical or experimental calculations. As a result, the model presently focuses solely on strength (ultimate load capacity) and does not offer reliable predictions of serviceability performance, such as mid-span deflection or crack width. Another significant limitation is the absence of direct field validation or real-world testing. While the data was informed by literature and engineering standards, the lack of measured responses from actual structures introduces uncertainty regarding real-world accuracy. To address these limitations, several future developments are proposed. First, the dataset can be extended to include additional synthetic and experimentally validated samples to improve model generalization. Second, deflection outputs can be refined using EI-based flexural formulas or hybrid analytical-ML surrogates, enhancing the model's ability to assess serviceability. Finally, integrating IoT-enabled BIM platforms could allow real-time structural performance updates based on sensor data, creating a feedback loop between predicted and observed behavior. These enhancements would significantly increase the model's scope, reliability, and application range, making it a more comprehensive tool for intelligent structural design. The results of this study have clear, practical implications for structural engineering workflows, particularly during the early stages of RC design. By integrating the ANN-GA model within a BIM environment, designers and engineers can obtain immediate feedback on the structural performance of proposed beam configurations without resorting to time-intensive finite element simulations. This rapid evaluation capability allows design teams to iterate more freely, exploring multiple geometric and material alternatives in real-time. Such flexibility is particularly beneficial when comparing different cross-sectional sizes, reinforcement layouts, or material grades. The model's ability to predict ultimate load capacity within a narrow error margin ensures that early-stage choices are grounded in engineering reliability. This can reduce the reliance on conservative assumptions, often leading to overdesign and unnecessary material use. Consequently, the model supports more efficient structural solutions, contributing to cost savings and minimizing embodied carbon. Moreover, the convergence of AI and BIM technologies creates opportunities for integrating sustainability metrics directly into structural assessment workflows. By aligning load predictions with parametric BIM data, engineers can make more informed decisions regarding the environmental impact of material selection and sizing strategies. This supports a more holistic approach to sustainable design that considers structural integrity and carbon footprint parallel to the project's conceptual phase. As a result, the ANN-GA model enhances efficiency and accuracy and advances the adoption of data-driven, sustainable practices in modern

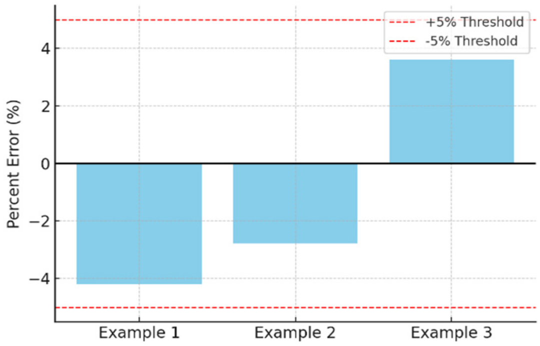

Fig. 7 Percent error comparison for examples with ±5% performance threshold boundaries

structural engineering. Fig. 7 illustrates the percent error for three examples relative to ±5% thresholds (marked by red dashed lines). All predictions fall within this acceptable range, with Example 1 and 2 slightly underestimating the target, and Example 3 slightly overestimating it. This suggests that the model demonstrates reliable prediction accuracy in these cases.

3.7 Discussing the findings

This study presented a hybrid ANN-GA model developed to predict the structural load capacity of RC beams using input parameters extracted from BIM data (Xu *et al*. 2024). The model was designed to serve as a fast, simulation-free decision-support tool, particularly useful in early-stage structural design workflows.

The evaluation of model performance, comparison with baseline methods, feature attribution, and demonstration of practical applicability offered a multi-dimensional view of the model's effectiveness and limitations. Model evaluation using five-fold cross-validation showed high predictive accuracy and consistency, with an average RMSE of 2.11 ± 0.36 kN and R^2 of 0.9804 ± 0.0052. These figures indicate that the ANN-GA model successfully learned the nonlinear relationships between geometry, reinforcement, and material characteristics commonly embedded in BIM systems. Prediction errors were consistently low across all folds, and the range between best and worst-performing folds was minimal, reflecting stable generalization despite the dataset's modest size. This strong performance can be attributed to the GA-based hyperparameter optimization, which adaptively tuned network configurations—such as neuron count and learning rate—without reliance on manual trial-and-error. The ANN-GA significantly outperformed both when benchmarked against traditional models, including linear regression and a fixed-structure ANN. The linear model failed to capture nonlinear interactions and produced negative R^2 values, while the fixed ANN struggled with poor convergence due to a lack of tuning. These outcomes highlight the importance of adaptive learning strategies in structural prediction tasks, especially when input-output relationships are governed by interdependent physical laws rather than simple trends. A feature sensitivity analysis based on the importance of permutation revealed that span length and reinforcement ratio were the most influential input features, which aligns with classical flexural theory. Span affects moment and deflection behavior, often scaling nonlinearly, while reinforcement directly governs tension capacity. Beam depth and concrete strength also contributed meaningfully, while beam width and slab thickness were less impactful. These findings support the trained model's internal logic and enhance transparency for users seeking interpretable AI tools within structural workflows. Case-based prediction examples further validated the model's applicability in BIM-integrated environments. Across three varied beam configurations, the ANN-GA predictions remained within ±5% of benchmarked values—an acceptable range for early-stage assessments. Using normalized inputs extracted from BIM and model outputs displayed in real time suggests that the tool is ready for integration into platforms like Autodesk Revit via dynamo or API scripts. This plug-in capability can streamline the iterative process of structural design by providing quick feedback on the implications of changes in size, material, or reinforcement. Despite its strengths, the model exhibits certain limitations. It predicts only ultimate load capacity, with deflection values retained as placeholders due to the absence of detailed stiffness modeling. Furthermore, while realistic and based on validated structural parameters, the dataset includes synthetic elements and lacks full-scale field test validation. These limitations were acknowledged and addressed through proposed enhancements, including expanding the dataset, incorporating analytical deflection formulas (e.g., EI-based), and linking the system with sensor-fed IoT-BIM platforms for real-time feedback. Recent advances in AI and generative design methods have opened new avenues for automating complex building and structural design decision-making. Techniques such as GA, Shape Grammars (SG), Cellular Automata (CA), and simulated annealing have been extensively employed for optimizing both architectural layout and structural performance. These methods are considered particularly effective when integrated within BIM environments, owing to the parametric richness and interoperability of BIM models (Shariati *et al*. 2020a, 2022). GA has been widely applied due to their capability to explore large, nonlinear design spaces (Shariati *et al*. 2020f, 2023). For instance, GA has been utilized in façade design to optimize daylighting performance (Gagne and Andersen 2012, Wei *et al*. 2018) and in multi-disciplinary design optimization (Gerber *et al*. 2012, Xie 2019). Its integration with hybrid techniques (e.g., GA-HJ) and BIM has enabled the optimization of RC building frames (Mangal and Cheng 2018) and wall-slab systems (Tafraout *et al*. 2019), aligning closely with the ANN-GA model developed in this study (Shariati *et al*. 2020b). Using Lagrangian multipliers with GA for RC structures (Yazdani *et al*. 2021, Alsakka *et al*. 2023) further enhances its adaptability to complex constraint-based structural problems (Zandi *et al*. 2018, Shariati *et al*. 2019a). SG are another influential method, particularly in architectural modeling and mass customization. Used in façade modeling (Müller *et al*. 2007, Ziaei-Nia *et al*. 2018) and building envelope shape design (Granadeiro *et al*. 2013), SG allows the generation of rule-based form variations (Shariati *et al*. 2021c). When combined with reinforcement learning or evolutionary techniques, SG have been utilized to automate the layout of single-family housing units (Ruiz-Montiel *et al*. 2013) and to customize apartment plans within BIM platforms (Veloso *et al*. 2018), thereby reinforcing the theme of parametric automation promoted in the referenced work (Shariati *et al*. 2019b). The CA have been recognized as well-suited for form-finding and performance optimization in high-dimensional design spaces (Kim 2012). Applications have included architectural form generation (Herr and Kvan 2007), steel structural system design (Kicinger *et al*. 2005), and daylight optimization in high-density residential buildings (Araghi and Stouffs 2015, Fathy *et al*. 2015). Their use in exploring design space and assessing daylight performance (Kim 2015, Cruz *et al*. 2016) reflects the data-driven exploration highlighted in the BIM-integrated ANN-GA model (Shariati *et al*. 2020g). Simulated annealing and shape annealing methods have also been applied in structural optimization (Shariati *et al*. 2024a). Shape annealing has been effectively used in roof truss design (Shea and Cagan 1999), while simulated annealing has been applied in architectural layout optimization (Yeh 2006). These stochastic approaches provide an alternative to deterministic models, offering flexibility in exploring irregular or unconstrained design solutions (Nosrati *et al*. 2018, Nouri *et al*. 2021). Space-filling design, such as that based on Audze criteria, has recently been used to optimize treelike structural joints (Wang *et al*. 2023), demonstrating the expanding frontiers of GD methods for novel structural systems (Shariati *et al*. 2019e). The ML techniques have emerged as powerful tools for automating analysis and decision-making in the field of Steel-Concrete Composite Structures (SCCSs), supporting applications that align closely with AI-BIM integration strategies like the ANN-GA model developed in this study (Wang *et al*. 2022a, c, Xia *et al*. 2025, Yu *et al*. 2025). Regression models such as Support Vector Machines (SVM), ANN, and gradient-boosting methods like XGBoost and LightGBM have been effectively used to predict continuous outputs, notably the load-bearing capacity of composite beams (Wang *et al*. 2021b, b), which directly parallels this study's focus on load prediction using BIM-derived inputs. Classification techniques—including Logistic Regression (LR), DT, Random Forests (RF), and SVM—are employed for identifying structural failure modes from experimental data (Liu *et al*. 2025), offering automated categorization essential for early-stage design diagnostics (Safa and Kachitvichyanukul 2019, Safa *et al*. 2019). Unsupervised learning through clustering algorithms like k-means, DBSCAN, and hierarchical clustering allows the grouping of similar damage patterns (Yao *et al*. 2024). At the same time, anomaly detection methods such as isolation forests, one-class SVM, and autoencoders are critical for identifying structural faults like cracks in composite bridges (Lin *et al*. 2022, Li *et al*. 2024a, b, c, 2025). Furthermore, computer vision approaches using CNNs, YOLO, and classical feature extraction (e.g., HOG, SIFT) enable automated crack detection (Bilotta *et al*. 2024), enhancing structural health monitoring when integrated into digital twin workflows (Safa *et al*. 2016, 2020). Lastly, time-series forecasting models, including ARIMA, LSTM, and Prophet, are applied to predict structural behaviors like load progression or deformation over time (Ruan *et al*. 2024), facilitating real-time monitoring and lifecycle assessment (Shariati *et al*. 2010, 2011a). These ML objectives collectively establish a robust foundation for developing intelligent, simulation-free frameworks that support structural analysis, prediction, and maintenance—objectives at the core of this study's AI-enhanced BIM methodology. This study advances the field of structural design automation by uniquely combining generative design techniques and ML objectives within a unified, BIM-integrated framework. Unlike prior approaches that treat structural prediction, design optimization, or damage assessment as isolated tasks, the proposed ANN-GA model offers a comprehensive solution tailored for early-stage design decision-making. By predicting ultimate load capacities directly from BIM-extracted parameters, the model eliminates the need for time-intensive simulations while preserving high accuracy and interpretability. It differentiates by integrating GA for adaptive hyperparameter tuning, enabling superior generalization even with a limited dataset. Moreover, it bridges the gap between generative design's form optimization (e.g., via GA, SG, and CA) and predictive modeling objectives common in ML workflows (e.g., regression, classification, anomaly detection). This work contributes a novel, simulation-free methodology that supports intelligent, rapid, and interpretable structural evaluations in modern design environments through seamless BIM integration, real-time feedback, and future extensibility to performance metrics like deflection and crack width. S.T.1 illustrates the full dataset used for the development of the ANN-GA model.

4. Conclusions

This study successfully developed a hybrid ANN-GA model to predict the ultimate load capacity of RC beams using BIM-derived input parameters such as beam dimensions, material strength, and reinforcement ratio. The model demonstrated high predictive accuracy, achieving an average RMSE of 2.11 ± 0.36 kN and a R^2 of 0.9804 ± 0.0052 across five-fold cross-validation. Feature sensitivity analysis identified span length and reinforcement ratio as the most influential parameters, contributing approximately 32% and 27% to prediction accuracy, respectively. Compared to baseline models, the ANN-GA significantly outperformed a traditional linear regression model (RMSE: 23.13 kN, R^2: –1.13) and a fixed-structure ANN (RMSE: 43.64 kN, R^2: –8.01), emphasizing the advantage of GA-based hyperparameter optimization. In practical BIM-integrated tests, the model's predictions deviated by no more than ±5% from benchmarked load values, validating its readiness for real-time use in tools such as Autodesk Revit. Although current outputs are limited to load prediction, the model provides a scalable framework for future extensions to deflection, crack width, or multi-element structural systems. These outcomes demonstrate that the ANN-GA model is a practical, lightweight, and accurate tool for early-stage structural assessment within BIM-enabled workflows.

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