Joint CSCE Construction Specialty & CRC Conference 2025
Conférence conjointe spécialisée en construction de la SCGC et CRC-2025

Montreal, Quebec
July 28-31, 2025 / *28-31 juillet 2025*

AI-Driven Optimization of Wind-Resistant Shear Wall Layouts in High-Rise Buildings

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ABSTRACT: The rapid growth of the global urban population has increased the demand for high-rise buildings, which address spatial limitations in densely populated areas. However, designing these structures poses significant challenges, including ensuring structural stability, managing lateral loads, and balancing safety with cost-effectiveness. Traditional design processes often rely on trial-and-error methods and the expertise of engineers, which are time-consuming and may not yield economically efficient solutions. This study proposes an automated framework that integrates artificial intelligence (AI) with optimization algorithms to achieve optimal structural layouts for shear wall buildings under wind loads while adhering to architectural and structural constraints. The principal innovation of this research is the development of a computationally efficient framework that synergizes convolutional neural networks (CNNs) as a surrogate model with a genetic algorithm (GA) for structural optimization. The CNN model, trained using a finite element method (FEM) dataset generated with OpenSees, predicts structural responses to vertical and lateral loads. The GA determines the optimal number and location of shear walls. Results demonstrate the GA's effectiveness in solving this optimization problem and the CNN model's accuracy in predicting structural behavior. This approach highlights the potential of AI-driven design to enhance economic efficiency and structural performance in high-rise construction. The study emphasizes the need for increased investment in research and development to advance intelligent design methodologies in the construction industry.

1. INTRODUCTION

Designing building structures is a complex process requiring both practical experience and technical expertise. With a growing emphasis on sustainability and efficiency, engineers increasingly rely on advanced computer-aided design (CAD) technologies and mathematical computation-driven optimization to achieve resource-efficient and dependable designs. Rapid urbanization and population growth, particularly in cities like Hong Kong and New York, have further driven the development of high-rise structures, necessitating sophisticated methodologies to balance safety, cost, and resource optimization. The Council on Tall Buildings and Urban Habitat (CTBUH) reported a record 177 buildings over 200 meters completed in 2023 (CTBUH 2023). This growth underscores the importance of optimization in both structural design, such as determining optimal dimensions and material configurations, and construction processes. The structural design process is divided into three key phases: conceptual design, detailed design, and construction drawings. Among these, the conceptual design phase is the most critical, as it establishes the project's structural framework and determines the appropriate structural system, guiding subsequent stages(Paulson 1976). This phase relies heavily on design experience and knowledge, making it ideal for leveraging artificial intelligence (AI). AI models can simulate this expertise through training, enhancing the efficiency and speed of the conceptual design process.

Modern tall buildings, despite their impressive designs, face heightened technical and economic challenges due to increased susceptibility to wind and seismic forces, as well as exponentially rising costs with height. These challenges, combined with the limitations of traditional trial-and-error design methods, necessitate structural optimization as a critical component of their design process. Numerous studies have made significant progress in the field of structural optimization, especially for high-rise buildings. Aldwaik and Adeli highlighted nature-based methods like neural dynamics and genetic algorithms as effective for large-scale optimization, achieving cost savings of 5-15% (Aldwaik & Adeli 2014). Afzal et al. analyzed 348 articles (1974-2018), identifying genetic algorithms as dominant across optimization categories, including material efficiency, cost, and sustainability (Afzal et al. 2020). Zakian and Kaveh explored seismic design optimization, noting the preference for metaheuristic methods due to their simplicity, though hybrid algorithms combining metaheuristic and gradient-based techniques are emerging for faster convergence (Zakian & Kaveh 2023). Mei and Wang reviewed 196 articles (1970-2020), revealing a rise in research focused on cost minimization, structural performance, and multi-objective optimization, with metaheuristic algorithms being widely used (Mei & Wang 2021). These studies collectively underscore the growing importance of advanced optimization techniques in addressing complex structural challenges.

High-rise buildings are increasingly taller and slenderer, posing challenges in resisting lateral loads such as wind and earthquakes. Wind load critically influences the building's shape and structural system due to its complex interaction with the building's cross-section and profile. Customized resistance systems are essential, as each design requires a unique approach to mitigate wind impact effectively. To mitigate wind-induced loads and vibrations in tall buildings, three strategies are used: structural modifications (increasing stiffness or mass), aerodynamic modifications (e.g., tapering, corner rounding, or twisting), and damping devices (passive, active, or semi-active systems) (Kareem et al. 2013). Jafari and Alipour highlighted the effectiveness of active systems and the potential of aerodynamic changes, even minor ones, to significantly reduce wind loads (Jafari & Alipour 2021). They also emphasized the need for updated codes for super-tall buildings and advanced tools like CFD and machine learning. Sharma et al. recommended combining aerodynamic adjustments with damping devices, as shape changes alone cannot fully eliminate wind effects. They highlighted that while aerodynamic modifications, such as tapering or rounding, can reduce wind loads by 30–60% by altering vortex shedding, these structural changes may also lead to increased costs (Sharma et al. 2018). Collectively, these studies underscore the importance of integrating these strategies with site-specific conditions, economic considerations, and architectural constraints to achieve optimal design outcomes.

In the realm of optimization of shear walls in tall buildings, Zhang and Mueller optimized shear wall layouts in tall buildings using a modified evolutionary algorithm, minimizing weight while meeting constraints like openings, torsion, and drift (Zhang & Mueller 2017). Their method also automated reinforced concrete design, with case studies proving its effectiveness under various loads. Pizarro and Massone used deep neural networks to predict wall dimensions in residential buildings, achieving $R^2 = 0.995$ with data from 165 projects and augmented simulations (Pizarro & Massone 2021). Lou et al. introduced a two-stage hybrid optimization framework, reducing shear wall weight by up to 14.3% using particle swarm algorithms (Lou et al. 2022). Feng et al. developed StructGAN-Rule, a rule-based generative adversarial network (GAN) that improved design efficiency 6 to 10 times while maintaining compliance with engineering standards (Feng et al. 2023). Liao et al. applied GANs to automate shear wall design under earthquake loads, showing major speed and accuracy improvements in real-world applications (Liao et al. 2021). Lu XZ et al. enhanced GANs with physics-based modeling (Struct-GAN-PHY), achieving 44% better designs and 90 times faster performance than manual methods (Lu et al. 2022). Deep generative algorithms for shear wall layouts rely on pixel images, requiring extensive computations and struggling to represent structural topology accurately and link to later design phases. Therefore, Zhao et al. replaced pixel-based designs with graph neural networks (GNNs), improving performance and aligning layouts with seismic and structural factors (Zhao et al. 2023). Magdy and Elshaer optimized shear wall placement under wind loads using genetic algorithms and artificial neural network (ANN) models, enabling cost-effective and sustainable designs (Alanani & Elshaer 2023).

The literature review highlights a critical challenge in structural design: traditional processes for high-rise buildings often depend on trial-and-error methods and engineer's experience, which are time-intensive and may not deliver economically optimal solutions. Although generative design AI-based models, such as GANs and GNNs, have demonstrated potential in optimizing structural designs, further investigation and refinement are needed to enhance their accuracy in predicting structural behavior across diverse building configurations. To address this gap, this study proposes an advanced automated framework that integrates AI with optimization algorithms to generate optimal structural layouts for shear wall buildings under wind loads while adhering to architectural and structural constraints. The primary innovation lies in the development of a computationally efficient framework that combines convolutional neural networks (CNNs) as a surrogate model with genetic algorithms (GAs) for shear wall optimization, offering a transformative approach to structural design.

2. METHODOLOGY

2.1 General

This study uses CNN and GA to optimize shear wall layouts in high-rise buildings, addressing challenges posed by wind loads and traditional trial-and-error methods. Shear walls are critical for resisting lateral forces, but their optimal layout is complex due to architectural and structural constraints. The proposed automated workflow integrates architectural data, wind load simulations, and structural analysis into three steps: (1) preparing data for the surrogate model, (2) training CNN to predict structural responses, and (3) combining CNN with GA to optimize layouts for wind resistance. This approach reduces computational effort, improves accuracy, and streamlines the design process. The following sections detail each step, techniques, and expected outcomes, showcasing an innovative solution for efficient shear wall layout optimization.

2.2 Generating Data Using OpenSees

A Python code was developed to automate the framework for shear wall layout optimization, including reading architectural plans, processing the data, generating wind loads, and conducting structural analysis. The process begins by reading an AutoCAD DXF file to identify potential shear wall locations based on the architectural layout, where walls are segmented into smaller elements (e.g., 1m in length) for flexibility in defining layouts. This segmentation enables optimization to minimize the number of shear walls while ensuring structural performance, with key properties like coordinates, area, and moment of inertia calculated for each element. The imported architectural plan is then analyzed using object-oriented programming (OOP) to organize shear wall elements as objects with properties such as dimensions, coordinates, and orientation. This approach simplifies model generation in OpenSees and ensures efficient data accessibility for further analysis and optimization. Wind loads are calculated according to the Hong Kong 2019 Code of Practice on Wind Effects, incorporating along-wind forces and torsional forces, applied simultaneously in the X and Y directions with combination factors from Table 3.1 in the code. Resultant wind loads act through the center-of-area at each building level to ensure accurate force distribution and reliable structural analysis. The final step involves conducting a structural analysis using OpenSees, an open-source finite element software for seismic and structural analysis by Mazzoni et al. (Mazzoni et al. 2006). The process integrates the structural model, and wind loads to simulate the building's response to various loading conditions, which are divided into two stages: stage one (single slab) and stage two (full structure). In stage one, the focus is on determining the slab's maximum vertical deflection under dead and live loads and calculating support reactions. This simplified analysis provides critical inputs for stage two. In stage two, the full structure is analyzed under combined vertical and lateral loads, incorporating dead, live, and wind loads. To optimize efficiency, slabs are represented as diaphragms, and vertical reactions from stage one are applied to wall joints in stage two. Outputs include lateral displacements in x and y directions.

The analysis relies on a binary vector representing the presence (1) or absence (0) of shear wall elements in the layout. This vector simplifies the structural layout and serves as the primary variable in the optimization process. By adjusting the binary vector, different shear wall configurations are explored to identify the most efficient design. This approach ensures computational efficiency and the binary representation integrates seamlessly into the workflow, enabling iterative optimization to enhance the structural design.

2.3 Build a CNN surrogate model

CNN, an advanced deep learning technique, has gained significant attention for its success in tasks like image processing, visual recognition, and other applications requiring the analysis of structured data (Tan & Le 2019). Unlike traditional ANN, CNN is specifically designed to handle structured inputs, such as images or spatially organized data, through convolutional layers that automatically extract and learn features. These layers capture both low-level features (e.g., edges, textures) and high-level patterns (e.g., shapes, structures), making CNN ideal for tasks involving spatial relationships and localized patterns. A basic CNN, as shown in Figure 1, consists of five primary layers: input, convolutional, pooling, fully connected, and output layers. It is divided into two parts: feature extraction (input, convolutional, and pooling layers) and task-specific processing (classification or regression). The input layer ensures consistent image dimensions, while the convolutional layer uses filters to detect features, creating feature maps. The pooling layer reduces the spatial dimensions of these maps using operations like max or average pooling, preserving key information while minimizing complexity and improving robustness. The task-specific part of a CNN includes the fully connected and output layers. The fully connected layer combines flattened feature maps to learn complex relationships, with each neuron connected to all neurons in the previous layer. The output layer generates predictions; for regression, it produces a continuous value with a linear activation function. This modular design enables CNNs to efficiently process structured data, performing tasks such as image recognition, object detection, and prediction of structural analysis outputs. The flowchart in Figure 2-b outlines the development of the CNN surrogate model to evaluate structural layouts efficiently. Proposed layouts are analyzed using OpenSees to compute outputs (e.g., lateral displacement), which are subsequently used to train the surrogate model to predict these outputs. Convergence is checked by comparing predictions to FEA results. If achieved, the model is verified; otherwise, it is refined and retrained. This process ensures a surrogate model that balances efficiency and accuracy.

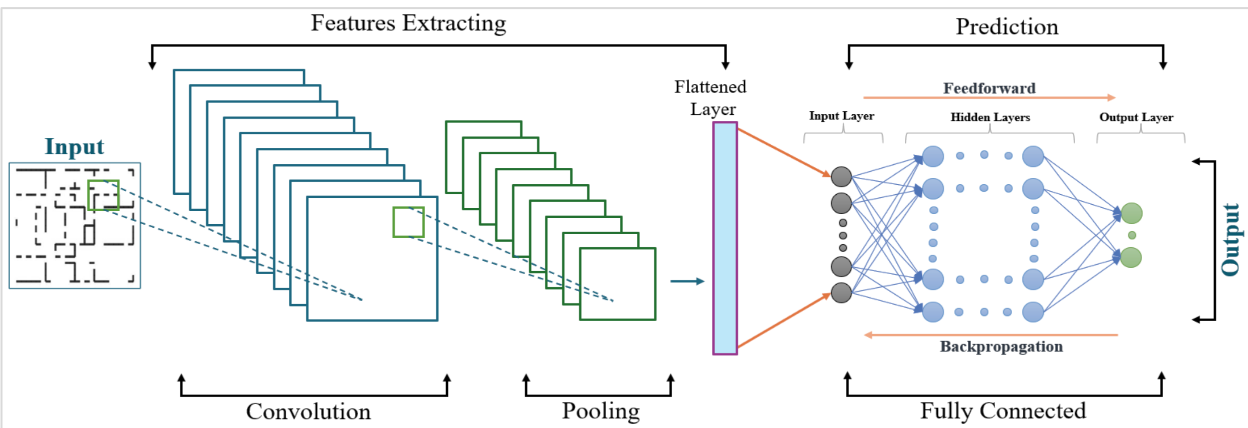


Figure 1: Schematic diagram of a basic CNN architecture

2.4 Optimization process

GA is a powerful optimization method inspired by natural evolution, and it is ideal for solving complex structural optimization problems like shear wall layouts in high-rise buildings. GA efficiently explores large, nonlinear solution spaces while satisfying constraints such as maximum lateral deflection. The process, outlined in Figure 2-a, starts by defining input parameters: a binary vector representing active/inactive wall elements, the objective function (minimizing active elements), and constraints. An initial population of wall layouts is randomly generated and evaluated using a fitness function. High-performing solutions submit to crossover to combine favorable traits and mutation to introduce variations, ensuring exploration of new solutions and avoiding local optima. The updated population is evaluated using a surrogate model (detailed in Section 2.3), and the best solutions progress to the next generation. The algorithm iterates until convergence, defined by minimal improvement or meeting constraints. The final output is the optimal shear wall layout, balancing structural performance and architectural requirements while minimizing effort. The optimization process is defined in Eq. 1.

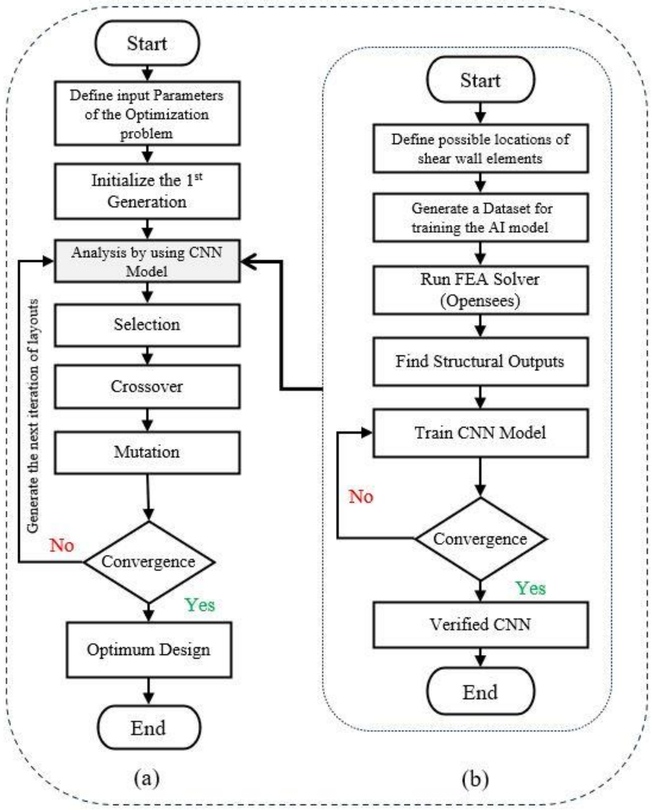


Figure 2: Overall process framework; a) GA optimization flowchart, b) Surrogate model building flowchart.

$$find\ \boldsymbol{S} = (S_1, S_1, \dots\dots, S_N)$$

$$min \sum_{i=1}^{N} \boldsymbol{S}_i \qquad [1]$$

$$Subjected\ to: \ C_{dis.X\&Y} \leq \ limit$$

$$Where \rightarrow \ Si \ \in \ \{0, 1\} \ (i \ = \ 1, 2, \cdots, N \ )$$

Where $\boldsymbol{S}$ denotes the total number $'\boldsymbol{N}'$ of the shear wall elements in the layout, which controls the total weight of the building. $C_{dis.X\&Y}$ is the constraint function for maximum lateral displacement in the x and y direction. The limitation of these constraints is (H/500), where H: is the height of the building.

3. CASE STUDY

A 20-story building with a 3.0 m story height is used to demonstrate the methodology, as described in a previous study (Alanani & Elshaer 2023). The building has a rectangular slab layout of 24.75 m × 18.75 m, featuring two flats per floor, as shown in Figure 3. In Hong Kong, a low seismic region, wind load governs the lateral forces for this 60 m tall structure. Gravity loading includes the self-weight of structural members, a 5 kN/m² superimposed load for non-structural elements, and a 3 kN/m² live load, uniformly applied across all slabs. The structure uses reinforced concrete with a compressive strength of 35 MPa, ensuring adequate strength and stiffness. This setup reflects realistic high-rise building conditions in wind-critical regions like Hong Kong.
The process begins by reading the AutoCAD DXF file of the architectural layout to identify shear wall locations. Walls are divided into 1-meter segments, resulting in 170 segments, each assigned a unique number (Figure 4). These segments form the basis of the optimization process. The layout is then analyzed,

and wall elements are organized into object-oriented structures for efficient processing. Figure 5 illustrates how wall elements are grouped by direction and connectivity, streamlining data handling and model generation for OpenSees analysis. A sub-code is then used to calculate wind loads per the Code of Practice on Wind Effects in Hong Kong 2019, ensuring accuracy for further analysis.

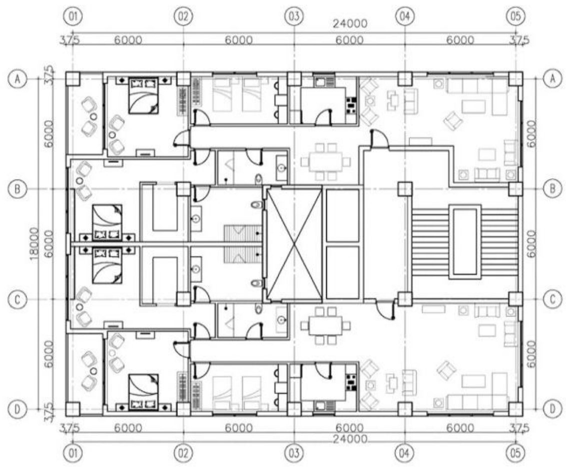


Figure 3: Architectural plan view. [Reproduced with permission from Ref. (Alanani & Elshaer, 2023) Copyright (2023) Elsevier]

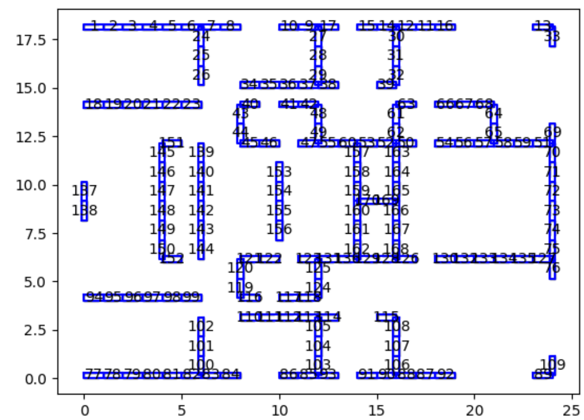


Figure 4: Segmented 1-meter shear wall elements with assigned element numbers.

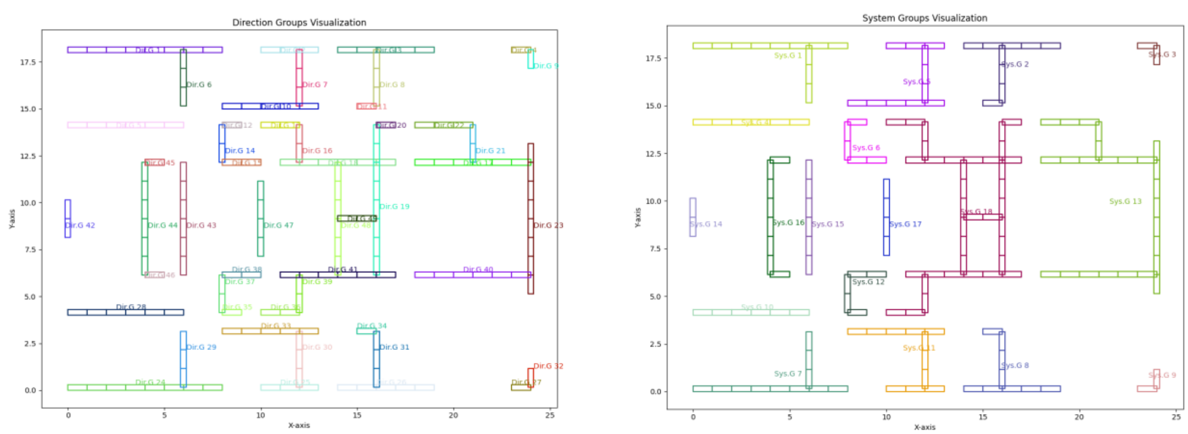
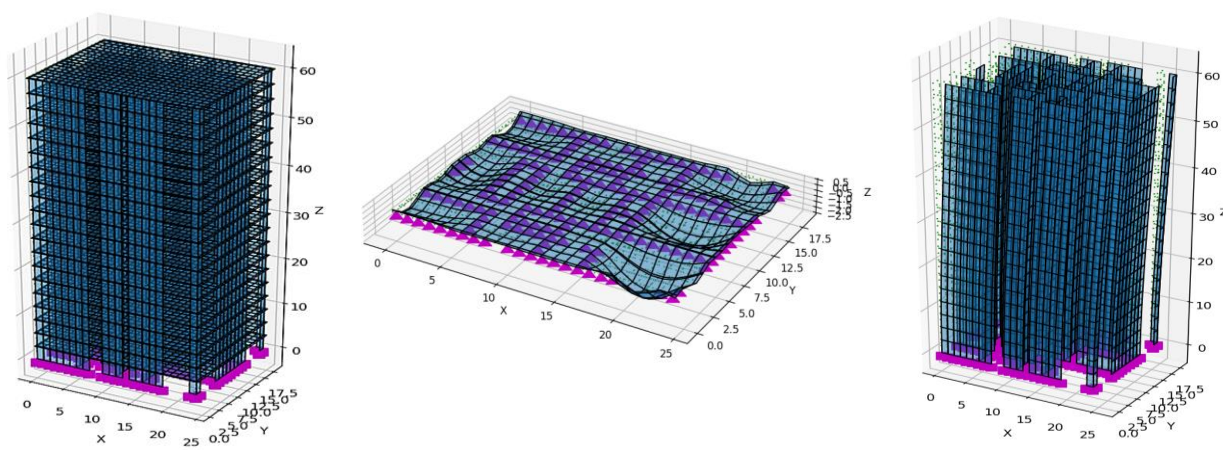


Figure 5: Segmented 1-meter shear wall elements with assigned element numbers.

Before structural analysis in OpenSees, a binary vector is generated to define effective walls and execute the analysis. Figure 6-a shows the 3D model in OpenSees. The analysis is performed in two stages: vertical and lateral analysis. In the first stage, vertical analysis determines the maximum slab deflection under dead and live loads, with the deformed shape shown in Figure 6-b. Reaction forces at wall supports are calculated and applied as equivalent slab loads in the second stage. This ensures code compliance and economic efficiency in wall layout optimization. The second stage focuses on lateral analysis under combined vertical and lateral loads. The deformed structure (Figure 6-c) highlights lateral displacements and the role of shear walls in resisting wind forces.

In the domain of CNN-based surrogate models, EfficientNet was selected as the backbone for the CNN model due to its balance of accuracy and computational efficiency. Specifically, EfficientNet-B0, the baseline model of the EfficientNet family, was employed. This model is renowned for its innovative architecture, which is divided into seven blocks based on channel depth, stride, and convolutional filter size. At its core, EfficientNet-B0 utilizes the Mobile Inverted Bottleneck (MBConv) as its primary building block, a concept derived from MobileNet. The MBConv structure comprises two 1×1 convolutional layers, a depthwise convolutional layer, a Squeeze-and-Excitation (SE) block, and a dropout layer. The first convolutional layer is responsible for expanding the channels, while the depthwise convolution reduces the number of parameters, enhancing computational efficiency. The SE block focuses on inter-channel relationships, assigning adaptive weightings to individual channels rather than treating them equally. Finally, the second convolutional layer compresses the channels to optimize the model's representational capabilities.

A custom dataset containing 8,000 training images and 2,000 validation images was used to train the model. Each image, representing a structural layout, was resized to 224×224 pixels and normalized to ensure consistency. The architecture leveraged feature extraction layers followed by fully connected layers that progressively reduced feature dimensions to generate final structural predictions. To capture non-linear relationships, Sigmoid activation functions were applied in the first two fully connected layers, while the final layer produced output predictions for structural analysis. The training process utilized the Mean Squared Error (MSE) loss function to minimize prediction errors and the Adam optimizer with a carefully tuned learning rate for efficient weight updates. The training was conducted over 200 epochs, and the model with the lowest validation loss was saved for further use. Figure 7 presents the training and validation loss trends for AI models over multiple epochs based on datasets related to lateral displacement. The plot demonstrates a clear pattern of convergence, with steadily decreasing loss values across epochs. This indicates that the models are effectively learning and progressively improving their predictive performance on these datasets. Figure 8 examines the correlation results between the FEA results and AI model predictions under varying loading conditions, including dead loads, live loads, and wind loads in both the X and Y directions. The consistently high correlation coefficients observed across these comparisons highlight the model's robustness in accurately capturing complex structural responses, such as lateral displacements, with exceptional precision.



(a) (b) (c)

Figure 6: Modeling and output by OpenSees;(a) 3D representation of the structure, Deformed shape, (b) Stage one, (c) Stage two.

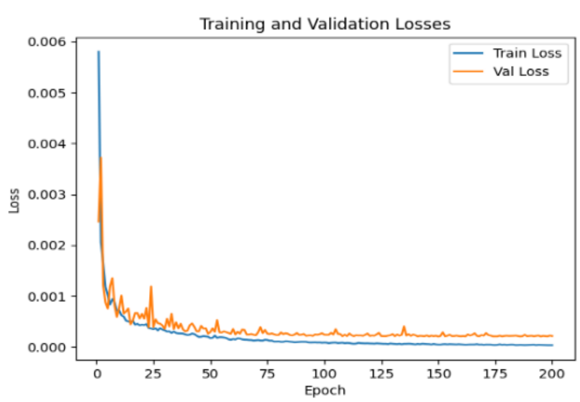
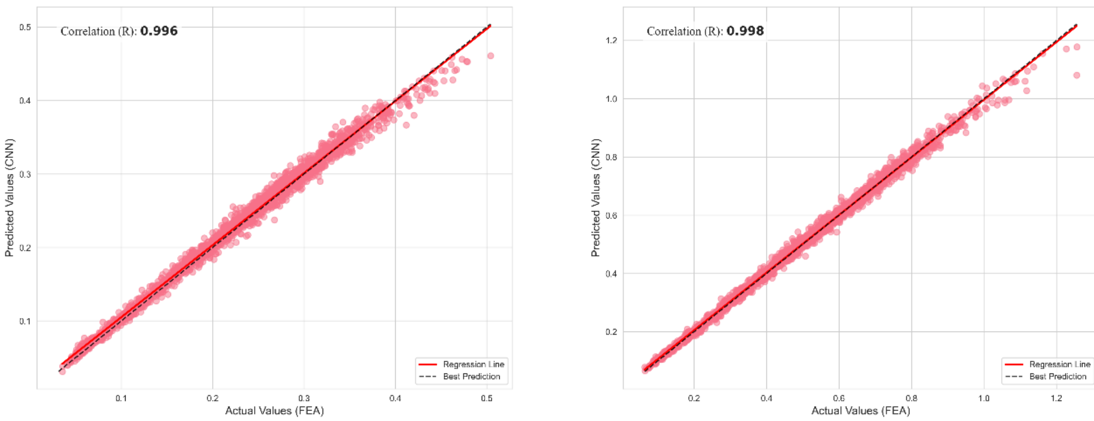


Figure 7: Training and validation losses of the CNN models versus the number of epochs



(a) (b)

Figure 8: Correlation of FEA vs CNN results of Lateral displacements due to Wind load;(a) X-direction, (b) Y-direction.

Figure 9 illustrates the optimization process results under predefined constraints, showcasing the trend in the reduction of wall elements over time. This aligns with the objective of minimizing active wall components while maintaining structural efficiency. Figure 10 displays the final optimized layout after 200 iterations, providing a clear representation of the Genetic Algorithm's (GA) effectiveness in refining the structural design. In the figure, the blue color represents active walls, while the gray color denotes inactive walls. These figures emphasize the GA's ability to achieve solutions that not only minimize the number of walls but also satisfy critical performance requirements, such as maintaining displacements and deflections within acceptable limits.

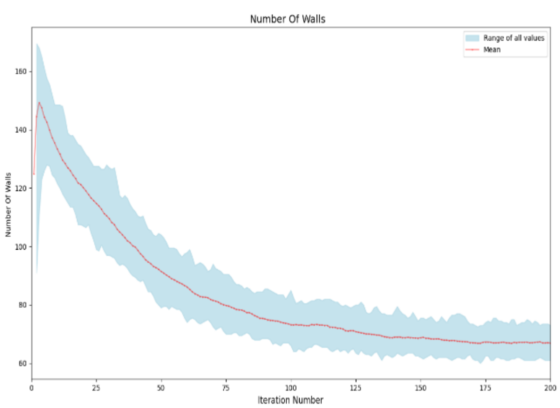


Figure 9: Change in the number of walls over iterations.

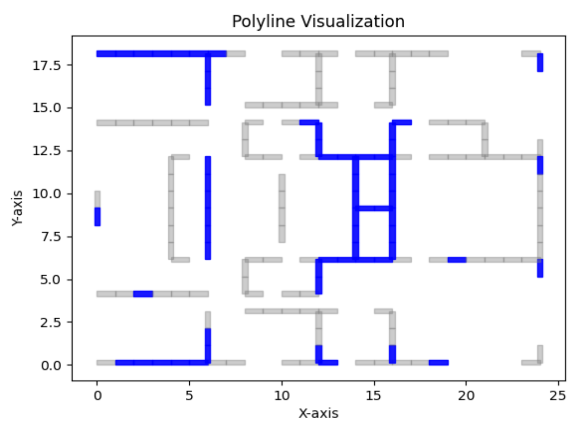


Figure 10: Optimal shear wall layout of optimization process subjected to all constraints

4. CONCLUSION

This study proposes a comprehensive methodology for optimizing the shear wall layout of high-rise buildings in wind-critical regions, such as Hong Kong. By integrating advanced computational tools and techniques, including FEA(OpenSees), CNN, and GA, the study effectively addresses the challenges of balancing structural efficiency, cost, and code compliance. The case study of a 20-story reinforced concrete building highlights the effectiveness of leveraging advanced technologies to optimize shear wall layouts. The two-stage analysis approach, vertical and lateral load analyses, successfully captured the interactions between dead, live, and wind loads, resulting in a robust foundation for design optimization. The incorporation of EfficientNet-B0 as the backbone for the CNN-based surrogate model underscores the importance of computational efficiency and accuracy in predicting structural responses. With a custom dataset of 10,000 images, the model achieved high predictive accuracy, as evidenced by the low validation loss trends and strong correlation with FEA results under varying loading conditions. This demonstrates the potential of AI-driven models to enhance the efficiency and precision of structural analysis. The Genetic Algorithm further refined the structural design by reducing the number of active wall elements while maintaining critical performance criteria, such as lateral displacements within acceptable limits. Over 200 iterations, the optimization process achieved significant reductions in wall components, as shown in the final optimized layout. This outcome validates GA's capability to produce practical and cost-effective designs without compromising safety or code compliance. In conclusion, this research successfully integrates advanced modeling, optimization, and AI techniques to achieve an innovative and efficient approach to high-rise building design. The methodology not only enhances structural performance but also offers a scalable framework for future applications in the structural engineering domain, particularly in wind-critical regions. The proposed method predicts the response of shear wall systems under static wind loads, as prescribed by equivalent static wind load codes, assuming uniform wall thickness. While it supports diverse geometric configurations, it remains constrained by specific limitations, including the exclusion of stress analysis, aeroelastic effects, and wall size optimization. Future work will enhance industrial applicability by a) incorporating stress-based design criteria, b) extending the approach to wind-structure interaction, and c) enabling optimization of wall thickness for improved performance.

ACKNOWLEDGMENTS

The authors greatly appreciate the support of the Hong Kong PhD Fellowship Scheme.

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