Optimization of Tall Buildings Subjected to Wind Load Using Genetic Algorithm and Image-Based Machine Learning

A thesis

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ABSTRACT

As the prevalence of tall buildings are on an upward trend in urban cities, the need to navigate their design intricacies becomes increasingly important. Tall buildings exhibit dynamic and nonlinear responses to applied load and are required to satisfy extensive design requirements, leading to the need for complex analysis techniques to evaluate very specific engineering problems. Technological advances in supporting research fields provide engineers with both computational resources and algorithms for use as tools not previously available, strengthening the case for Machine Learning (ML) and surrogate modelling techniques to assist with the interpretation and exploration of design spaces in advanced analysis. This thesis studies the use of Convolutional Neural Networks (CNNs) designed to simultaneously facilitate the optimization of Reinforced Concrete (RC) shear wall topology and size. As an image-based approach, the work assesses the capability of the proposed algorithms to generalize the abstract relationship between structural layout and numerical performance metrics of tall building designs. The resulting models display significant capability of replicating Finite Element Analysis (FEA) corresponding to structural layout images. Further, an optimization framework is developed which utilizes these models and a Genetic Algorithm (GA) to automate the design processes which typically rely on the expertise of engineers. As a result, both architects and engineers can utilize the proposed framework to identify design solutions corresponding to a reduced quantity of shear wall volume, and/or total number of piers required, achieving cost savings in real-world applications. This work reveals the potential of CNN-based surrogate models in the design of tall buildings, especially when proposed for structural and multidisciplinary optimization.

KEYWORDS

Tall buildings, wind load, shear wall, Reinforced Concrete (RC), Latin Hypercube Sampling, Convolutional Neural Network, Genetic Algorithm (GA), multi-objective optimization, wind engineering, surrogate model, deep learning, performance-based design, Computational Fluid Dynamics (CFD), structural optimization, Design Space Exploration (DSE), Finite Element Analysis (FEA).

CO-AUTHORSHIP STATEMENT

This thesis has been prepared in an Integrated-Article format. As such, portions of section 2.3, and the entirety of Chapter 3 and Chapter 4 of this thesis are published or have been submitted and are under current review for journal publication. Consequently, the thesis has been co-authored as part of publication by Dr. Ahmed Elshaer (A.E.) and Dr. Magdy Alanani (M.A.), both of Lakehead University's Department of Civil Engineering. Their contributions are specified using the Contributor Roles Taxonomy (CRediT) indicated accordingly, below. However, thesis chapters may have been modified to ensure consistency and coherence within the thesis format. Information originating from external sources have been cited as appropriate.

Chapter 2.3: Literature Review – Machine Learning and Surrogate Modelling

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Chapter 4: Multi-Objective Optimization of Tall Buildings Subject to Wind Load via Genetic Algorithm and Image-Based Surrogate Modelling

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$\boldsymbol{\Gamma}$	Modal Participation Factor
$\boldsymbol{\gamma}$	Surrogate Model Weight Momentum
$\boldsymbol{\nabla L(w_i)}$	Surrogate Model Error
$\boldsymbol{\eta}$	Surrogate Model Learning Rate
$\boldsymbol{DV_i}$	Design Variable
$\boldsymbol{h}$	Storey Height
$\boldsymbol{L_w}$	Shear Wall Length
$\boldsymbol{N}$	Surrogate Model Number of Layers
$\boldsymbol{N_p}$	Number of Piers
$\boldsymbol{N_s}$	Number of Storeys
$\boldsymbol{n}$	Total Number of Surrogate Model Samples
$\boldsymbol{RII}$	Torsional Sensitivity Factor
$\boldsymbol{s_i}$	Surrogate Model Sample
$\boldsymbol{V}$	Volume of Concrete
$\boldsymbol{v_i}$	Surrogate Model Weight Velocity
$\boldsymbol{w_i}$	Surrogate Model Weight

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
ASCE	American Society of Civil Engineers
CAARC	Commonwealth Advisory Aeronautical Research Council
CDRFG	Consistent Discrete Random Flow Generation
CFD	Computational Fluid Dynamics
CMHC	Canadian Mortgage and Housing Corporation
CNN	Convolutional Neural Network
DL	Deep Learning
DSE	Design Space Exploration
FEA	Finite Element Analysis
FEM	Finite Element Method
GA	Genetic Algorithm
GAN	Generative Adversarial Network
GNN	Graph Neural Network
GPR	Gaussian Process Regression
GPU	Graphics Processing Unit
LES	Large Eddy Simulation
LFRS	Lateral Force Resisting System
LHS	Latin Hypercube Sampling
MAE	Mean Absolute Error
ML	Machine Learning
MWFRS	Main Wind Force Resisting System

NBCC	National Building Code of Canada
NSGA	Non-Dominated Sorting Genetic Algorithm
OAPI	Open Application Programming Interface
PBD	Performance Based Design
PBSD	Performance Based Seismic Design
PBWD	Performance Based Wind Design
R	Pearson Correlation Coefficient
RC	Reinforced Concrete
ReLU	Rectified Linear Unit
RMSE	Root Mean Squared Error
SFRS	Seismic Force Resisting System
SGDM	Stochastic Gradient Descent with Momentum
SVR	Support Vector Regression
SVM	Support Vector Machine
ULS	Ultimate Limit State
XGB	Extreme Gradient Boosting

Chapter 1 Introduction

1.1 Background

The demand for tall buildings continues to grow, driven by urbanization, sustainability initiatives and government policy, to the degree that apartment style residential and commercial spaces have become an integral part of daily life across the globe. This is likely to continue, as the United Nations predicts that the global urban population will continue to increase by the billions in coming decades (United Nations 2018). In Canada, the composition of new residential housing has been dominated by apartment-style construction starts since approximately 2011 (Canada Mortgage and Housing Corporation (CMHC)). As this trend is expected to continue, a sustained demand for tall buildings is likely for the foreseeable future.

Structural optimization remains a popular topic among researchers, especially within the context of tall buildings. This is likely due to the nature of tall buildings as being large-scale projects, with many opportunities for improvement, cost savings, and increased building efficiency remaining to be found. The evolution of urban environments triggered research into new fields including structural pounding, urban microclimates, and pedestrian-level wind comfort studies (Adamek et al. 2017; Brown and Elshaer 2022; Yang et al. 2023). These factors paired with others, such as climate change and sustainability, begin to describe the landscape of increasing complexities engineers must consider during building design.

To accommodate this, engineers endeavour to develop analysis tools, often relying on judgement to establish simplifications when the task at hand becomes to complex or computationally burdening. However, Machine Learning (ML) continues to prove it's worth in developing innovative tools in structural engineering and may be capable of increasing the precision of analyses when considering a more comprehensive list of considerations during design stages.

1.2 Research Problem

The design of tall buildings is an expansive research topic. The optimization of these structures can utilize many approaches and can be broadly considered to have two main categories: aerodynamic and structural optimization. While these approaches are discussed in further detail in Chapter 2, a few details are important to highlight in describing the gaps of existing research. In Canada, determination of applied wind load can either follow the provisions of the National Building Code of Canada (NBCC), or in some circumstances, requires experimental wind tunnel testing. However, with the continuing development of Computational Fluid Dynamics (CFD) techniques, numerical analysis is becoming increasingly reliable. Paired with the Performance Based Wind Design (PBWD) guidelines released by the American Society of Civil Engineers (ASCE) in 2019, the design of tall buildings with complex layouts may soon have several recognized options for wind load discretization.

Regarding structural optimization, researchers have studied countless algorithms for applications in optimizing single- and/or multiple-objective problems. However, proposing an optimization framework capable of evaluating both the structural topology and structural sizing of elements remains difficult to accomplish simultaneously. Additionally, many optimization algorithms in recent years are trending towards utilizing ML, data-driven approaches. Upon further inspection, these can be categorized as having numerical *or* image-based approaches. Typically, studies focusing on only one of these data types, either relating numerical study parameters, or for example, correlating architectural drawings to structural layouts. While these are certainly interesting approaches, their challenges and limitations are discussed further in Chapter 3.

Lastly, the development of an optimization framework of this magnitude can be a time-consuming endeavour. Often, research consisting of ML algorithms of this calibre can have difficulty being widely used as they are developed for specific tasks under very specific circumstances. Considering the versatility and adaptability of the proposed framework by applying it to various underlying data structures is an effective way to assess an algorithms performance in multiple scenarios.

1.3 Objectives

Therefore, this thesis proposes several objectives to address the gaps in existing research. The analyses conducted will consist of tall buildings designed with Reinforced Concrete (RC) shear walls as the Lateral Force Resisting System (LFRS), after an architectural floorplan developed based on the Commonwealth Advisory Aeronautical Research Council (CAARC) building. The following objectives have been developed:

1. **Develop an Image-to-Numerical ML Model:** Assess the capability of an image-based ML model in directly generalizing the numerical performance of shear walls under wind-induced response of tall buildings.
2. **Conduct Simultaneous Size and Topology Optimization:** Develop a method using the image-based ML models to enhance optimization capabilities by considering both shear wall size and topology concurrently.
3. **Conduct Multi-Objective Optimization Via Image-Based Surrogate Model:** Develop a Genetic Algorithm (GA) utilizing the image-based ML model to solve single- and multi-objective optimization problems while considering several geometric, code-based, and numerical constraints.

1.4 Outline

This thesis is organized into five chapters. Chapter 1 (this chapter) is a general introduction to the thesis, identifies the research gap, and states the objectives of the research. Chapter 2 is a literature review, providing greater context to the state of relevant research fields in optimization and ML. Chapter 3 assesses the capability for a Convolutional Neural Network (CNN) to predict the peak interstorey drift of tall building structural layout images. The underlying dataset consists of linear dynamic wind load time histories as described in section 3.2.1. Chapter 4 builds on the previous chapter by developing several surrogate models capable of interpreting both the structural layout as well as size of shear wall elements. Additionally, the wind load determined in this chapter relies on the NBCC dynamic wind load procedure. Lastly, this models in this chapter are trained to predict several design metrics. Chapter 5 summarizes the findings of the research, draws conclusions, and identifies recommendations for future research.

Chapter 2 Literature Review

2.1 Background

From the perspective of an engineer, the design of tall buildings poses significant challenges. Major differences in the design of these structures compared to low-rise or conventional single-family housing are primarily due to the presence of increased lateral load effects, namely wind and seismic action, experienced by a building. To convolute the problem, the natural slenderness of tall structures renders them vulnerable to advanced physics-induced phenomena. Factors such as harmonic motion, nonlinear material behaviour, and fatigue due to cyclical loading during structural responses can exacerbate lateral load conditions and compromise building performance. Such structures are considered dynamically sensitive and susceptible to nonlinear behaviour, and as such, static analysis is inadequate.

Dynamically sensitive structures are primarily concerned with the hysteretic dependency of a building's response to lateral excitations and thus requires modal analysis and/or the development of load time histories to adequately assess structural conditions. Regarding seismic action, spectra of ground-induced motion are well recorded across the globe, and when paired with an appropriate modal analysis technique, the impacts of applied seismic load can be accurately determined. For wind-induced loading, tools such as experimental wind tunnel testing, and/or time history analysis determined from computational fluid dynamics (CFD) are necessary to accurately assess aerodynamic effects. Aerodynamic analysis of the atmospheric boundary layer is highly influenced by building architecture and greater environmental conditions. Recent research into urban intensification studies have identified various wind-related effects not previously foreseen, including wind speed-up areas and wind-induced structural pounding (Brown and Elshaer 2022; Yang et al. 2023).

To layer further complexity to the design of high-rise structures, analysis approaches are highly dependent on the employed structural systems. In recent decades, significant research has provided confidence in the suitability of-alternative types of Lateral Force Resisting Systems (LFRS) to be accepted as appropriate lateral load mitigation mechanisms. LFRS often act as both the Main Wind-Force Resisting System (MWFRS) and Seismic Force Resisting System (SFRS). These systems can often be considered as the same structural components as is the case with shear walls. Alternatively, they can also include systems specifically targeted and mitigating a certain hazard type, as is the case with various types of dampers and base isolation systems specifically designed for seismic purposes. The design of tall structures is a formidable challenge, requiring the expertise of engineers of many specialties to implement safely and reliably. Further, developing efficient, intelligent, or otherwise optimized implementations of engineering knowledge represents countless opportunities to improve the design of structures. The following review is broken down into the following categories: aerodynamic optimization, structural optimization, and ML and surrogate modelling. Together, these considerations describe the nature of the role that optimization plays in the design of tall structures.

2.2 Optimization of Tall Buildings

With the design of ever-increasingly-complex structures, innovative building mitigation mechanisms, and advancing technological capabilities (both hardware and software), comes advancements in structural analysis techniques. Aerodynamic optimization of high-rise structures employs the approach of improving building performance by means of reducing the applied loads experienced by the structural system. This is completed through studying the nature of the expected wind hazard, and the interaction between atmospheric boundary zone wind with bluff bodies. The architecture of bluff bodies has significant impact on aerodynamic performance, and fall into two commonly studied categories: local aerodynamic optimization and global aerodynamic optimization (Elshaer et al. 2017). Local optimization is concerned with the evaluation of discrete regions or components of buildings as opposed to the entire structure. Conversely, global optimization aims to improve the aerodynamic performance of the entire structure. Local optimization includes techniques such as parapet walls, modifying cladding surfaces, and reshaping building elements, and global optimization includes significant changes to the general shape of the structure. By optimizing the aerodynamics of a building, factors such as applied load, drag, pressure, and turbulence coefficients can be improved to minimize effects on the building.

On the other hand, structural optimization is concerned with the efficient management of the persisting applied loads. This is achieved through three widely accepted approaches: shape, size, and topology optimization (Aldwaik and Adeli 2014; Zavala et al. 2014). Shape optimization is concerned with the cross-sectional properties of an element in efficiently resisting applied stresses. Size optimization is concerned with utilizing appropriate dimensions of materials, and topology optimization is the study of the distribution of structural elements in resisting applied loads at the structural system level. When working with RC buildings, rigid diaphragm action promotes the distribution of forces across the entire structural floor plan to resist load. Design Space Exploration (DSE), a term often related to the use of surrogate modelling, utilizes these principles of aerodynamic and structural optimization mechanisms to consider their impact on design in the form of objective functions (Forrester et al. 2008). These manifest as minimization algorithms and can consist of both ML and non-ML approaches, as discussed in the following section. DSE can consider multiple combinations of these optimization mechanisms and pair them with overarching economic considerations and project constraints to deliver high-quality solutions.

2.3 Machine Learning and Surrogate Modelling

Surrogate modeling, also known as metamodelling, is the practice of creating approximate models to replicate complex relationships of computational relationships or experimental studies.

As a heavily theory-based industry, structural engineering benefits from physics and theory of structures, allowing for direct quantification of building performance under normal conditions. In structural engineering, particularly in tall building design, surrogate models offer an alternative to expensive finite element simulations, computational fluid dynamics, and wind tunnel testing, enabling faster evaluations and enhanced decision-making. This in turn allows for surrogate models to be used in applications regarding structural reliability, optimization, and in developing digital twin technologies.

These models can be categorized by their overarching approaches, which include both statistical and data-driven techniques. Traditional surrogate models do not rely on machine learning but rather use mathematical approximations and regression techniques. Numerical problems with low complexity can be approximated using algorithms such as polynomial regression. Polynomial and Response Surface Models are used for approximating objective functions in optimization problems. While these functions are well known, they have significant limitations when it comes to approximating relationships with a high degree of complexity as seen in tall building design. Probabilistic frameworks such as Bayesian-based models and Gaussian Process Regression rely on statistics to provide uncertainty quantification. Deger and Taskin use GPR to predict backbone curves of RC shear walls (Deger and Taskin 2022). Other commonly used statistical surrogate models in structural engineering include Response Surface Methodology and Kriging. Response Surface Methodology is based on polynomial approximations and expresses the objective function as a lower-order polynomial. It is commonly used for optimizing structural parameters like stiffness and weight. Kriging, like Gaussian Process Regression, is a spatial interpolation method that considers both observed data and their spatial correlation. The impact of Kriging-based surrogate models for Performance Based Wind Design is described in

Micheli et al (Micheli et al. 2020). Support vector regression fits data to hyperplanes in order to provide a numerical allowance for noise in data (Rasifaghihi 2023). There is no shortage of statistics-based algorithms with applications in structural engineering. For example, Parsa and Naderpour estimate concrete wall shear strength using SVR, Particle Swarm, and Harris Hawks optimization (Parsa and Naderpour 2021).

Data-driven approaches are machine learning-based models including Artificial Neural Networks, Convolutional Neural Networks, Decision Trees, and Ensemble Learning models. Machine learning-based surrogate models are increasingly used in tall building design and optimization. Some of the common ML models include Artificial Neural Networks, which are used to approximate structural response under various loading conditions. Convolutional Neural Networks and GANs can be applied when input features include image-based data, including in building layout analysis (Gu et al. 2018; Pizarro et al. 2021; Zhao et al. 2023). Random Forest and Gradient Boosting Models are used in predictive modeling of structural parameters. Artificial neural networks (ANN) have been used in predicting shear capacity of shear walls of various natures (Mo and Lin 2015; Nguyen et al. 2021; Pizarro and Massone 2021; Siam et al. 2019; Solorzano and Plevris 2022, 2023). Research focusing on shear walls is expansive and includes many types of ML models, including SVR-RSM techniques (Keshtegar et al. 2021). Although a popular topic, these research topics are not limited to the study of reinforced concrete shear walls. Das et al studied machine learning algorithms for heavy timber buildings, adding interesting discussion to what the future possibilities for what the implementation of alternative materials for tall buildings may look like (Das et al. 2024). Nourbakhsh et al. use a neural network as a surrogate model to FEA in predicting stresses of 3D trusses (Nourbakhsh et al. 2018). In contrast, non-ML approaches have also been used as surrogate models for predicting the strength of high-performance concrete mixes (Hariri-Ardebili and Mahdavi 2023).

Ensemble methods refer to algorithms with several components building upon each other to provide some benefit. Ensemble methods are commonly employed as research begins to consider increasing complex approaches (Wang et al. 2022). Long et al. consider the use of both SVM and XGB to determine seismic ground motion (Long et al. 2024). Zheng et al. use both ANNs and SVM in predicting wind speeds (Zheng et al. 2023). While ensemble methods excel at improving overall model performance, to its detriment, it becomes increasingly convoluted to implement as the complexity of the task at hand increases. The benefit of using a specific algorithm, be they gaussian versus ML-based, is unclear and application-dependant. As a result, researchers often compare the performance of various models at completing the same task (Alanani and Elshaer 2024; Yetilmezsoy et al. 2021; Zhang et al. 2024; Zheng et al. 2023). These few examples provided simply serve to describe the landscape of possibilities when it comes to their applications for the optimization of tall buildings. The surrogate models identified only begin to outline the complexity of numerical problems they are capable of replicating. As research continues, surrogate models will play an increasingly critical role in multi-dimensional optimization problems associated with tall buildings.

Machine learning, a subset of artificial intelligence, enables systems to learn patterns from data without explicit programming. In structural engineering, machine learning is applied in predictive modeling, structural health monitoring, and optimization. When applied to tall buildings, machine learning assists in automating the design process, predicting structural behavior, and optimizing performance parameters such as material efficiency or aerodynamic behavior. Breakthroughs in the development of deep learning algorithms in recent years has led to increasingly powerful and versatile numerical tools to come out of machine learning, often overcoming the limitations of both classical machine learning and statistical approaches. Machine learning models can be broadly classified into supervised and unsupervised learning. Supervised learning uses labeled data for training and includes regression models such as Linear Regression, Polynomial Regression, and Random Forest Regression, as well as classification models like Support Vector Machines, Decision Trees, and Neural Networks. Unsupervised learning works with unlabeled data for clustering and anomaly detection, including methods like K-Means and Principal Component Analysis.

The review of machine learning by Thai advocates for the applications of ML algorithms at conducting structural analysis and design (Thai 2022). Further, they can be used in determining mechanical properties of construction materials, assess structural framing action, and even be applied to structural health monitoring, damage detection, and fire assessment of structures. Reviews of the field begins to identify increasingly challenging applications, such as information retrieval from images, and written text in supplementing the ML process (Sun et al. 2021). These findings are in line with Wang et al who describe the applications of ML for civil engineering analysis as having three core applications; replicating numerical relationships at the structural material, structural member, and structural system levels (Wang et al. 2023a). Building on these levels, the applications of ML algorithms have been successfully applied to wind behaviour, seismic performance, digital twins, (Du and Chen 2023; Kobayashi and Alam 2024; Liu et al. 2023b; Mangalathu et al. 2022; Thaler et al. 2021; Wang et al. 2023b; Zheng et al. 2023).

Beyond these foundational approaches, various advanced machine learning techniques have been developed for applications in tall building design and optimization. The Seed Growth Algorithm proposed by Hosseini et al focuses on heuristic approach to improve neural network performance at replicating computational relationships (Hosseini et al. 2024). At the structural element level, RC compressive strength can be predicted several ways (Liu et al. 2023a; Pal et al. 2023). Extreme Gradient Boost (XGBoost) has been utilized in modeling the behavior of reinforced concrete coupling beams (Hu et al. 2023). Neural networks have been developed for a variety of applications, including in structural reliability analysis (Lieu et al. 2022). Building efficiency has been assessed using reinforcement learning and decision tree algorithms (Mangalathu et al. 2020), and even identification of seismic failure modes has been evaluated by several methods (Zhou et al. 2023).

While these examples identify key capabilities of machine learning approaches for tall building design and optimization, the degree of analysis capable is constantly being pushed forward by researchers. A branch of research focuses on the use of physics-based information and can be seen having applications for tall buildings (Zaker Esteghamati and Flint 2023). Structural health monitoring (Dadras Eslamlou and Huang 2022), structural damage (Karbassi et al. 2014), and even building economic factors (Shoar et al. 2022) can be predicted via machine learning. Combined, these studies represent the wave of advanced analysis becoming capable with the use of machine learning.

Based on these categories, the most utilized machine learning models in tall building design include Neural Network-based surrogate models, which are used for predicting wind load effects based on building geometry. Neural Networks, including both Artificial and Convolutional Neural Networks, have also been shown to have high accuracy in predicting interstorey drift and optimizing the shear wall design of tall buildings. Machine learning is predominantly used for predictive modeling to estimate building response to different loading conditions, pattern recognition to identify failure modes in structures, and optimization automation to enhance the iterative design process in balancing cost, safety, and efficiency.

Chapter 3 Image-Based Surrogate Model for Predicting Wind-Induced Interstorey Drift of Tall Buildings

3.1 Background

The demand for tall buildings has steadily increased over the past century, and society stands at a point where adaptation to modern cities consisting of densely built-up areas is well underway. In Canada, data from the Canadian Mortgage and Housing Corporation (CMHC) depicts this trend nationwide, as the composition of new residential housing has been dominated by apartment-style, multi-unit urban starts since approximately 2011 (Canada Mortgage and Housing Corporation (CMHC)). The growing importance of climate change, sustainable development, and building efficiency initiatives further exacerbate the high-level pressure on the housing economy. This has manifested in policy-driven intervention incentivizing tall buildings as suitable solutions to urban development. In Ontario, for example, the Growth Plan for the Greater Golden Horseshoe delineates acceptable urban growth boundaries. It requires a minimum target for infill development within existing limits to promote population density and mitigate urban sprawl (2020). Hence, as sustained demand for tall buildings is likely in the foreseeable future, an opportunity exists to consider improvements to their implementation.

3.1.1 Review of current optimization approaches

Although engineers typically understand the trade-offs of design variables used to inform decisions, the complexity in considering many of the convoluting effects present during a tall building's project life cycle highlights the need to perform precise evaluations in pursuing their efficient implementation. This represents significant engineering challenges, and one can see that implementing even a single *optimized* tall building project is convoluted, much less designing them *en masse* to satisfy incoming housing demand, demonstrating the need to consider versatile and adaptive methods. (Aldwaik and Adeli 2014) describe existing research as applying to practical, code-based provisions or academic-based applications not tailored to industry. Recent examples of advanced analysis of supertall structures are best described as having complex structural systems (He et al. 2022; Xu and Zhao 2020). In these cases, the National Building Code of Canada (NBCC) does not have comprehensive guidelines for considering the design and review of these structures. Although there is no consensus among the broader society about what exactly constitutes a tall building, there are more explicit considerations from an engineering perspective. The slenderness of tall buildings – described as the ratio of building height to minimum width – is a categorical evaluation of dynamic sensitivity outlined in the NBCC (NRCC 2022). What is unique about tall buildings is the presence of significant lateral loads, namely wind and seismic loads, and their impact on dynamically sensitive structures.

Performance-based design (PBD) has been growing in popularity over recent decades and signals divergence from an Ultimate Limit State (ULS)-dependent approach seen in the NBCC. While no PBD guidelines exist in Canada, the American Society of Civil Engineers (ASCE) first published performance-based seismic design guidelines (American Society of Civil Engineers 2017) in the early 2000s, and the Prestandard for Performance-Based Wind Design (PBWD) in 2019 (American Society of Civil Engineers 2019). The PBWD guideline enables dynamic analysis of tall buildings and redefines design acceptance criteria to improve building envelope performance (American Society of Civil Engineers 2019). While the benefits of these prerogatives advocate for themselves, developing new guidelines is a lengthy process, requiring long vetting periods before widespread adoption can occur. These examples describe a more systemic approach to achieving tangible improvements in building design, requiring the direction and efforts of the entire engineering community. In the meantime, there is an opportunity to consider further improvements to building design at the scale of individual engineers through advanced structural optimization.

3.1.2 Machine learning in structural engineering

Machine Learning (ML) and corresponding Artificial Intelligence (AI) sub-fields enable such advanced analysis. A significant advancement in ML is the development of Deep Learning (DL) models, which are responsible for greatly expanding model capabilities. These algorithms are often used as surrogate models to create generalized relationships between inputs and outputs with limited sample points, to interpret and understand complex design relationships, to handle stochastic and noisy data, and to improve computational efficiency (Forrester et al. 2008). The capabilities of DL-based surrogate models represent an opportunity for engineers to narrow the gap between engineering judgment and advanced analysis.

A recent review in the AI/civil engineering field echoes the current sentiment of the greater AI community and describes the landscape of AI within the civil engineering community (Wang et al. 2023a). The review categorizes various research applications that utilize ML algorithms for static and dynamic feature studies, many of which can be considered DL models. Over the past decades, many algorithms have consisted of input-output relationships of exclusively numerical engineering parameters. However, widely commercially available Graphics Processing Units (GPUs) significantly increase available computing power, specifically in matrix operations (i.e., images), and have also enabled researchers to explore increasingly advanced DL algorithms. (Pizarro et al. 2021) proposed Convolutional Neural Networks (CNNs) to generate reinforced concrete shear wall layouts from architectural drawings based on engineers' designs. (Zhao et al. 2022) proposed a Generative Adversarial Network (GAN) to achieve a similar task. Research conducted by (Wang et al. 2022) represents the ability of DL models to conduct increasingly comprehensive engineering tasks. These algorithms strongly motivate using ML in future research within structural optimization.

However, algorithms containing architectural and structural drawings as the main features effectively apply pattern recognition between architects and engineers. While this is certainly a philosophically exciting topic to consider, fundamental challenges to the approach may limit its adoption by industry. First, being a data-driven approach, the databases used to train these models often consist of limited samples of building designs. Without a well-documented benchmark database relating architectural designs to structural designs, there remains some ambiguity between the quality and limitations of the dataset, any models produced from them, and how to adapt the approach for other applications. Additionally, without directly relating the DL model to any physics-based structural engineering metrics, such as Finite Element Analysis (FEA) data, the model relies entirely on an implicit understanding of drawings. As it is difficult to explicitly evaluate the impacts of applying pattern recognition on engineers' designs, it is equally challenging to evaluate the benefit of the geometric patterns learned by a model used across the entire design domain. While these models may still be able to guide designers to high-quality solutions, there remains an opportunity to consider how image-based DL models can be used to simulate numerical performance metrics directly. ML algorithms can be used as powerful surrogate models in place of FEA and Computational Fluid Dynamics (CFD) software. Our emphasis on the potential use of DL algorithms as surrogate models is not solely to describe computational efficiency for its own sake but to highlight that these methods allow for both computational and time constraints to be focused on DSE as opposed to conducting individual design simulations.

3.1.3 Structural optimization via surrogate modelling

A convenient metric to evaluate appropriate surrogate models is to consider the degree of complexity and dimensionality between the design variables when assessing the performance of various ML algorithms used in engineering (Kianifar and Campean 2020). Dimensionality is concerned with the quantity of design parameters and data relevant to the problem, and complexity is concerned with the degree of non-linearity in data transformation between the input and output relationship. While classical ML algorithms exhibit limited capabilities in representing datasets of high dimensionality and high complexity, DL algorithms are popular for their superior performance in these areas. Being a data-driven approach, it is essential to understand the significance of the underlying dataset before developing an algorithm capable of replicating it. In structural engineering, these factors include hazard characterization, structural analysis, and optimization techniques. To elaborate on the nature of the dimensionality and complexity of datasets in the context of tall building design requires an intricate understanding of their fundamental design principles. The effect of dynamic sensitivity to external stimuli such as wind load, which is the load type discussed exclusively herein, requires engineers to evaluate the natural vibration modes of structures to determine which frequencies of cyclical motion (building sway) are susceptible to resonance (Braun and Awruch 2009). To quantify and, therefore, assess these impacts, Computational Fluid Dynamics (CFD), when verified through wind tunnel testing, is a suitable physics-based approach. Advancements in Large Eddy Simulation (LES) research showcase the increasing capability of accurately simulating wind pressure experienced by buildings (Braun and Awruch 2009). When combined with an inflow generation technique such as consistent discrete random flow generation (CDRFG) to introduce an element of stochasticity, high-quality dynamic wind load time histories can be simulated (Aboshosha et al. 2015). This information can then inform linear dynamic structural analysis using Finite Element Analysis (FEA).

Elshaer et al. provide a succinct outline for approaching tall buildings' aerodynamic optimization (Elshaer et al. 2017; Elshaer and Bitsuamlak 2018). The aerodynamic effects impacting bluff bodies can be mitigated through two broader categories: local optimization and global optimization techniques. For example, a reduction in wind pressure coefficient, and therefore wind load transferred to the structure, can be found locally through modifications to the building corners and globally by twisting or otherwise minimizing the surface area exposure to a given wind direction. On the other hand, structural optimization can be thought of in three broader tasks – size, shape, and topology optimization – to improve the efficiency or utilization of structural members (Aldwaik and Adeli 2014; Zavala et al. 2014). While the first two types are self-explanatory, topology optimization is concerned with the distribution of structural materials to provide efficient design. DSE can consider any combination of these approaches, project constraints, and multi-objective optimization criteria to represent increasingly comprehensive attempts to deliver high-quality solutions. Altogether, as more advanced analyses are considered, the dimensionality and complexity of future problems are expected to increase proportionately. Datasets resulting from this analysis method represent high-dimensional and highly complex relationships that classical ML algorithms have difficulty representing.

This study identifies the Convolutional Neural Network (CNN) as a widely studied DL model that continues to prove its versatility in accurately representing data relationships of various types, including both numerical and image-based data. Its architecture can be customized for various tasks, including regression, classification, object identification, and semantic segmentation. It can handle time-dependent tasks, such as sequence-to-sequence and recurrent network architectures (Goodfellow et al. 2016). The powerful capabilities of CNNs are mainly due to the mechanisms inherent in their design, including sparse interactions, parameter sharing, and equivariant representations (Goodfellow et al. 2016). These properties highlight CNNs as having immense potential for engineers to use in tall building design. The quantity of unique ML algorithms reviewed by (Wang et al. 2023a) highlights that although algorithms can be grouped by similarity, no two applications and no two algorithms are precisely equivalent. This narrates the trend that exhaustively researching the ultimate algorithm is not only bound to reap diminishing returns but may become irrelevant so long as current models can sufficiently complete the task from a practical standpoint. A shift towards focusing on a robust DL architecture for many applications could greatly benefit the engineering community. However, a significant variance in local, regional, and national engineering practices poses another barrier, as DL may require data consisting of specific code-based analyses or construction materials to be practical. To overcome this, hyperparameter optimization can automatically tune DL architectures and allow similar models of diverse databases to be easily trained for various applications. The current state of CNNs, when subjected to a hyperparameter optimization algorithm, is suitable for broad use as surrogate models in the design of tall buildings.

3.1.4 Study outline

Convincing the greater engineering community to use AI-based algorithms represents a significant challenge, with the main concern being the difficulty in model interpretation (Wang et al. 2023a). This highlights the general difficulty in understanding how ML or DL algorithms operate and identifying and preventing their vulnerabilities for use in practice. Models based on implicit pattern recognition or with ‘end-to-end' capabilities often have significant barriers due to ambiguity or significant limitations. While ML algorithms are usually associated with a long list of limitations, developing large-scale models is also a key research direction to expand model applicability (Wang et al. 2023a). Currently, the trade-off between interpreting innovative DL algorithms versus the benefit of their often-limited applications represents a significant challenge in their uptake. The time investment required to comprehend an algorithm may not result in proportional value added. One way to address this is to develop models based purely on regression of input-output relationships.

Thus, the current study advocates towards using CNNs as a versatile DL algorithm capable of acting as a surrogate model for DSE and structural optimization. The proposed CNN is tested on the dataset published in (Alanani et al. 2024; Alanani and Elshaer 2024), consisting of 1000 tall building designs subjected to linear dynamic wind load analysis, corresponding to high dimensionality and complexity. An image-based approach, the proposed CNN is trained to directly represent the data relationships determined through the LES and linear dynamic structural analysis by predicting the interstorey drift of a tall building subjected to dynamic wind load. The resulting surrogate model is then exported for future use in multidisciplinary optimization. The study is subdivided into four sections. This section (Section 3.1) introduces structural optimization, ML, and image-based algorithms, providing context to their importance in the proposed work.

Subsequently, section 3.2 describes the processes utilized in developing the underlying dataset and the surrogate model developed. Section 3.3 provides an in-depth assessment of the training process and performance of the proposed CNN algorithm. Section 3.4 summarizes the findings of the CNN algorithm for unambiguous interpretation. The implications of the proposed research broadly enable the use of image-to-regression CNN surrogate models in designing tall buildings. Ultimately, the study aims to demonstrate the potential of CNNs for structural engineering when considering structural and multidisciplinary optimization.

3.2 Methodology

The problem at hand is to create an image-based surrogate model capable of accurately conducting regression of performance metrics. Showcasing the proposed algorithm's versatile capabilities requires elements of uncertainty, dimensionality, and complexity – as previously described in section 3.1 – to be present in the dataset. Developing a database with these features is an intricate task described throughout the following sections. The dataset used consists of 1000 samples of tall building designs subjected to a linear dynamic wind load analysis pursuant to the ASCE's PBWD. This is accomplished using CFD software Star-CCM+ 2020.2 (15.4.008-R8), FEA software ETABS V18.1.1, and MATLAB version 9.14.0.2489007 (R2023a) Update 6. The process employed in this study is shown in Figure 3.1 and forms the following sections. The 1000 samples of tall building designs are implemented by utilizing the ETABS Open Application Programming Interface (OAPI) from the MATLAB environment. Each of the 1000 designs are algorithmically generated into separate FEA models, which then conduct the analysis and record the desired analysis results. Further details of the permitted shear wall layouts, wind hazard characteristics, and structural analysis applied to these models are discussed below.

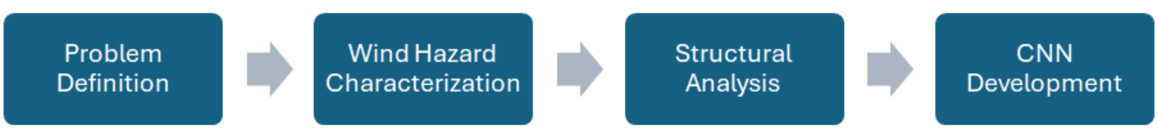

Figure 3.1 – Study flowchart

The building of interest is modelled after the CAARC structure, which is widely studied in wind engineering and aerodynamic sciences for its characteristic rectangular outer shape, as shown in Figure 3.2. Regarding this study, the structural system which accompanies this shape consists of reinforced concrete shear walls and stands at a total building height of 70 metres. The building surface exposed to wind remains constant across design cases to enable LES to characterize the dynamic wind load time histories for structural analysis. To enable the surrogate model to facilitate topology optimization, a discrete design domain consisting of 170 possible shear wall locations is identified in the plan shown in Figure 3.2. A Latin hypercube sampling (LHS) technique was employed to algorithmically generate the 1000 samples of shear wall layouts for use in FEA to form a subset of designs. The database is then processed for use in developing the proposed CNN, which relates topological shear wall layouts to peak interstorey drift in both X and Y cardinal directions as the input-output relationship. By training the proposed model on the results of CFD- and FEA-based analyses, the relationship between shear wall topology and interstorey drift can be directly simulated. The resulting CNN surrogate model is then evaluated for its accuracy in predicting interstorey drift, and its capabilities for use in structural optimization are highlighted.

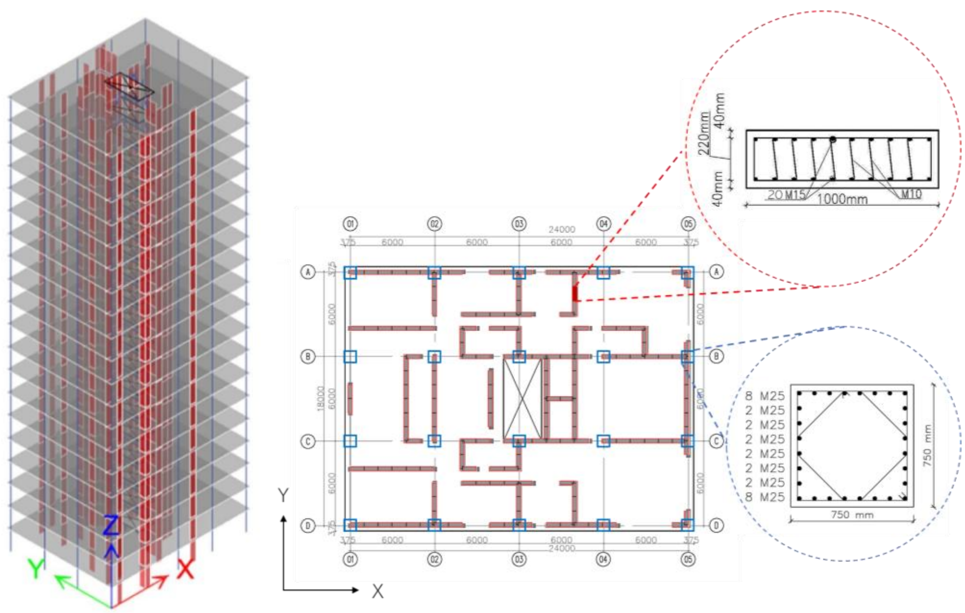

Figure 3.2 – Study building a) isometric view b) plan view with shear wall details (Alanani and Elshaer 2023)

3.2.1 Wind hazard characterization

The CAARC structure is well-known for wind load analysis, and research suggests that LES is becoming increasingly capable of closely simulating real-world wind hazards (Melbourne 1980). From a computational standpoint, using this method to generate wind load time histories provides sufficient fidelity for training the proposed DL algorithm. The CFD model used in this study is validated against experimental wind tunnel tests conducted by Monash University and the National Physics Laboratory (Melbourne 1980). To include an element of uncertainty present in characterizing wind load, the CDRFG technique proposed by (Aboshosha et al. 2015) is used to simulate real-world turbulent inflow. The remaining technical details pertinent to conducting LES are consistent with (Elshaer et al. 2016) and are described in further detail in the analysis performed in (Alanani and Elshaer 2024). As the current study relies on these LES results verbatim, the remaining emphasis is to explain how the analysis informs FEA. By relying on the time-dependent wind pressure coefficient experienced by the structure during the LES, the wind load time history related to each storey is determined through the force integration method. This is applied to the structure at every storey, and under various wind angles of attack to determine a comprehensive set of stochastic wind loads the structure is likely to endure. This process is visualized in Figure 3.3, which depicts the simulated mean wind flow field, mean pressure coefficient exerted on the building, and a resulting wind load time history. These time histories are then applied in FEA when conducting structural analysis, as described in the following section.

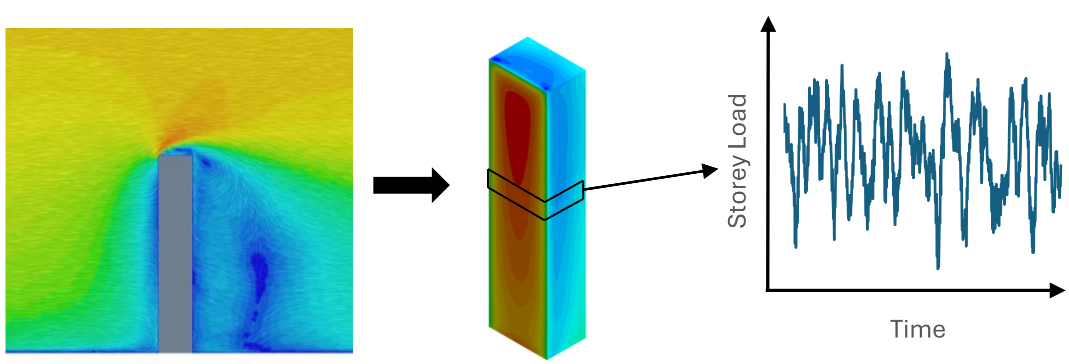

Figure 3.3 – Conceptual visualization of wind hazard characterization

3.2.2 Structural analysis & data generation

ETABS FEA software, through the open application programming interface (OAPI) and MATLAB, facilitates the structural analysis of the case study building. As the NBCC has limited applicability to the design of dynamically sensitive structures, the PBWD provisions provided by the ASCE are used to define acceptance criteria of the building designs used in the study. While a comprehensive list of acceptance criteria can be found in the PBWD guidelines, we identify that interstorey drift is a simplified metric sufficient to evaluate the generalization capability of the proposed CNN model in simulating a high degree of complexity. As described, the structures designed consist of reinforced concrete shear walls as the Main Wind Force Resisting System (MWFRS). The structures are 20-storeys tall with a storey height of 3.5 metres and consist of normal-strength concrete and reinforcing steel. Linear time history analysis is conducted on the structure using the wind load time history results from LES, as described in section 3.2.1. The shear wall domain in Figure 3.2 identifies all possible locations of shear wall elements used in the study. A visual representation of the structural analysis process can be seen in Figure 3.4, where the output results in 1000 samples of the peak interstorey drift expected by the structure.

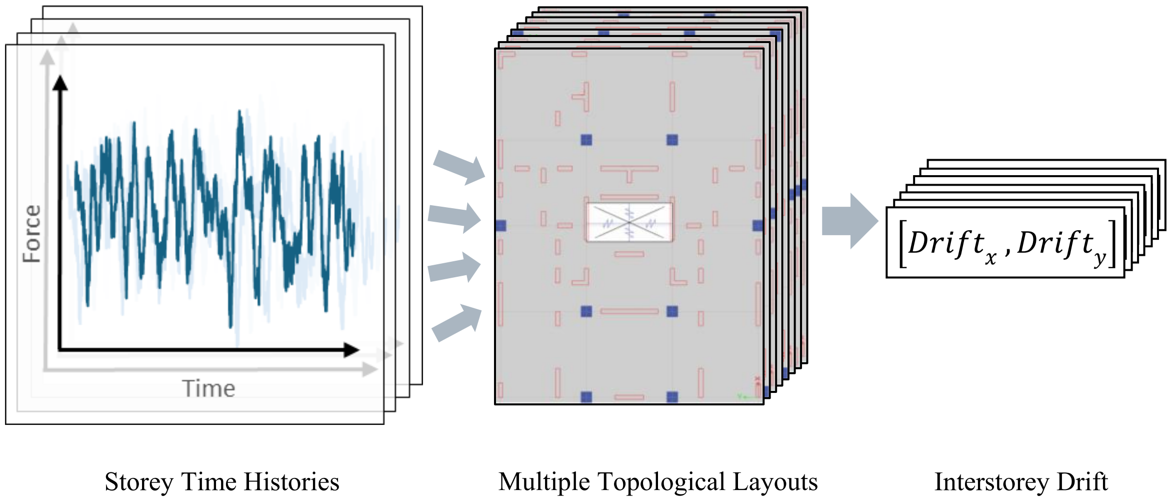

Figure 3.4 – Conceptual visualization of linear dynamic structural analysis

3.2.3 CNN surrogate model

With a well-defined database relating shear wall layouts to peak interstorey drift, what remains is the development of the CNN surrogate model. Figure 3.5 depicts the surrogate model methodology used in the study, explained in full detail below. Starting from the database already described, necessary data preprocessing is performed. Then, the CNN model parameters are defined, along with model performance metrics and a Bayesian hyperparameter optimization algorithm. Upon completion of the hyperparameter optimization, the best-performing model is evaluated for its generalization capacity in the discussion and results section.

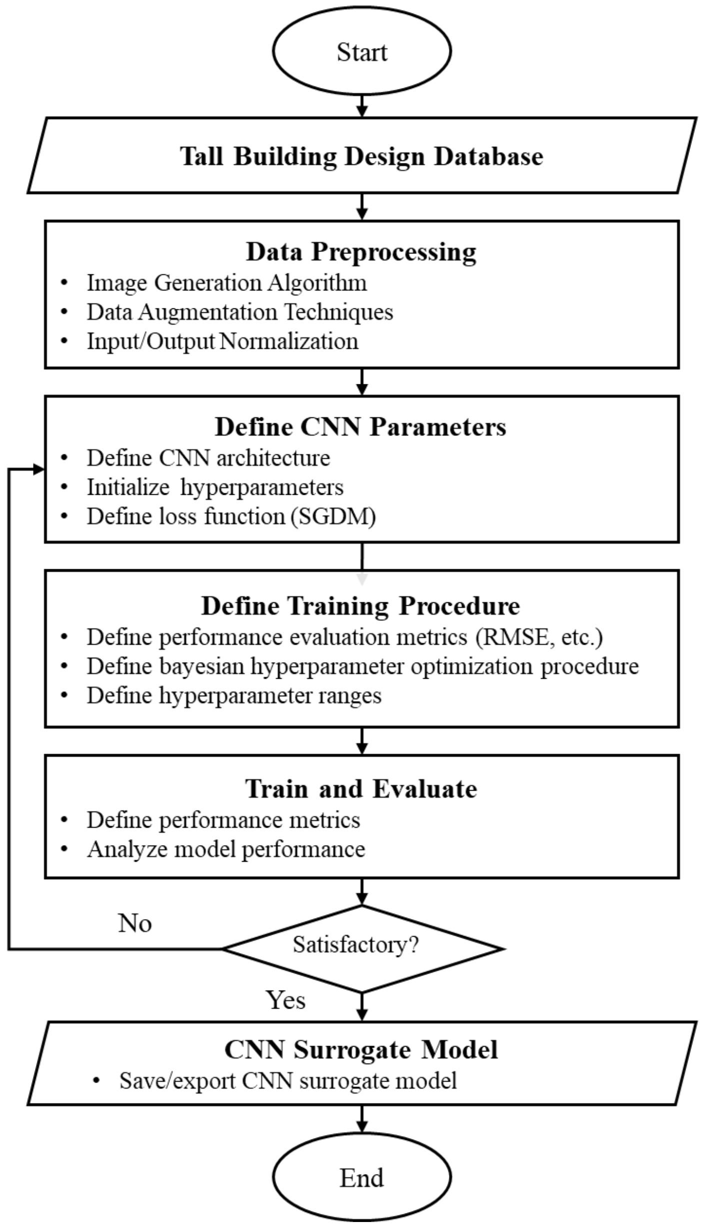

Figure 3.5 – CNN development workflow utilized in the study

Three primary considerations are afforded to the preprocessing of the data. Firstly, an image generation algorithm is developed to create a low-resolution image of the structural shear wall layouts for computational efficiency. Secondly, the transformation of the numerical information in the dataset using normalization is considered. Lastly, data augmentation measures are considered to expand the sample size available for training. Creating custom images, as opposed to images generated by the FEA software, is to control the resolution of images to appropriately represent structural shear wall layouts without resulting in unnecessary computational demand. A MATLAB code was developed to read the coordinates of possible shear wall segments shown in the shear wall domain in Figure 3.2. The images have been generated using the minimum feasible resolution that preserves the aspect ratio of the actual size of the shear wall segments. In other words, a practical scale of one pixel, equivalent to 100 mm, was considered to represent the shear wall layouts. This corresponds to images of 185 x 245 pixels and overall design dimensions of 18.5 m by 24.5 m, of which the shear wall domain is presented in Figure 3.6.

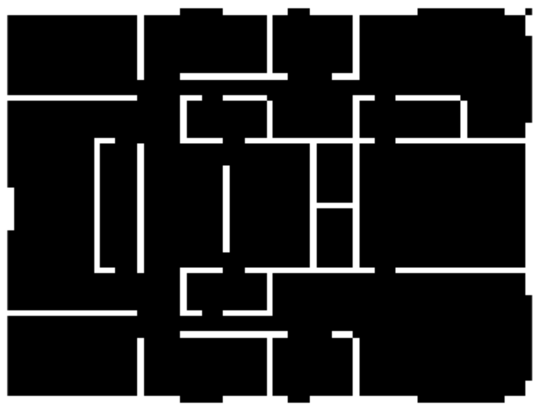

Figure 3.6 – Shear wall domain shown as custom-generated low-resolution input image

The dataset was deemed suitable for data augmentation by mirroring input images in both X- and Y- axes to quadruple the sample size and assist with the DL algorithm's convergence. Augmentation such as this trains the algorithm to accept several input solutions and is a technique that has been used similarly in (Zhao et al. 2022). An example of the data augmentation utilized is shown below in Figure 3.7. Normalization is also considered in the preprocessing of the data. During image generation, a black/white format is used where image cells contain values of 0 or 1. Thus, applying normalization to the input data is not considered. Regarding output data, the peak interstorey drift values are commonly of magnitude E10-3 metres, and the loss minimization function is expected to encounter difficulties due to the exploding gradient problem. Therefore, z-score normalization is used to perform statistical transformation to the output data to convert the drifts to standard deviations from the mean to benefit the training process of the CNN algorithm. After successful training, results from the surrogate model can be converted back to the original number format.

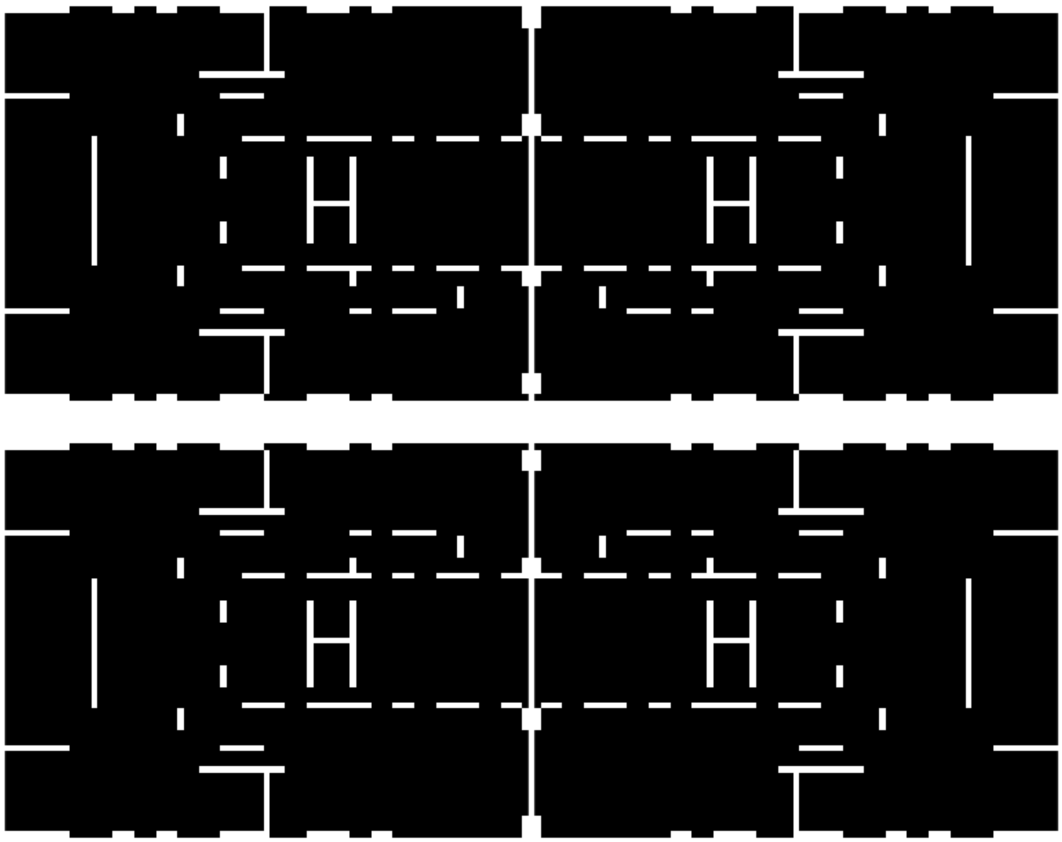

Figure 3.7 – Example of applied dataset augmentation on input images

The convolution neural network's design is based on attaining high-level pattern recognition by passing input information through several convolutional and pooling layers, followed by a rectified linear activation function (ReLU), dropout, and numerical regression layer. The convolutional layers follow a down-sampling and 'pyramid' approach. The image undergoes convolutional and pooling operations in repeated sequences to reduce image size while increasing the number of output channels to assist with the ability to conduct high-level pattern recognition. The architecture utilized in the study can be seen in Figure 3.8, below. A comprehensive list of hyperparameters considered in the development of the CNN is provided in Table 3.1. The final architecture is determined through Bayesian hyperparameter optimization, facilitated by predeveloped code in MATLAB's Deep Learning Toolbox. The hyperparameter optimization variables are identified in Table 3.1 and are chosen based on the results from a preliminary study published in the 2024 Annual CSCE conference (Vasilopoulos et al. 2024), where manual hyperparameter tuning was conducted.

Table 3.1 – Bayesian hyperparameter optimization variables

Hyperparameter	**Considered Values**	**Final Value(s)**
Sample Segmentation *[Training,* *Validation,* *Test]*	$[70-80\%$, $10-20\%$, $10-20\%]$	$[80\%$, 10%, $10\%]$
Number of Conv. Layers *Filter Size* *Stride* *Padding* *Channels*	$1-6$ kernel sizes $3-6$ 1 1, value of 0 8,16,32,64,128,256	6 kernel size 4 1 1,value of 0 8,16,32,64,128,256
Number of Pooling Layers *Type of Pooling Layer* *Filter Size* *Stride* *Padding*	*Equal to # of conv.* *Average, Max pooling* *2* *2* *none*	*Equal to # of conv.* *Max pooling* *2* *2* *none*
Dropout Layer	$5-50\%$	40.397%
Loss Function *Learning rate approach* *Initial learning rate* *Drop factor* *Drop period* *Shuffling of Datasets* *Minibatch Size* *Validation frequency* *Maximum Epochs*	*SGD w/ Momentum* *Piecewise* $1e^{-5}$- $1e^{-2}$ *0.1* *67% of epoch* *Shuffling at every epoch* *32-80* *twice per epoch* *25-60*	*SGD w/ Momentum* *Piecewise* $9.6398e^{-3}$ *0.1* *67% of epoch* *Shuffling at every epoch* *50* *twice per epoch* *60*

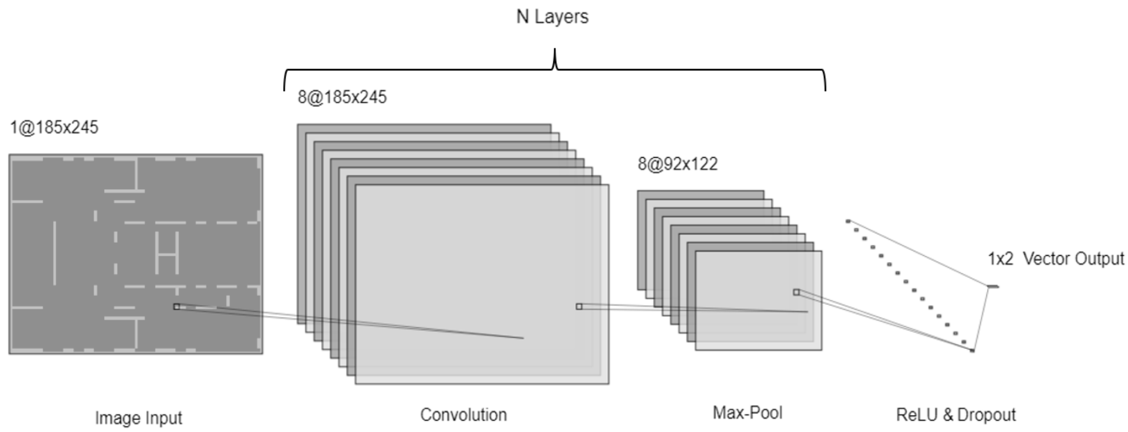

Figure 3.8 – Proposed CNN architecture

The loss minimization function employed in the CNN training procedure is stochastic gradient descent with momentum (SGDM). Chosen for its ability to handle uncertainty and noise and avoid local minima in optimization, this function pairs well with the nature of stochastic wind load present in the underlying dataset. Eq. (1) defines SGDM, with the loss function equivalent to standard error between the predicted value of the CNN algorithm and the 'true' value as determined by the underlying dataset shown in Eq. (2). Evaluation of the model through numerical performance metrics includes the use of root-mean-squared error (RMSE), mean absolute error (MAE), and Pearson Correlation Coefficient (R), as defined in Eq. (3), Eq. (4), Eq. (5), and Eq. (6), below.

$$w_{i+1} = w_i - v_{i+1} = w_i - \gamma v_i + \eta \nabla L(w_i) \qquad \text{Eq. (1)}$$

Where w_i are model weights, v_i is the velocity term, γ is the momentum term, η is the learning rate, and $\nabla L(w_i)$ is defined in Eq. (2), below.

$$error = \nabla L(w_i) = Drift_{Predicted} - Drift_{True} \qquad \text{Eq. (2)}$$

Where Drift predicted is the interstorey drift of the CNN surrogate model and Drift true is the interstorey drift from the database

$$\%error = \frac{Drift_{Predicted} - Drift_{True}}{Drift_{True}} \times 100 \qquad \text{Eq. (3)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} error^2}{N}} \qquad \text{Eq. (4)}$$

Where N is the total number of samples

$$MAE = \sum_{i=1}^{N} |error| \quad \text{Eq. (5)}$$

$$R = \frac{\sum\left(Drift_{Predicted,i} - \overline{Drift_{Predicted}}\right)\left(Drift_{True,i} - \overline{Drift_{True}}\right)}{\sqrt{\sum\left(Drift_{Predicted,i} - \overline{Drift_{Predicted}}\right)^2 \sum\left(Drift_{True,i} - \overline{Drift_{True}}\right)^2}} \quad \text{Eq. (6)}$$

3.3 Results & Discussion

The Bayesian hyperparameter optimization algorithm identified a high-performing solution for the proposed CNN architecture. The resulting model architecture is shown in Figure 3.9, below. A training progress plot depicting the model convergence is shown in Figure 3.9, which monitors RMSE through each training iteration. The plot shows satisfactory convergence without significant adverse effects such as overfitting, underfitting, or memory. A summary of the model's performance on the training, validation, and test datasets is provided in Table 3.2, and a very high-quality data replication using the proposed surrogate model is narrated.

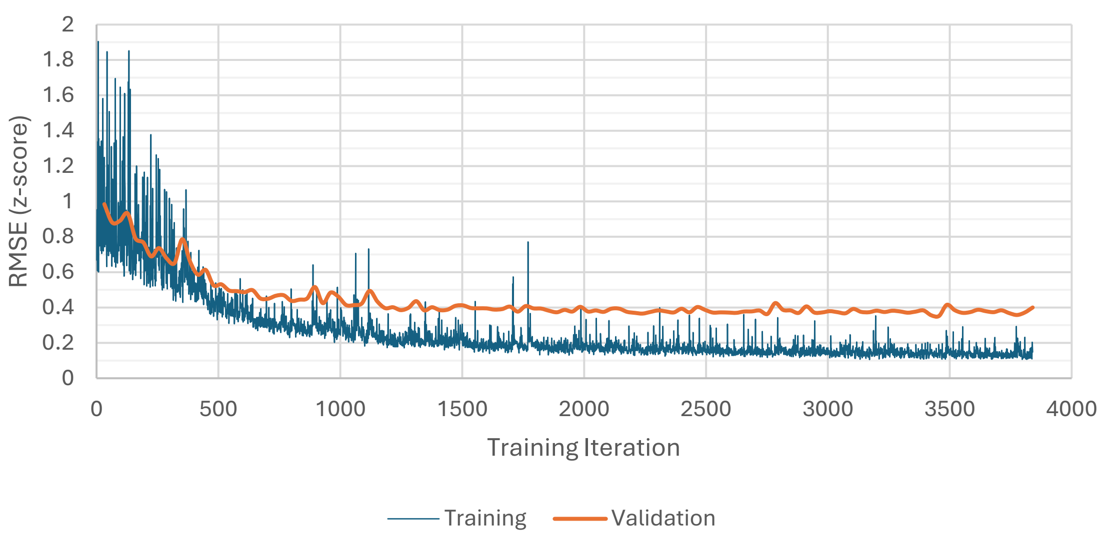

Figure 3.9 – Training progress plot

Figure 3.10, Figure 3.11, and Figure 3.12 plot the linear regression between the predicted and true values of the training, validation, and test datasets, respectively, and show strong agreement in the performance and generalization capabilities of the trained CNN algorithm. Each linear regression plot shows the broad trend of the surrogate model to slightly underestimate the 'true' interstorey drift. The corresponding error histograms show that the error distribution is central to zero, and in the test dataset, 62.38% of samples are contained within +/- 10% of the 'true' value. Additionally, 91.00% of samples are contained within +/- 20% of the 'true' value, and as this dataset was designed with PBWD criteria, using the proposed surrogate model for designs below the peak permissible interstorey drift remains accurate. Lastly, the RMSE and MAE values across the entire dataset remain substantially below the mean value of the output dataset (seen as the mean peak interstorey drift in Table 3.2, equal to 1.712E-03 m), and further indicates the high-quality performance of the surrogate mode.

Table 3.2 – CNN Model Performance Summary

	Training Data	**Validation Data**	**Test Data**
Sample Size	3200	400	400
R	0.9973	0.9627	0.9583
R^2	0.9946	0.9268	0.9184
RMSE (m)	7.865E-05	2.639E-04	3.150E-04
MAE (m)	5.284E-05	1.677E-04	1.807E-04
Tall Building Database Summary			
Total Design Samples		4000	
Mean of Peak Interstorey Drift		1.712E-03 m	
Standard Deviation of Peak Interstorey Drift		6.653E-04 m	

The data used to train this surrogate model is divided into training, validation, and test subsets. 80% of data are reserved for the training dataset which is directly provided to the algorithm during the adjustments of weights and biases. 10% of the data is used for the validation subset, which is used by the Bayesian hyperparameter algorithm to evaluate the performance of the model during hyperparameter tuning. Finally, after the final state of the model has been determined, 10% of the data is reserved as the test subset, which assesses the model's overall performance and validates its ability to replicate unseen design scenarios. With a test-set regression value R of 0.9583, this image-based surrogate model outperforms the numerical regression algorithm proposed in (Alanani and Elshaer 2024). While the performance of both algorithms boasts impressive capabilities, the current CNN surrogate model features several key advantages. The proposed CNN conducts simultaneous regression of interstorey drift in both X- and Y- directions, whereas the former research requires separately trained instances. More importantly, using structural layout images poses significant benefits and allows for a more natural interpretation of the corresponding outputs during model use. The CNN has, in essence, been trained to directly represent the spatial impacts of shear wall topology. As discussed in the introduction, models containing vectored numerical inputs are inherently incapable of direct spatial representation, and they employ methods such as genome identifiers to represent unique layouts. Additionally, recent image-based research contains images as both input and output with no exposure to physics-based data from CFD or FEA during the training process. Therefore, this is a feature that is not well-studied as it pertains to algorithms capable of directly correlating spatial distribution to structural design performance. These results reveal that CNNs are a strong candidate in being a surrogate model for use in structural and multidisciplinary optimization.

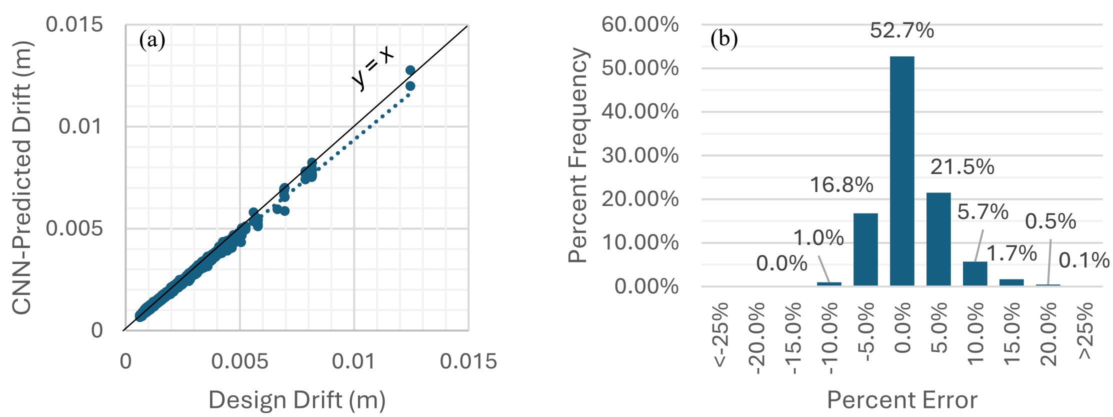

Figure 3.10 – Training data results a) linear regression b) error histogram

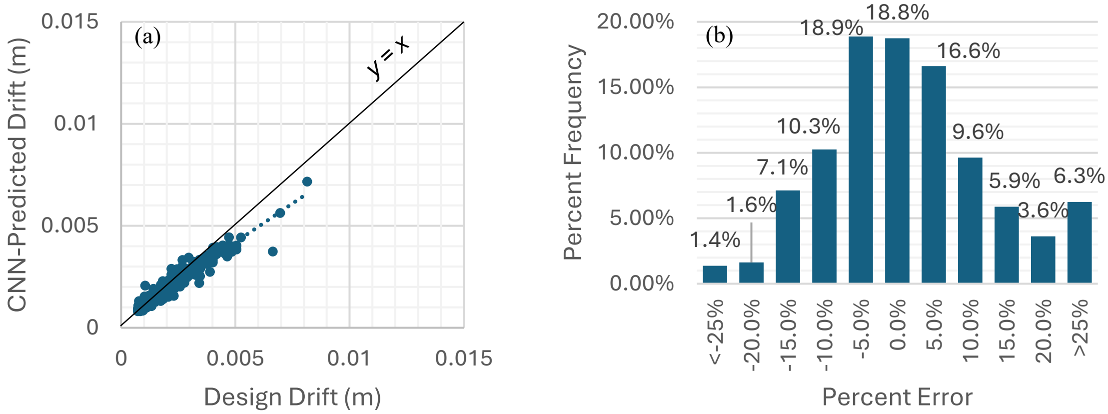

Figure 3.11 – Validation data results a) linear regression b) error histogram

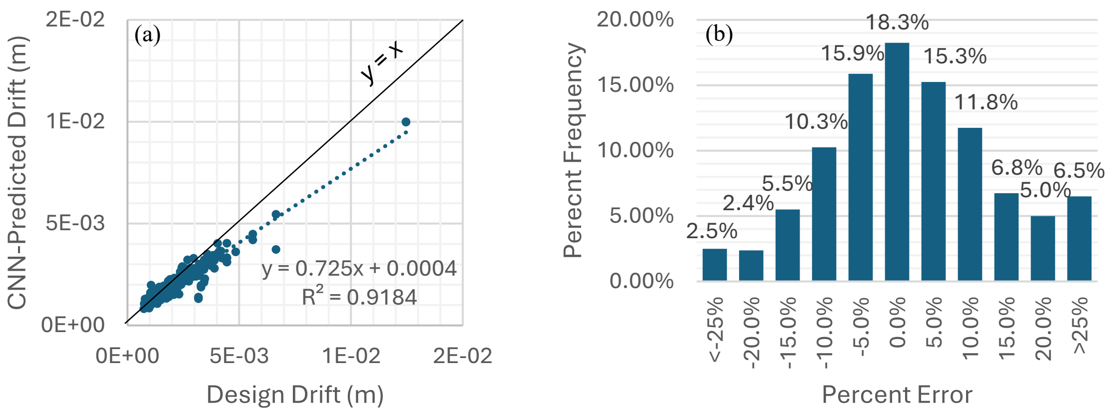

Figure 3.12 – Test data results a) linear regression b) error histogram

The resulting CNN has subsequently been exported as a surrogate model in tall buildings' structural and multidisciplinary optimization. Formatted for compatibility with the non-dominated sorting genetic algorithm as used in (Alanani and Elshaer 2024), the CNN model is ready for further use in considering multidisciplinary constraints, enabling structural topology optimization, and overcoming existing limitations. The model affords greater capabilities to physical interpretation by directly using images, as well as towards large-scale modelling practices by being able to accept a wider range of unique design inputs. We maintain that CNNs pose substantial benefits to the development of powerful computational tools in engineering and that by including hyperparameter optimization in their development, they can be applied in a vast range of engineering applications. Future research using this method may strengthen this notion and empower engineers to conduct DSE and provide high-quality engineering judgement decisions.

3.4 Summary

This research assesses the capability of a CNN surrogate model at predicting the interstorey drift of a 70-metre-tall case study on a bluff body building under linear dynamic wind load analysis. The purpose of the case study is to determine to what degree an image-based DL model can directly simulate building performance metrics through regression. To accomplish this, a dataset consisting of 1000 tall building designs were algorithmically generated. The developed CNN algorithm was trained using a Bayesian hyperparameter optimization algorithm and yielded a high-performing model. Namely, the results of the testing sample data consist of RMSE = 3.150E-04 m, R = 0.9583, MAE = 1.807E-04 m. Additionally, 62.38% and 91.00% of test samples consisted of a percentage error less than +/-10% and +/-20%, respectively. The performance of the model describes the ability of CNNs to simulate the data relationship with a high degree of accuracy while overcoming existing limitations of similar approaches. This work narrates the high potential of CNN-based surrogate models in the design of tall buildings, especially when proposed for structural optimization. Further implementation of image-based algorithms poses the benefit of acting as a powerful and versatile computational tool in DSE ahead of rapidly evolving urban environments and demand in tall buildings.

Chapter 4 Multi-Objective Optimization of Tall Buildings Subject to Wind Load via Genetic Algorithm and Image-Based Surrogate Modelling

4.1 Background

As architectural and engineering design trends towards taller structures with additional dwelling units, an opportunity exists to improve structural efficiency while addressing interdisciplinary constraints. The complexity of designing these structures stems from the need to satisfy both code-based ultimate limit state (ULS) and performance-based criteria (Abdelwahab et al. 2023). Added to these technical challenges are sustainability and socioeconomic considerations, which further shape the evolution of urban architecture. Finally, interdisciplinary impacts due to architectural, mechanical, and electrical requirements often impose on the design of structural systems (Qu et al. 2021). Thus, holistically considering these competing factors quickly becomes a convoluted and potentially computationally cumbersome endeavour.

Recent studies regarding AI in civil engineering have demonstrated the vast potential of deep learning for various structural applications (Sun et al. 2021; Wang et al. 2023a). Of note is the diffusion of image-based algorithms through various research fields. With increasing accessibility to Graphics Processing Units (GPUs), the feasibility of studying image-based algorithms has become more widely available. While many deep learning models feature impressive image processing capabilities, existing structural optimization methods tend to be more focused on a limited quantity of numerical engineering metrics. The performance of RC concrete shear walls has been the topic of several ML-based approaches (Aladsani 2022; Keshtegar et al. 2021; Solorzano and Plevris 2023). Many of which focus more specifically on applications under seismic loading (Atabay 2009; Banerjee et al. 2023; Cerè et al. 2022; Chou et al. 2022; Lou et al. 2021; Mangalathu et al. 2020; Zakian and Kaveh 2020; Zhang et al. 2022). The topology optimization of tall buildings subjected to wind load has been approached in different ways, including (Alanani et al. 2024; Bobby et al. 2014; Fu et al. 2018; Gomez et al. 2021; Lu et al. 2019; Zhang and Mueller 2017).

As advancements in deep learning and generative AI, recent research directions have begun to consider increasingly comprehensive methods, including image-based approaches (Feng et al. 2023; Liao et al. 2024; Pizarro et al. 2021; Pizarro and Massone 2021; Zhao et al. 2022, 2023). However, these complex algorithms are not unique to structural engineering. (Akinosho et al. 2020; Brown and Elshaer 2022; Ko et al. 2023; Mavrokapnidis et al. 2019; Weber et al. 2022; Yang et al. 2023) are ideal examples of upcoming imperatives of various disciplines. Impressive advancements in analytical capabilities being developed in many research fields leave engineers with the insurmountable task of attempting to accommodate all forms of advanced analysis. Thus, shifting towards the use of surrogate models provides a vessel for engineers to rapidly evaluate design scenarios corresponding to parameters identified from adjacent disciplines. The capabilities of surrogate models in facilitating engineering analysis is further discussed in (Brown et al. 2024; Elshaer et al. 2017; Elshaer and Bitsuamlak 2018; Forrester and Keane 2009; Kianifar and Campean 2020; Westermann and Evins 2019). What remains to be studied is the use of surrogate models for increasingly abstract relationships, including relating image-based inputs to structural engineering analysis results. Developing surrogate models capable of accurately correlating abstract relationships would enable engineers to better accommodate interdisciplinary, socioeconomic and sustainability factors during design.

Previous work by Alanani et al. has developed a framework for applying surrogate modeling in structural analysis, demonstrating its effectiveness in predicting structural responses to dynamic wind load analysis. However, these prior studies have primarily focused on shear wall topology optimization and do not incorporate variations in shear wall thickness – a critical parameter influencing structural performance (Alanani et al. 2024; Alanani and Elshaer 2023). This limitation highlights the need for an approach that captures both the spatial distribution and material properties of shear walls with an additional opportunity to incorporate it into an image-based framework.

This study proposes a novel image-based surrogate model approach to representing structural lateral force resisting systems (LFRS), with a primary focus on the design of reinforced concrete shear walls to resist wind loads – a dominant lateral force under NBCC-compliant design. By simultaneously optimizing shear wall topology and size, this study aims to overcome past limitations that consider these factors separately. The use of images facilitates direct spatial representation in the surrogate model, enhances user interpretability, and enables countless design possibilities. A domain mask is applied to the structure domain to identify probable shear wall locations, thereby incorporating interdisciplinary constraints and maintaining computational feasibility. These models then act as the computational engine behind a genetic algorithm configured to assess several optimization problems to demonstrate the versatility of the proposed framework at evaluating complex design trade-offs. The framework is split into four sections. Section 4.1 – this section – provides context to the potential use of the developed algorithms, and the following sections: section 4.2 – methodology, section 4.3 – results and discussion, and section 4.4 – summary, forms the remainder of the study. The proposed method serves to enable rapid design evaluation, proposes a novel image-based approach, and holds potential for industry application by quantifying complex interdisciplinary design trade-offs.

4.2 Methodology

The current study aims to address the multi-objective optimization of a tall building subjected to interdisciplinary constraints. By enabling rapid assessment of complex design spaces subjected to arbitrary domain masks, the development of this tool permits quantification of any combination of shear wall size and topology, allowing for optimal solutions to be discovered while satisfying interdisciplinary constraints such as architectural, mechanical, electrical spatial limitations. Consequently, four methodology stages have been identified in Figure 4.1 to provide context to the framework utilized: definition of the problem scope, the use of machine learning as a surrogate model to facilitate both the generalization of the design space and rapid prediction of design results, a multi-objective optimization module utilizing a non-dominated genetic algorithm, and lastly, the summary and interpretation of results including design trade-offs of corresponding optimization problems. This work has been completed with the use of FEA software ETABS V22.1.1 (Computers and Structures, Inc. 2022), and MATLAB version 9.14.0.2489007 (R2023a) Update 6 (The Mathworks, Inc. 2023). A MATLAB code has been developed to automate FEA using ETABS OAPI Version 1, as required at several points identified in the methodology, and in keeping all working information within the MATLAB environment. The study methodology provided in Figure 4.2 provides a detailed description of the overarching processes utilized in the work. These stages correspond to the following sections: section 4.2.1 Defining Problem Scope, 4.2.2 Machine Learning Module, section 4.2.3 Genetic Algorithm Optimization, and section 4.3 Results and Discussion. This figure outlines the linear path required to replicate the analysis conducted within this study.

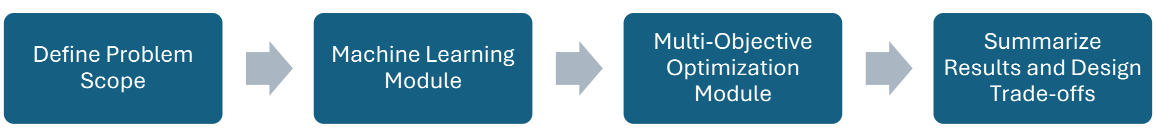

Figure 4.1 – Core optimization framework stages

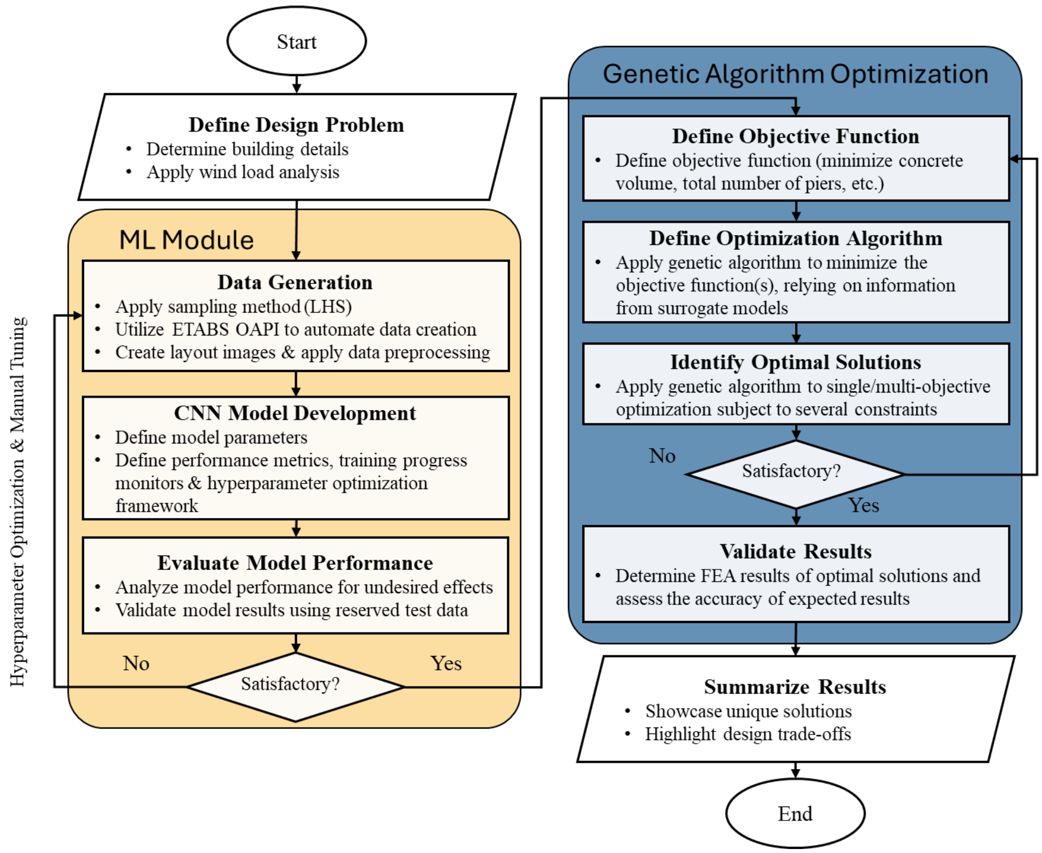

Figure 4.2 – Image-based optimization framework

4.2.1 Defining Problem Scope

The first stage of the framework is to determine the problem scope. The design problem posed in the study conducts simultaneous shear wall topology and size optimization on a 70-metre-tall building with a rectangular floorplan, modelled after the Commonwealth Aeronautical Advisory Research Centre (CAARC) building, a commonly studied benchmark structure in resisting applied wind load (Melbourne 1980). With outside dimensions of 24.75 metres in length by 18.75 metres in width, the structure consists of 20 storeys at 3.5 metres in height. The building is subjected to wind load pursuant to the National Building Code of Canada (NBCC) dynamic wind load procedure (NRCC 2022). As the study pertains to the design and optimization of the Lateral Force Resisting System (LFRS), no design considerations for the optimization problem have been afforded to the design of slabs, substructure (basement levels), or components and cladding. However, these structural features are still considered for their role in providing structural stability, applied dead load, and rigid diaphragm action. The LFRS utilized in the design are reinforced concrete shear walls consisting of normal-strength concrete with a compressive strength of 35 MPa and reinforcing steel comprised of 400 MPa yield strength. The building features an example of an arbitrary architectural layout to discretize the shear wall topology into a computationally manageable domain. Additionally, to limit the variability of the shear wall size design domain, the structure has been grouped into three sections of stories with similar shear wall thickness. Figure 4.3, below, provides a visual representation of the design variables $DV_{171-173}$, which dictate the variable shear wall thickness used across all storeys of the structure. By discretizing the structure into these segments, we preserve the impact of considering shear wall size simultaneously to topology, while maintaining a realistic approach both in terms of computational demand and practical design.

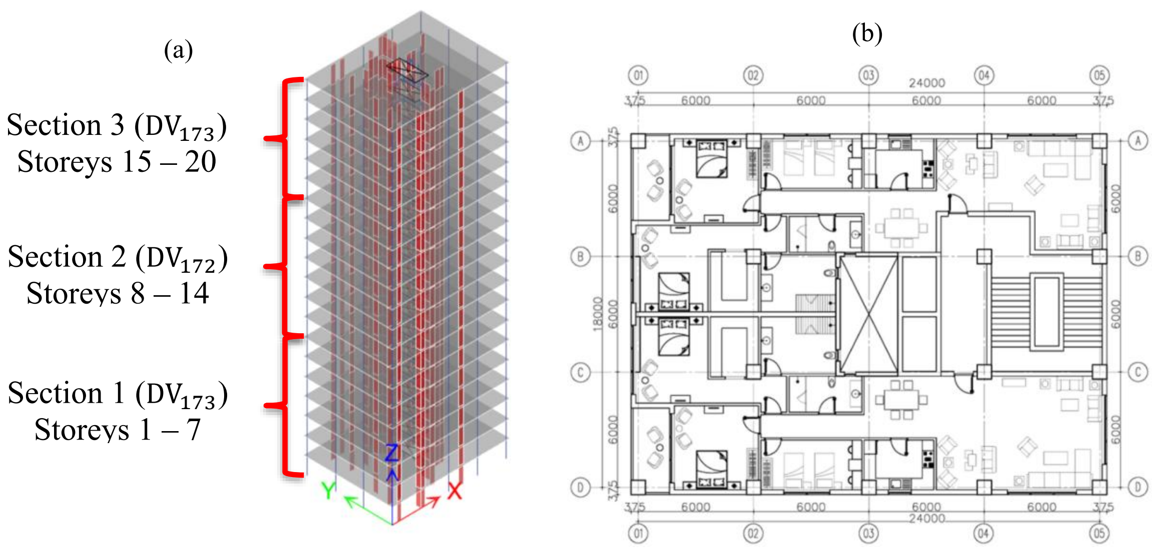

Figure 4.3 – Study building a) isometric conceptual view b) plan view with architectural details

While the study ultimately conducts shear wall topology and size optimization, several optimization problems are identified in Table 4.1 and are discussed further in section 4.3. The problems posed represent several important high-level design metrics, useful in finding ideal solutions in terms of underlying economic principles while satisfying structural and multidisciplinary considerations. The problems feature the minimization of volume of shear wall concrete, the total number of piers, and the torsional sensitivity of the structure (via modal mass participation factors). To simplify the determination of torsional sensitivity, and to provide a meaningful performance metric to be minimized, this work proposes the RII relationship, defined in Eq. (7). In this formula, RII is a measure of torsional sensitivity, and Γ_{zi} is the modal participation factor in the torsional direction for the i^{th} mode resulting from eigenvalue modal analysis in the first two modes of the structure. This is due to the common ideal design condition, requiring that torsional modes are not dominant in the first two vibration modes. The use of modal analysis in machine learning has been studied similarly (Shan et al. 2024).

Several constraints are used to satisfy design criteria including an interstorey drift limit of 0.2% as per the NBCC, geometric compatibility criteria, namely, the shear wall thickness across all floors cannot contain a reduction in shear wall thickness in successive storeys downward. Lastly, an image-based shear wall domain mask is indirectly applied to the optimization problems, as seen in Figure 4.4. These optimization objectives represent several driving design metrics responsible for mitigating sustainability and socioeconomic principles, for example, by tying the structural design to embodied carbon, cost of materials, or other factors. As an additional benefit, the domain mask is customizable by the user to identify likely locations for possible shear walls while limiting the complexity of the design space to a computationally manageable level. This allows for forced inclusion and forced exclusion areas of shear walls in the design, although not implemented in the current study. For example, the location of shear walls encasing stairwells or elevator systems can be forced to be present in all design case scenarios as their location within the structure is likely to remain static. In doing so, further refinements can be made to optimal solutions by user intervention.

$$RII = \sum_{i=1,2} \Gamma_{zi} \qquad \text{Eq. (7)}$$

Table 4.1 – Study Optimization Problems

Optimization Problem	**Objective(s)**	**Design Variables**	**Constraints**
Problem 1 (Single-Objective)	(1) Minimize shear wall volume	(1) Discrete Shear Wall Domain (DV_{1-170}) (2) Shear Wall Thickness ($DV_{171-173}$)	Interstorey Drift Limit: 0.2% Geometric Compatibility ($DV_{171} \geq DV_{172} \geq DV_{173}$)
Problem 2 (Single-Objective)	(1) Minimize piers		
Problem 3 (Multi-Objective)	(1) Minimize shear wall volume (2) Minimize piers		
Problem 4 (Multi-Objective)	(1) Minimize shear wall volume (2) Minimize piers (3) Minimize torsional sensitivity		

Custom images are generated as the main input feature in the following image-based algorithms. The images are created using the shear wall domain mask seen in Figure 4.4, below, and utilize a 3-channel image to represent the shear walls located in all three storey sections, as identified in the figure. Each channel, shown as layers in Figure 4.4 (b), corresponds to one of the storey sections identified in Figure 4.3, which represent the specific thickness of shear wall applied to all of the shear walls contained within the appropriate storeys. These images presented are stored as a 4-D array in MATLAB with dimensions of 187x248x3x1000 in the format Spatial, Spatial, Channel, Batch (SSCB), and using a standard RGB colour scheme where shear wall presence is visually indicated by the colours Black, Red, Yellow, and White. The scale of the images generated is 1:100, where one pixel represents 100 centimetres. This size and scale of an image was found to be computationally efficient by limiting total image size while preserving the aspect ratio and dimensions of shear walls in the designs. The format SSCB indicates the first two dimensions represent spatial distribution, and the third dimension represents the total number of channels in the image (directly corresponding to DV_{171}, DV_{172}, and DV_{173}), with a batch size of 1000, which corresponds to the sample size utilized in the design of experiments, discussed in section 4.2.2. The use of images as inputs is a key feature of the proposed method, as the spatial distribution of the information used directly in the computational engine represents a step towards preserving the dimensionality and nature of topology in engineering design.

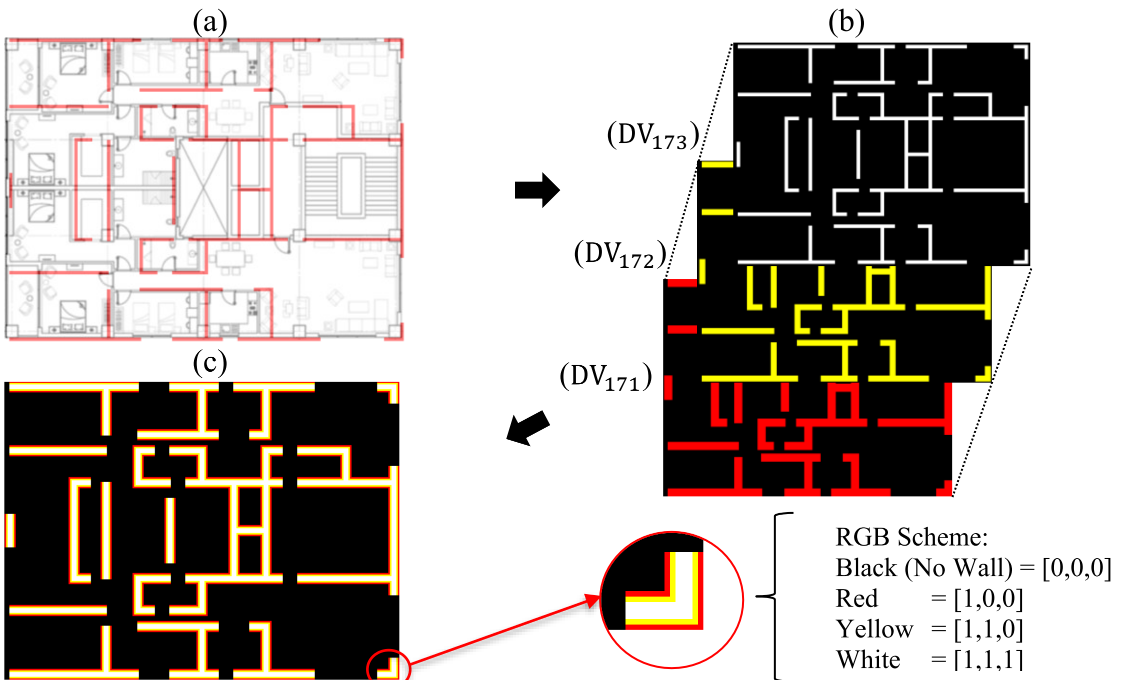

Figure 4.4 – (a) Shear wall domain mask (b) Multi-channel image generation (c) Stacked image

Aside from the benefit of direct spatial representation, utilizing images as design inputs allows for the total possible combinations of shear wall placements within the image to be a near-infinite number from a practical or computational standpoint. This highlights further need for the domain mask to limit the design space for the sake of computational efficiency. For example, with the mask applied, there exist 170 linear metres of shear walls identified for topology optimization. Counting the number of possible combinations of layouts by selecting half of that amount, 85 linear metres of shear wall, results in approximately 10^{49} random combinations as potential candidates. To add further complexity to the problem, considering the effects of shear wall size acts as a multiplier to the design space. These effects are discussed further in the following section when considering the design of experiments. The correlation between images and meaningful engineering FEA results is abstract, requiring the use of machine learning to interpret this relationship ahead of use in an optimization framework.

4.2.2 Machine Learning Module

The development of a machine learning algorithm with reasonable accuracy at conducting image-to-numerical regression requires a thorough approach, which, in this case, requires a design of experiments, data generation, data preprocessing, model development, and hyperparameter optimization. These core steps are utilized in the current study and are explained in this section. Developing the machine learning algorithm based on a Convolutional Neural Network (CNN) allows for numerical regression to be conducted between the custom-generated input images and FEA-based design results and will be used as a surrogate model to inform the genetic algorithm of predicted design results during optimization. Further context to the efficacy of this ML-based approach has been assessed in previous work (Vasilopoulos et al. 2025).

The design of experiments, which controls the distribution of data samples in the database, is a Latin Hypercube Sampling (LHS) method, which has been implemented to generate 1000 samples of random and evenly distributed shear wall locations contained within the domain mask. Additionally, combinations of shear wall thicknesses that satisfy the conditions identified in Eq. (8) are applied in an even distribution to the shear wall topology. In this equation, DV_{1-170} represent shear wall activations, $\mathrm{DV}_{171-173}$ represent shear wall thicknesses, and $\mathrm{s_n}$ are the samples generated by the LHS algorithm. By randomly activating shear walls across all design samples, the ability of a surrogate model to perform regression accurately on a reserved test set of data indicates to what degree of quality the model may be able to generalize all possible combinations in the design space.

$$
\text{LHS Matrix} = \begin{array}{c|cccccccc}
 & DV_1 & DV_2 & DV_3 & \cdots & DV_{169} & DV_{170} & DV_{171} & DV_{172} & DV_{173} \\
s_1 & 1 & 0 & 0 & & 1 & 1 & 400 & 300 & 200 \\
s_2 & 0 & 1 & 0 & \cdots & 1 & 0 & 400 & 300 & 300 \\
s_3 & 0 & 1 & 1 & & 0 & 0 & 400 & 400 & 300 \\
\vdots & & \vdots & & \ddots & & & \vdots & & \\
s_{999} & 1 & 1 & 0 & & 0 & 1 & 600 & 600 & 500 \\
s_{1000} & 0 & 0 & 1 & \cdots & 0 & 1 & 600 & 600 & 600
\end{array} \quad \text{Eq. (8)}
$$

$DV_i \in \{0,1\}, \forall i \in [0,170]$

$DV_i \in \{200, 300, 400, 500, 600\}, \forall i \in [171,173] | DV_i \geq DV_{i+1}$

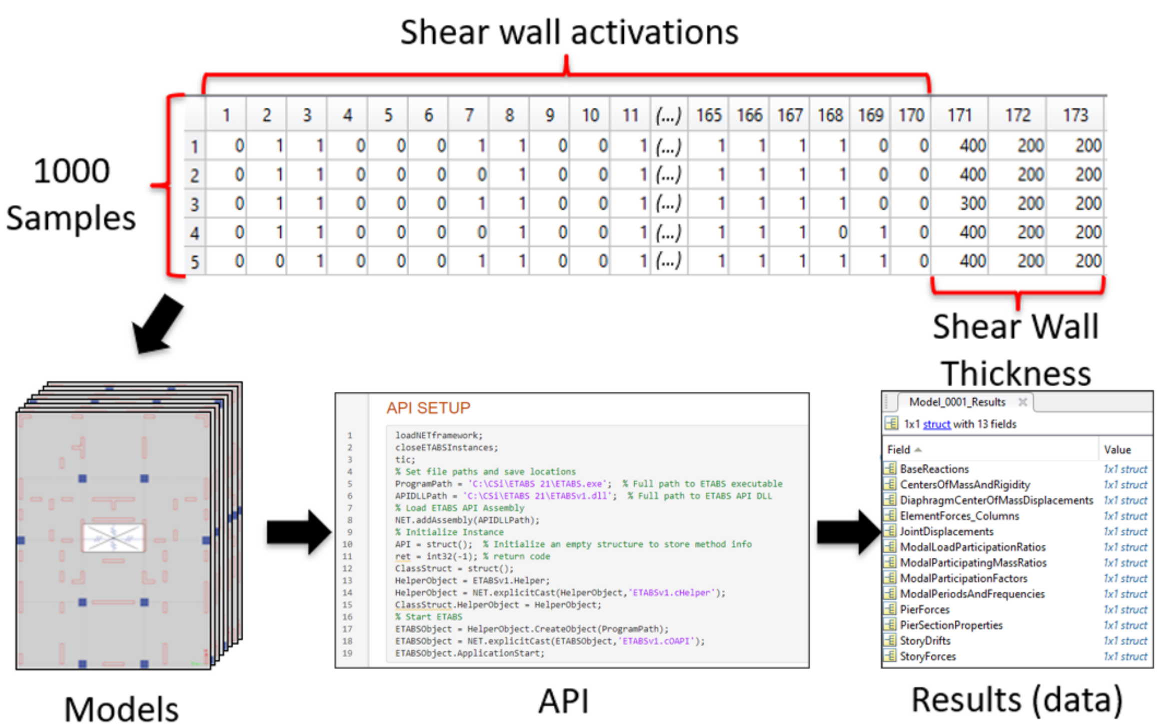

Figure 4.5 – Visual representation of data generation workflow

Utilizing the 1000 samples determined by the LHS algorithm, Figure 4.5 conceptually depicts the processes that are required to generate FEA models, apply NBCC dynamic wind load, conduct analysis, and extract analysis results. These tasks are completed with the aid of thousands of lines of MATLAB code developed to control each step using the MATLAB OAPI and populate a database consisting of model details for all 1000 samples. After the database has been generated, data preprocessing is applied to format the model input and output data ahead of training three different machine learning models. The output data of each of the three models proposed are related to the interstorey drift, shear wall bending moment, and RII - the torsional modal participation factor. These three models are trained using a CNN framework with the model structure seen in Figure 4.6. During data preprocessing, the total data sample of 1000 samples is amplified using an image augmentation technique which mirrors the input images across both axes to expand the available training data from 1000 to 4000. The 4000 samples are then split into training, validation, and testing data sets before being subject to a Bayesian hyperparameter optimization algorithm. While the discussion and results section are primarily concerned with test data set performance, the hyperparameter optimization algorithm utilizes the performance seen in the validation set, while the test data is reserved for analysis and interpretation after the final state of the models is determined. Table 4.2, below, indicates the hyperparameters and their possible range of values that each model may be subjected to in searching for the best performing model. These values are based on the results presented in with minor edits to the hyperparameter ranges to promote model performance and stability in dealing with output data of different nature compared to (Vasilopoulos et al. 2025).

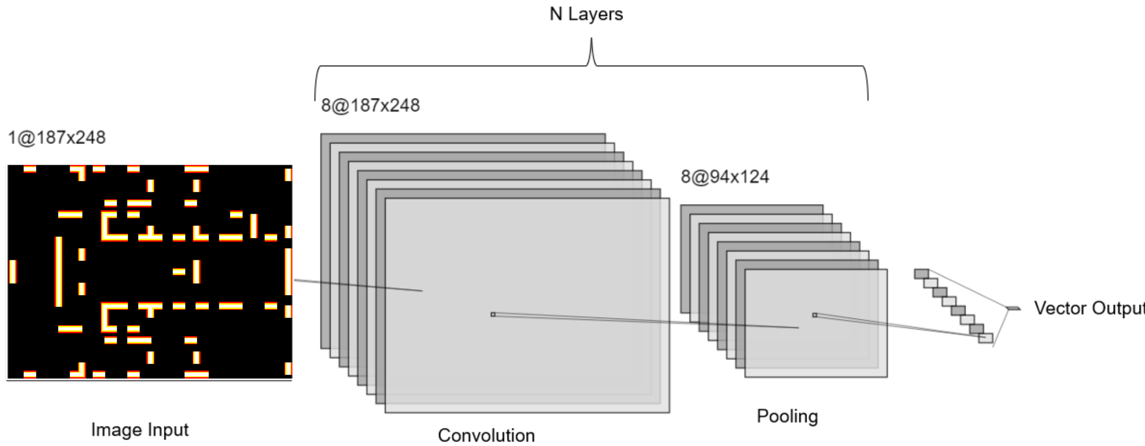

Figure 4.6 – CNN Surrogate Model Architecture

Table 4.2 – Bayesian hyperparameter optimization variables

Hyperparameter	**Values considered**
Sample Segmentation [Training, Validation Test]	80%, 10%, 10%
Number of Layers *Number of Convolutional Layers per Layer* *Filter Size* *Stride* *Padding* *Channels*	$3-6$ $1-3$ kernel sizes $3-6$ 1 1 pixel, value of 0 8, 16, 32, 64, 128, 256
Number of Pooling Layers *Type of Pooling Layer* *Filter Size* *Stride* *Padding*	*Equal to Number of layers.* *Average, Max pooling* *2* *2* *none*
Dropout Layer	$5-50\%$
Loss Function *Initial learning rate* *Momentum* *Decay* *Shuffling of Datasets* *Minibatch Size* *Validation frequency* *Maximum Epochs*	*SGD with Momentum* $1e^{-5}$- $1e^{-3}$ *0.8-0.99* *1E-3 – 1E-2* *Shuffling at every epoch* *20-250* *once per epoch* *25-60*
Output Normalization	*None, z-score, [0,1]*

The loss minimization function employed in the CNN training procedure is stochastic gradient descent with momentum (SGDM). Chosen for its ability to handle uncertainty and noise and avoid local minima in optimization, this function pairs well with the nature of wind load present in the underlying dataset. Additionally, it's versatility enables the hyperparameter optimization algorithm to accurately fit the model architecture to outputs of various classes. Eq. (7) defines SGDM, with the loss function equivalent to standard error between the predicted value of the CNN algorithm and the 'true' value as determined by the underlying dataset shown in Eq. (9). Where w_i are model weights, v_i is the velocity term, γ is the momentum term, η is the learning rate, and $\nabla L(w_i)$ is defined in Eq. (10), below. Evaluation of the model through numerical performance metrics includes the use of percent error, root-mean-squared error (RMSE), mean absolute error (MAE), and Pearson Correlation Coefficient (R), as defined in Eq. (11), Eq. (12), Eq. (13), and Eq. (14), below. In Eq. (12), N represents the total number of samples generated by the LHS matrix.

$$w_{i+1} = w_i - v_{i+1} = w_i - \gamma v_i + \eta \nabla L(w_i) \quad \text{Eq. (9)}$$

$$error = \nabla L(w_i) = Drift_{Predicted} - Drift_{True} \quad \text{Eq. (10)}$$

$$\%error = \frac{Drift_{Predicted} - Drift_{True}}{Drift_{True}} \times 100 \quad \text{Eq. (11)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} error^2}{N}} \quad \text{Eq. (12)}$$

$$MAE = \sum_{i=1}^{N} |error| \quad \text{Eq. (13)}$$

$$R = \frac{\sum\left(Drift_{Predicted,i} - \overline{Drift_{Predicted}}\right)\left(Drift_{True,i} - \overline{Drift_{True}}\right)}{\sqrt{\sum\left(Drift_{Predicted,i} - \overline{Drift_{Predicted}}\right)^2 \sum\left(Drift_{True,i} - \overline{Drift_{True}}\right)^2}} \quad \text{Eq. (14)}$$

4.2.3 Genetic Algorithm Optimization

After developing the machine learning models, they can be employed as surrogate models in a genetic algorithm to optimize shear wall size and topology. MATLAB's global optimization toolbox facilitates this process by providing tools for single and multi-objective genetic algorithm optimization. Non-Dominated Sorting Genetic Algorithm (NSGA-II) is a widely used multi-objective optimization algorithm designed to minimize all objectives without prioritizing any single solution (The Mathworks, Inc. 2023). The algorithm maintains a population of candidates, evolving them through selection, crossover, and mutation, mimicking natural evolution. An elitist mechanism ensures the best solutions persist across generations, while the crowding of solutions is prevented through a Euclidian distance metric, preserving diversity by favoring less crowded solutions within the objective space. It achieves this by leveraging multidimensional Pareto fronts and evaluating solution distance based on a 'phenotype' approach, promoting the spread of the numerical results determined by the fitness function. Lastly, the algorithm cumulatively migrates towards better solutions by iteratively refining the population and offering a diverse set of optimal solutions. These properties suit the multi-objective optimization of tall buildings well, balancing competing objectives and finding designs that align with user preferences and requirements.

Table 4.3 – Genetic algorithm parameters

Parameter	**Value**
Fitness function	*Varies per problem*
Lower bound	*0, 2*
Upper bound	*1, 6*
Nonlinear constraints	*See Table* 4.1
Population Size	*100*
Maximum Generations	*1000*
Maximum Stall Generations	*100*
Function Tolerance	*1e-6*
Constraint Tolerance	*0*
Random Number Generator (for replication)	*Twister*

$$\mathrm{V} = \sum L_w \frac{\sum_{i=171}^{173} DV_i}{3} \times h \times N_s \qquad \text{Eq. (15)}$$

$$N_p = n + 1 \qquad \text{Eq. (16)}$$

Table 4.3 presents the standard genetic algorithm properties used for all optimization problems. The fitness function corresponds to the objectives identified in Table 4.2, and are explicitly stated in Eq. (7), Eq. (15), and Eq. (16). The volume objective function is defined in Eq.

(15), where V is the reinforced concrete shear wall volume, L_w is the linear length of all active shear walls, DV_i is the storey section, h is the storey height of 3.5 metres, and N_s is the number of storeys (i.e., 20). Eq. (16) defines the objective function for determining number of piers, where N_p is the number of piers, and n is the points of discontinuity between consecutive shear walls. The input for the genetic algorithm follows a genome approach like the format seen in Eq. (8). The first 170 entries consist of shear wall activations, restricting inputs to binary activations of zero or one, similar to the approach seen in (Alanani et al. 2024). The remaining three entries are the shear wall thicknesses corresponding to sections 1, 2, and 3, respectively. Arbitrary shear wall thickness values ranging between 200 mm to 600 mm have been chosen for the study. This genome is then run through an image-generation algorithm and passed to the CNN surrogate model, making it possible to directly predict building performance from structural layout images. Cumulatively, the approach of using image-based surrogate models and a genetic algorithm in this manner represents the abstract relationship between images, topology, and size optimization which is the primary focus of the study.

4.3 Results and Discussion

The following sections present the results and discussion of this study: section 4.3.1 presents the performance of the surrogate model, while section 4.3.2 evaluates the performance of the genetic algorithm. These sections provide a detailed description and interpretation of the performance of the developed models and identified optimal solutions, considering the accuracy of their predictions and limitations of the study. Table 4.4, below, identifies the mean values of the surrogate model output parameters across the entire generated database and is used for context when discussing error-related performance. High level discussion of the performance of the proposed framework can be understood with better meaning when compared to the corresponding mean value seen in the dataset. For example, the error histograms seen in Figure 4.7, Figure 4.8, and Figure 4.9 are relative to mean of peak interstorey drift, mean bending moment, and mean of RII, respectively.

Table 4.4 – Tall Building Database Summary

Total Design Samples	4000
Mean of Peak Interstorey Drift	0.210%
Standard Deviation of Peak Interstorey Drift	7.549E-04
Mean Bending Moment Distribution	1.484E+03 kN·m
Mean of RII	0.475

4.3.1 Surrogate Model Performance

As stated in the methodology section, three surrogate models tasked with conducting image-to-numerical regression are developed to predict various key engineering performance metrics. The three models developed and discussed in this section are trained to predict peak interstorey drift, the standard deviation of bending moments in reinforced concrete shear walls at the base of the structure, and the evaluation of RII – a modal analysis metric proposed in this study – to evaluate the torsional sensitivity of the proposed structural design. The three models are developed in an identical fashion, with only minimal model architecture adjustments being made to accommodate varying model output sizes. The surrogate model architectures are then subjected to the Bayesian hyperparameter optimization algorithm identified in section 4.2.2 to tune the model and achieve a high-performing state automatically. The results of the hyperparameter optimization algorithm are presented in Table 4.5 below, and further analysis of the performance of each surrogate model is discussed in the subsequent sections.

Table 4.5 – Bayesian hyperparameter optimization results

Hyperparameter	**Model 1 - Drift**	**Model 2 - Moment**	**Model 3 - RII**
Sample Segmentation *Training,* *Validation* *Test*	80%, 10%, 10%		
Number of Layers *Number of Convolutional Layers per Layer* *Filter Size* *Stride* *Padding* *Channels*	3 1 kernel size 6 1 1 pixel, value of 0 8,16,32	4 1 kernel sizes 3 1 1 pixel, value of 0 8,16,32,64	4 3 kernel size 3 1 1 pixel, value of 0 8,16,32,64
Number of Pooling Layers *Type of Pooling Layer* *Filter Size* *Stride* *Padding*	*Equal to Number of layers.* *Average, Max pooling* *2* *2* *none*		
Dropout Layer	5.96%	40.2%	46.57%
Loss Function	*SGD with Momentum*		
Initial learning rate *Momentum* *Decay* *Shuffling of Datasets* *Minibatch Size* *Validation frequency* *Maximum Epochs*	*1.424E-4* *0.990* *1.087E-2* *At every epoch* *100* *once per epoch* *60*	*1.327E-4* *0.987* *1.051E-3* *At every epoch* *160* *once per epoch* *60*	*7.458E-3* *0.922* *0.01* *At every epoch* *50* *once per epoch* *60*
Output Normalization	*z-score*	*[0,1]*	*None*

A summary of the performance of all three surrogate models are provided in Table 4.6 below, for direct comparison of the capabilities of each model in considering only the test data set. The data used to train these surrogate models are divided into training, validation, and test subsets. As Table 4.5 displays, 80% of data is reserved for the training purposes. 10% of the data is used by the Bayesian hyperparameter algorithm to evaluate the performance of the model during hyperparameter tuning. Finally, 10% of the data is reserved as the test subset, which assesses the model's overall performance and validates its ability to replicate unseen design scenarios. These results indicate that, although strong positive correlation was achieved across all three models, the degree of difficulty or computational complexity in the relationship between input images and output values is visible across the three data types. Specifically, the interstorey drift model achieved the highest degree of performance on unseen data, whereas the modal analysis model displayed relatively higher difficulty in predicting the RII metric proposed in this study. This is despite the adjustments made by the hyperparameter optimization algorithm, which made significant architecture changes across the three models as shown in Table 4.5. As the computational complexity required for modal analysis is innately higher than predicting interstorey drift, this observation is not surprising. However, the differences in performance across these three models indicate that either the parameters used in the Bayesian hyperparameter optimization algorithm, or the parameter search ranges permitted during training provide insufficient variance in the model architecture required to achieve equivalent performance.

Table 4.6 – CNN Surrogate Model Performance Summary

	Model 1 - Drift	**Model 2 - Moment**	**Model 3 - RII**
R	0.929	0.825	0.857
RMSE	3.238E-04	305.3 kN·m	0.109
MAE	2.358E-04	223.8 kN·m	0.085

Only the results determined on the test data sets are provided in this summary as they represent the expected 'worst-case' scenario in terms of prediction accuracy. Additionally, error results are presented in their native units as seen in Table 4.4, which are unitless for Model 1 and Model 3, and kN·m in Model 2. In the following sections, detailed numerical results are presented to further describe the performance of the model over the entire database generated. As the size of the database is derived from only 1000 samples of effectively infinite potential design combinations, as discussed in section 4.2.2, the overall performance of each of the models indicates a formidable accuracy in predicting design results, likely due to the LHS and Bayesian hyperparameter optimization algorithms providing an unbiased approach to the generalization of structural images to structure behaviour.

4.3.1.1 Interstorey Drift Model

This surrogate model has a strong positive correlation on the test set with R=0.9285. Additionally, the results across both validation and test data suggests consistent performance across the design space. The error histogram reports that 37.7% of predictions are within 5% error, 57.2% are within 10% error, and 85.7% are within 25% error of the true values. Lastly, RMSE and MAE metrics are relatively low compared to the population mean interstorey drift of 0.21%, indicating good performance. In summary, the model can closely replicate the relationship between structural images and interstorey drift.

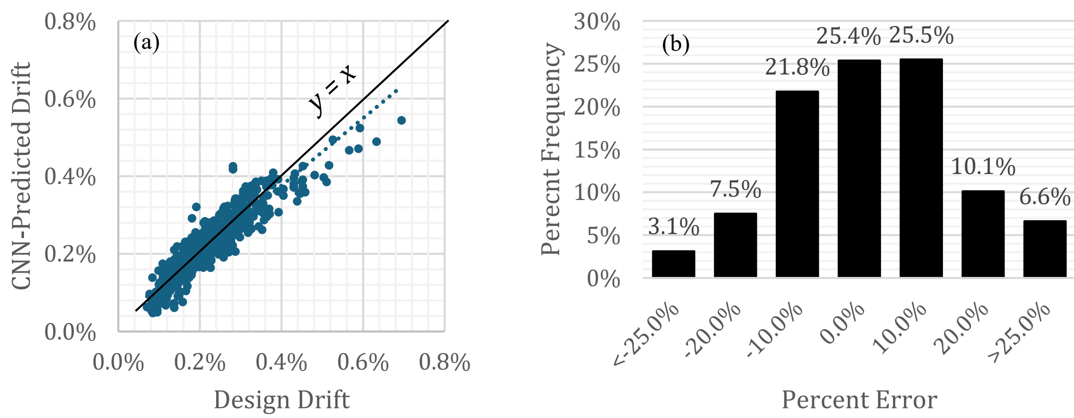

Figure 4.7 – Model 1 test data results a) linear regression b) error histogram

Table 4.7 – Model 1 Detailed Performance Summary

	Training Data	Validation Data	Test Data
Sample Size	3200	400	400
R	0.961	0.926	0.929
RMSE	2.476E-04	3.123E-04	3.244E-04
MAE	1.742E-04	2.350E-04	2.358E-04

4.3.1.2 Bending Moment Model

This surrogate model has a positive correlation on the test set with R=0.8252. The results across both validation and test data suggests consistent performance across the design space. The error histogram reports that 9.7% of predictions are within 5% error, 16.3% are within 10% error, and 81.6% are within 25% error of the true values. Lastly, RMSE and MAE metrics are also relatively low compared to the mean value shown in Table 4.5. In summary, while the model still has a good correlation, higher error is expected across individual predictions. Notably, 18.4% of predictions consist of an error of greater than 25% of the true value. While precision is ideal, overestimating the bending moment distribution across shear walls errs on the conservative side of design and should have limited negative impact.

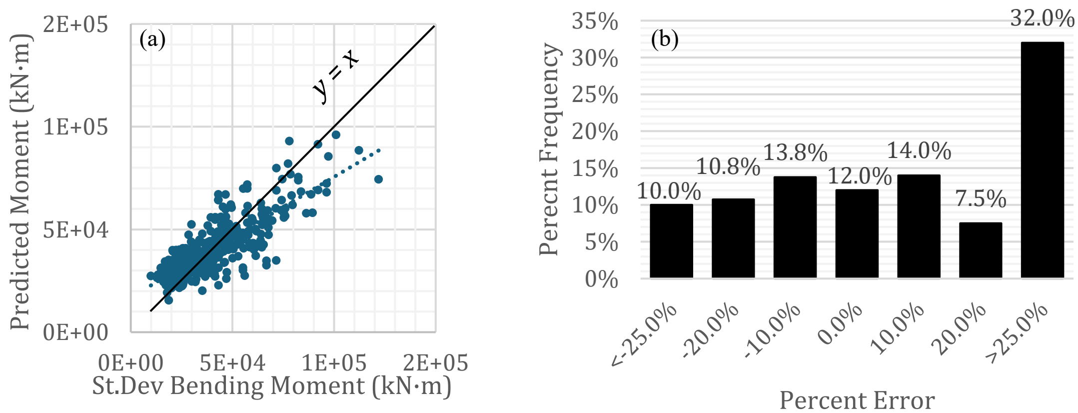

Figure 4.8 – Model 2 test data results a) linear regression b) error histogram

Table 4.8 – Model 2 Detailed Performance Summary

	Training Data	**Validation Data**	**Test Data**
Sample Size	3200	400	400
R	0.837	0.846	0.825
RMSE	270.4 kN·m	246.2 kN·m	305.3 kN·m
MAE	192.3 kN·m	187.9 kN·m	223.8 kN·m

4.3.1.3 RII Model – Modal Analysis Prediction

This surrogate model has a positive correlation on the test set with R=0.8574. The results across both validation and test data suggests consistent performance across the design space. The error histogram reports that 31.8% of predictions are within 5% error, 48.3% are within 10% error, and 76.4% are within 25% error of the true values. RMSE and MAE metrics are again relatively low compared to the mean value shown in Table 4.4. With 23.3% of predictions consisting of an error of greater than 25%, and upon further analysis, this model has difficulty predicting cases where modal participation factors in both the first and second modes sum to a value near zero.

Occurring in a low frequency of cases, the absolute value of the prediction is reasonably low to predict any adverse effects during optimization.

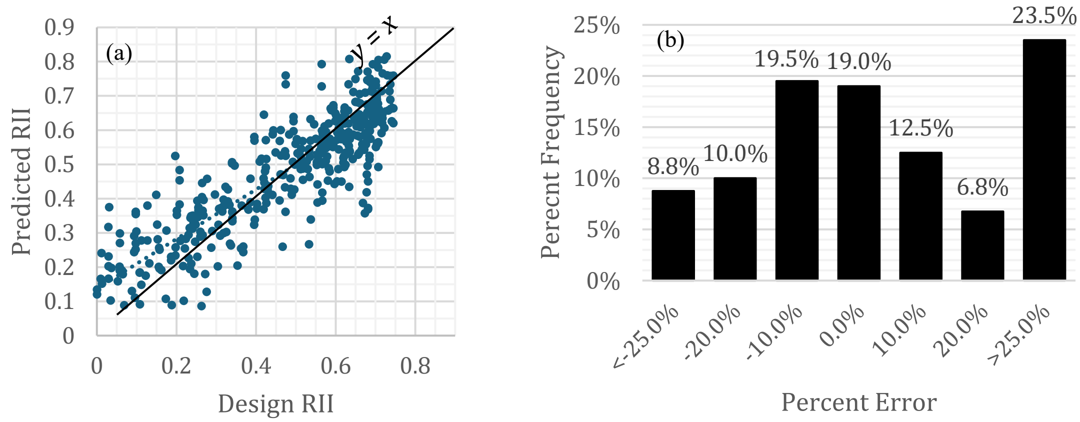

Figure 4.9 – Model 3 test data results a) linear regression b) error histogram

Table 4.9 – Model 3 Detailed Performance Summary

	Training Data	Validation Data	Test Data
Sample Size	3200	400	400
R	0.957	0.816	0.857
RMSE	0.064	0.109	0.109
MAE	0.049	0.086	0.085

4.3.2 Genetic Algorithm Results

Cumulatively, the results presented by all four optimization problems provide a unique insight into the impacts applying a domain mask and various design constraints on the performance of tall buildings. While the algorithms accuracy varies in each problem posed, the overall quality of solutions provided by the framework allows for complex design trade offs to be quantitatively considered with ease. The optimization results for all problems are summarized in Table 4.10, below. Across all design problems, various shear wall topology and size solutions have been identified and are discussed in further detail individually in the following sections. Summarizing the results of the proposed framework, a total of 42 design solutions have been identified, consisting of reinforced concrete volumes ranging from 1022 m³ to 2492 m³, total number of piers n = 13 to n = 21, and RII ranging from 8.941E-5 to 0.216, indicating complications due to torsional sensitivity are likely avoided across the corresponding design alternatives.

Table 4.10 – Study Optimization Results

Optimization Problem	**Objective(s)**	**Results**
Problem 1	Minimize shear wall volume	Minimum Volume: 1022 m^3
Problem 2	Minimize piers	Minimum Piers: 16
Problem 3	Minimize shear wall volume, Minimize piers	Solution 1: [1208 m^3, 17 Piers] Solution 2: [1225 m^3, 16 Piers] Solution 3: [1241 m^3, 15 Piers] Solution 4: [1258 m^3, 14 Piers] Solution 5: [1290 m^3, 13 Piers]
Problem 4	Minimize shear wall volume, Minimize piers, Minimize torsional sensitivity	Solution 1: [2492 m^3, 17 Piers, RII = 8.941E-5] Solution 2: [1274 m^3, 21 Piers, RII = 0.136] Solution 3: [1405 m^3, 15 Piers, RII = 0.216] Solution 4: [1549 m^3, 18 Piers, RII = 0.091] Solution 5: [1339 m^3, 17 Piers, RII = 0.206]

4.3.2.1 Problem 1: Minimization of Volume

In Problem 1, the genetic algorithm is run with an objective function of minimizing the volume required of reinforced concrete shear walls while maintaining peak interstorey drift limits and geometric constraints. In Figure 4.10 a)., two data series are presented to depict the mean and best values of the population considered in each generation. The algorithm stalled at generation 306, with no improvement seen for 100 generations, the minimum volume found is 1022 cubic metres. Compared to a mean value of 1968 cubic metres in the same generation, the algorithm proposed an optimal solution with 48% volume savings compared to the mean. The optimal solution contains a predicted interstorey drift in both x and y cardinal directions as indicated in Figure 4.10 b). The optimal solution is then analyzed in ETABS to determine that the true interstorey drift is 0.22% and 0.19% in the x- and y- directions, respectively. The result of the optimization algorithm indicates that a significant degree of accuracy was achieved in simulating the design space.

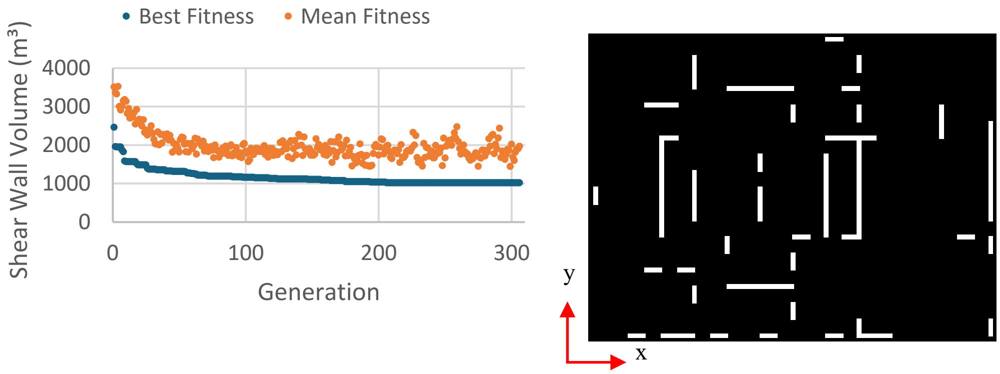

Figure 4.10 – Problem 1 a) Genetic Algorithm Convergence b) Optimal design solution image

Table 4.11 – Problem 1: Predicted versus true results

	Drift (x-direction)	**Drift (y-direction)**
Predicted Design Results	0.20%	0.20%
True Design Results	0.22%	0.19%
Percent Error	10.84%	5.585%

4.3.2.2 Problem 2: Minimization of Piers

In Problem 2, the genetic algorithm is run with an objective function of minimizing the total number of consecutive piers in the layout, with no regard to volume or torsional sensitivity. Figure 4.11 a) depicts that a design was found to satisfy the constraints with a minimum of 16 piers. The algorithm stalled at generation 173, indicating that it converged relatively quickly, with predicted interstorey drift of 0.06% and 0.14% in x- and y- directions, respectively. The optimal solution analyzed in ETABS determined that the true interstorey drift is 0.13% and 0.31% in the x- and y- directions, respectively. This relatively high degree of error is likely due to the optimal solution being of very low magnitude for interstorey drift. Since the genetic algorithm searches for the best performing design solution, the lower values of drift in these ideal solutions inflate the percent error. Practically speaking, the solution identified continues to provide a high degree of performance. Additionally, the nature of the training data set used in the surrogate modelling. As the LHS algorithm is concerned with randomly assigning shear walls across design samples, the algorithm generates samples which consist of designs with 30-58 piers. Attempting to minimize the design in this fashion resulted in using the surrogate model to predict design combinations with relatively poor representation in the training data, leading to increased error compared to problem 1. Still, what accuracy was maintained showcases the overall generalization capability of the surrogate models given such a limited database size.

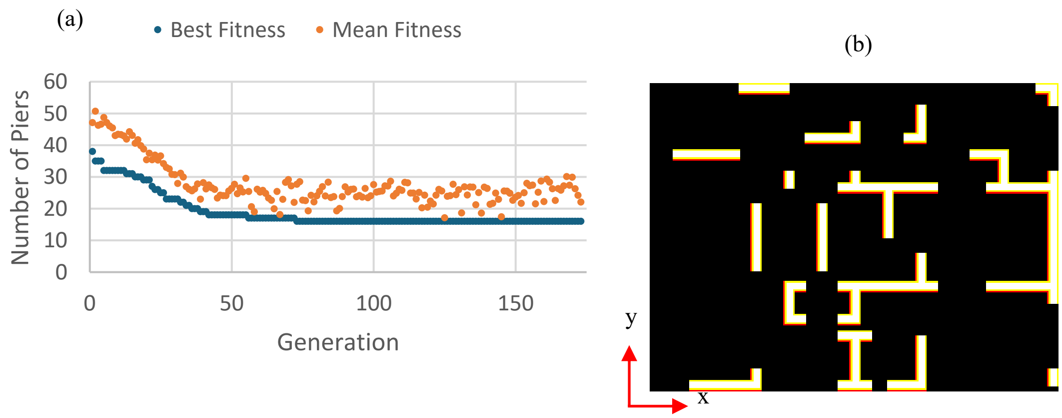

Figure 4.11 – Problem 2 a) Genetic Algorithm Convergence b) Optimal design solution image

Table 4.12 – Problem 2: Predicted versus true results

	Drift (x-direction)	**Drift (y-direction)**
Predicted Design Results	0.06%	0.14%
True Design Results	0.13%	0.31%
Percent Error	51.27%	53.06%

4.3.2.3 Problem 3: Minimization of Volume and Piers

As the first multi-objective optimization problem in this study, the simultaneous minimization of both volumes and piers provides a direct evaluation of the design trade offs between these to variables, shown in Figure 4.12. The design trade-off clearly shows a range of solutions corresponding to a difference of 84 cubic metres of concrete over a spread of designs consisting of 13-17 piers. In these instances, the true values of these solutions determined through ETABS shows high accuracy, even in design case scenarios with a low number of piers, contrary to the discussion from Optimization Problem 2. In this instance, the multi-objective optimization revealed several design solutions, with an accuracy ranging from 0.538%-19.33% error as shown in Table 4.11. Visual analysis of the design trade-offs shown in Figure 4.13 visually depicts the similarities between results, assisting with interpretation and directly allowing for engineers to infer potential design solutions based on the common shear wall elements seen in the images.

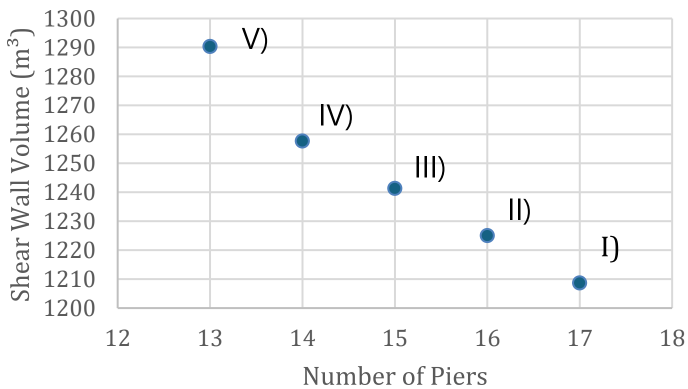

Figure 4.12 – Problem 3: Volume-Pier design trade-off

Table 4.13 – Problem 3: Predicted versus true results

	Drift (x-direction)	Drift (y-direction)
Solution I		
Predicted Design Results	0.20%	0.20%
True Design Results	0.24%	0.20%
Percent Error	19.33%	2.69%
Solution II		
Predicted Design Results	0.20%	0.10%
True Design Results	0.23%	0.18%
Percent Error	16.83%	10.19%
Solution III		
Predicted Design Results	0.20%	0.20%
True Design Results	0.21%	0.20%
Percent Error	3.98%	2.80%
Solution IV		
Predicted Design Results	0.20%	0.19%
True Design Results	0.20%	0.19%
Percent Error	1.92%	0.538%
Solution V		
Predicted Design Results	0.20%	0.20%
True Design Results	0.23%	0.18%
Percent Error	17.18%	11.37%

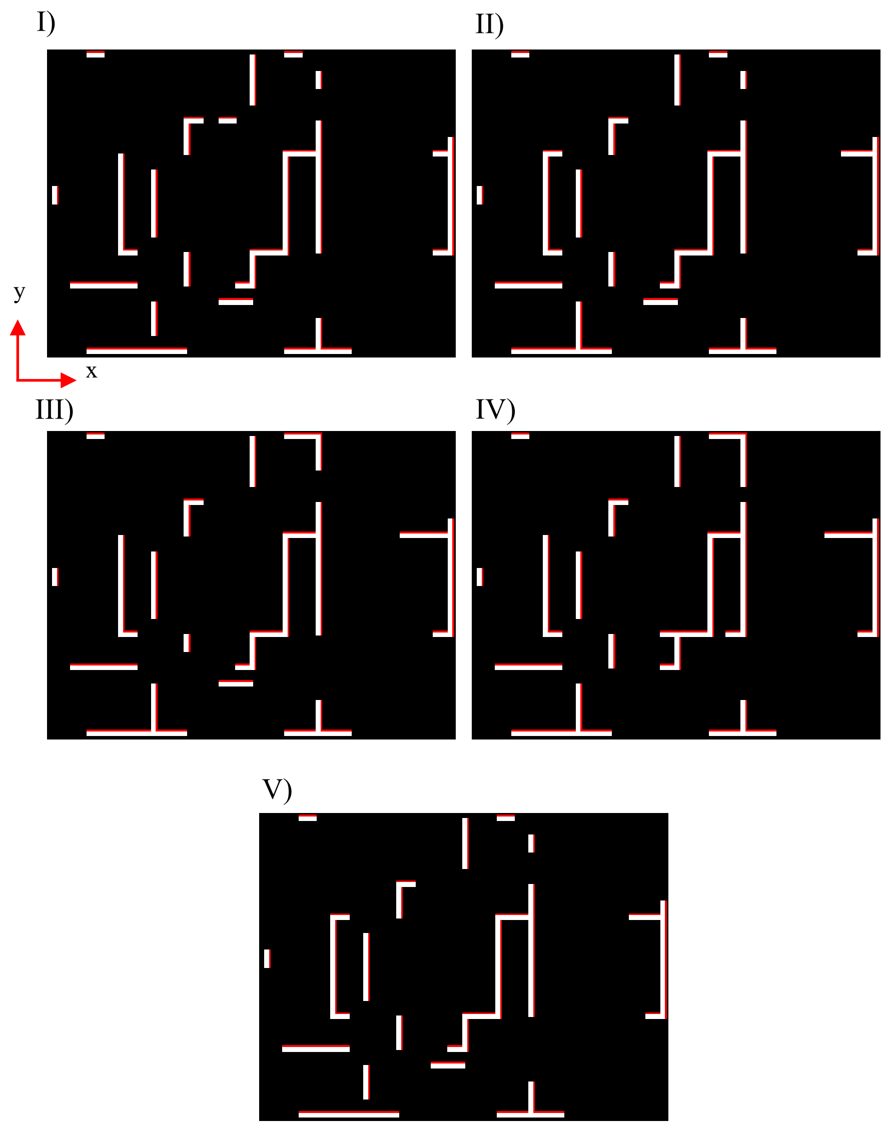

Figure 4.13 – Problem 3: Highlighted Multi-objective Solutions

4.3.2.4 Problem 4: Minimization of Volume, Piers, and RII

Problem 4 conducts the 3-dimensional multi-objective optimization of the design space and represents the most complex analysis conducted with the proposed framework. In this problem, volume, number of piers, and torsional sensitivity are evaluated and minimized. The genetic algorithm in this problem expended the entire 1000 generations allotted to determine the best design solutions and returned 35 possible configurations. In Figure 4.14, below, a pareto front is provided which showcases a 3-dimensional design trade-off. The points identified in red are selected as highlighted solutions and the corresponding predictions and errors from validated data are shown in Table 4.14.

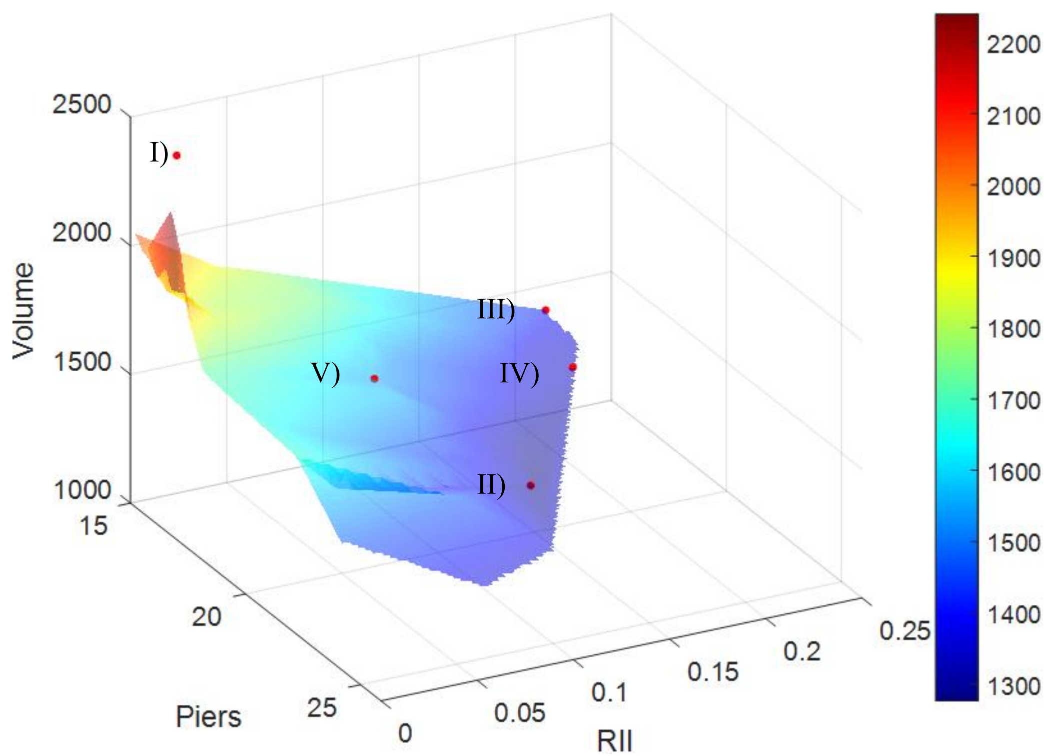

Figure 4.14 – Problem 4: Design trade-off pareto front

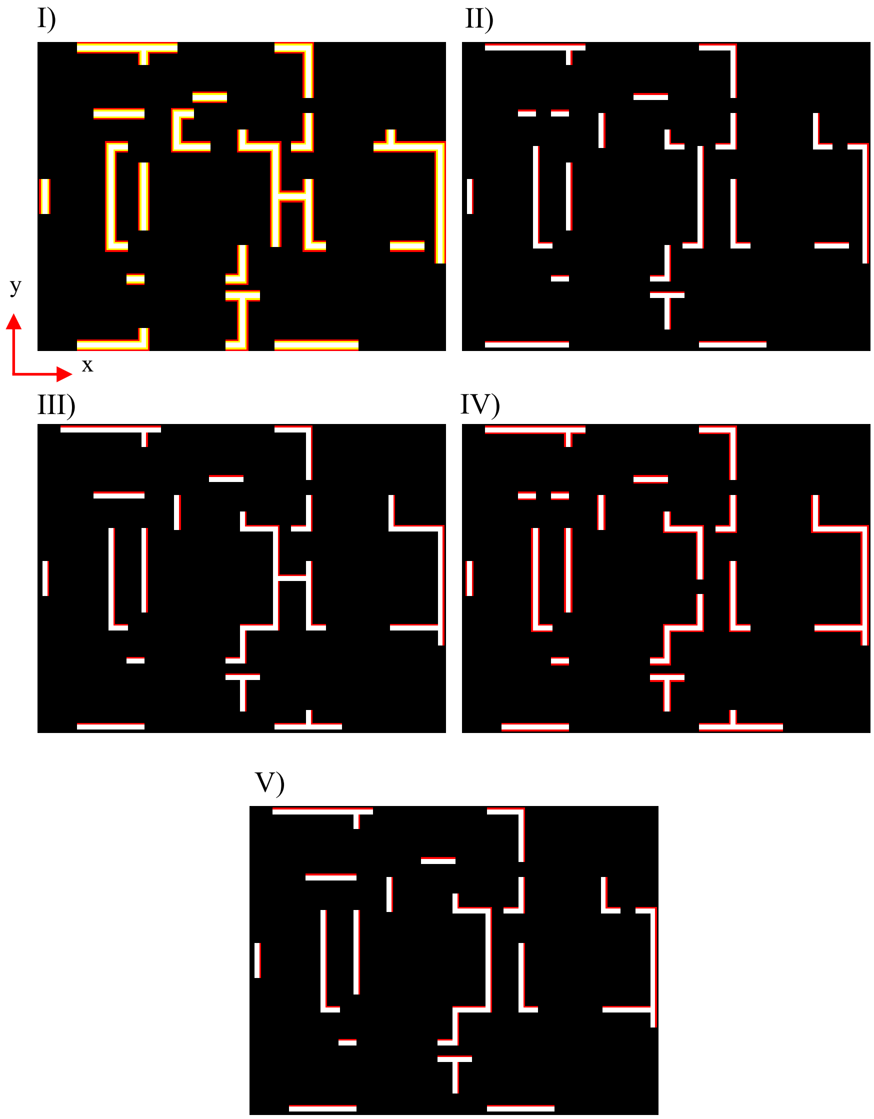

Figure 4.15 – Problem 4**:** Highlighted Multi-objective Solutions

Table 4.14 – Problem 4: Predicted versus true results

	Drift (x-direction)	**Drift (y-direction)**
Solution I		
Predicted Design Results	0.09%	0.11%
True Design Results	0.17%	0.14%
Percent Error	47.06%	20.98%
Solution II		
Predicted Design Results	0.20%	0.20%
True Design Results	0.24%	0.17%
Percent Error	16.64%	14.22%
Solution III		
Predicted Design Results	0.17%	0.20%
True Design Results	0.17%	0.16%
Percent Error	0.675%	25.65%
Solution IV		
Predicted Design Results	0.15%	0.17%
True Design Results	0.19%	0.18%
Percent Error	18.39%	4.56%
Solution V		
Predicted Design Results	0.18%	0.19%
True Design Results	0.20%	0.16%
Percent Error	11.68%	20.04%

4.4 Summary

A novel approach to simultaneously optimizing the structural topology and size of a tall building comprised of reinforced concrete shear walls is proposed. The approach relies on the use of image-based surrogate modelling for rapid prediction of building performance. The surrogate models were successfully trained to predict three classes of design metrics with good accuracy: Interstorey drift (R=0.929), Bending Moment (R=0.825), and RII (R=0.857), the design metric based on modal participation factors and used in an optimization framework to mitigate presence of torsional sensitivity in design solutions. Considering the complexity of the design space, such performance on a relatively limited database of 1000 samples suggests the integration of image-based surrogate modeling with genetic algorithms highlights a promising pathway for future studies.

These surrogate models act as the computational engine behind a genetic algorithm posed with four design problems, consisting of single- and multi- objective evaluations. The genetic algorithm is configured to permit shear walls based upon a domain mask, an image-based geometric constraint to simulate adherence to diverse interdisciplinary design constraints. The solution to problem 1 adheres to NBCC interstorey drift limit of 0.20% and provides a design requiring only 1022 m^3 concrete volume, providing significant savings from an economic and carbon-emissions point of view. Similarly, problem 2 converges to a design solution with a minimal number of piers (n = 16). Problem 3 develops a multi-objective design trade-off that quantifies competing design factors of shear wall volume (ranging from 1206 m^3 to 1290 m^3) and total number of piers (ranging from n = 13 to n = 17), quantifying the design space of these alternatives for consideration by the designer. Problem 4 identifies a 3-dimensional pareto front representing the design trade off between concrete volume, number of piers, and torsional sensitivity, representing a design scenario that assigns increased importance to adhering to architectural, interdisciplinary, or occupant comfort criteria. 35 solutions were identified, 5 of which are highlighted to describe the extents of the design alternatives identified. These solutions consist of reinforced concrete shear wall volumes between 1274 m^3 to 2492 m^3, n = 15 to n = 21 number of piers, and RII values between 8.941E-5 to 0.216, indicating low torsional sensitivity.

The design solutions identified showcase the ability to rapidly quantify several design solutions which include shear wall topology and size as key optimization variables. A total of 1072 finite element models were algorithmically generated corresponding to various shear wall designs, consisting of both the optimal design solutions and surrogate model training data. Across all optimization problems, several design alternatives are identified and inform core underlying design metrics which can be used to satisfy design criteria, interdisciplinary constraints, and project economics and sustainability targets. Comprehensive optimization frameworks such as this show promising performance and potential to be adapted for use in industry in quantifying and improving all facets of project design alternatives and trade-offs during early design stages.

Chapter 5 Conclusion

This thesis assesses the capability of a CNN surrogate model at predicting the interstorey drift of a 70-metre-tall case study version of the CAARC building. The purpose of the these is to determine to what degree an image-based ML model can directly simulate building performance metrics through regression. This was accomplished by developing two datasets consisting of linear dynamic wind load analysis and NBCC dynamic wind load procedure. Combined, these datasets posed numerical relationships with inherent uncertainty, high complexity, and high dimensionality.

The CNN algorithm developed to complete this task was trained using a LHS algorithm and a Bayesian hyperparameter optimization algorithm to systematically control the model training state, prevent bias, and produce the best-performing model possible. This allowed for multiple numerical performance metrics to be assessed, including interstorey drift, bending moment, and the proposed RII factor, which is a measure of the buildings overall torsional sensitivity. The performance of the models showcased in Chapter 3 and Chapter 4 describes the ability of CNNs to simulate the data relationship with a high degree of accuracy while overcoming existing limitations of similar approaches.

Further, these surrogate models were adapted to conduct simultaneous structural topology and size optimization as displayed in Chapter 4. The model enhanced surrogate model was subjected to single- and multi-objective optimization using GA optimization. Successful convergence of these problems resulted in many optimal design solutions being identified. This ability to quantify complex design solutions while simultaneously considering shear wall size and topology is a novel result. Additionally, the framework was configured to permit shear walls based upon an input domain mask which provides a simplified method to impose geometric constraints and has significant capability for use in satisfying interdisciplinary design constraints.

Considering the complexity of the design spaces developed, the performance achieved across all models and on a relatively limited database of 1000 samples suggests the use of image-based surrogate modeling provides an appropriate degree of numerical dimensionality, somewhat matching the dimensionality of tall building design problems when paired with a hyperparameter optimization algorithm. This narrates a high potential of CNN-based surrogate models in the design of tall buildings, especially when proposed for structural optimization. The results identified showcase the ability to rapidly quantify several design solutions which include shear wall topology and size as key optimization variables. An important outcome of this research both the precision and speed which these analyses are capable of converging.

Further implementation of image-based algorithms poses the benefit of acting as a powerful and versatile computational tool in DSE ahead of rapidly evolving urban environments and demand in tall buildings. Comprehensive optimization frameworks such as this show promising performance and potential to be adapted for use in industry in quantifying and improving all facets of project design alternatives and trade-offs during early design stages.

5.1 Research Contributions

The outcomes of this thesis are reformulated from the discussion, summaries, and conclusion of the thesis in terms corresponding to the research objectives identified in Chapter 1. The major contributions achieved by this thesis are as follows:

1. **Develop an Image-to-Numerical ML Model:** The relationship between structural layout input images and numerical performance metrics including interstorey drift, bending

moment, and RII (a measure of building torsional sensitivity) was successfully implemented into several ML models based on a CNN architecture.

2. **Conduct Simultaneous Size and Topology Optimization:** The use of structural layout images, including to-scale thicknesses of shear wall elements was successfully implemented into the CNN ML model developed in Chapter 4. This model was then used as a surrogate model by the proposed GA to conduct simultaneous shear wall topology and size optimization.
3. **Conduct Multi-Objective Optimization Via Image-Based Surrogate Model:** The developed GA successfully utilized the developed surrogate models in both single- and multi-objective optimization problems, where the topology and size of thousands of building layouts were assessed to converge to optimal solutions with good accuracy. These solutions adhered to imposed geometric and code-based domain constraints.
4. **Novel Torsional Sensitivity Metric Proposed – RII:** The use of a novel building metric named RII was defined in Eq. (7) by relying on analysis results obtained from modal analysis to characterize the torsional sensitivity of buildings. A surrogate model was successfully developed to predict this metric, which was then used in a multi-objective optimization problem to quantify torsional sensitivity in a 3-dimensional design trade-off. This resulted in an enhanced capability to interpret the impacts of torsional sensitivity across the optimal design solutions identified.

5.2 Recommendation for Future Work

The possibilities for future work deriving from this thesis are nearly limitless. However, several key directions are identified below, which provide logical continuation points for further analysis, improvement, and development of the proposed work.

- **Applications for multiple LFRS:** As this thesis focuses solely on the study of RC shear walls, applying the framework in a likewise manner to the design of buildings containing structural steel, mass timber, or alternative LFRS could provide further opportunity to evaluate the frameworks versatility.
- **Implementing more design parameters:** This work can be easily adapted to apply to any number of design parameters. For example, future studies could include variations in applied gravity load, storey heights, or material properties to suit any task.
- **Propose alternative ML algorithms:** A main contribution of this thesis is the development of the image-to-numerical CNN model developed to generalize the relationship between structural layout images and building performance metrics. However, attempting to implement alternative image-based algorithms for a similar purpose could very well provide equal or better results.
- **Expand study building database:** The model building studied in this thesis exclusively remained a version of the CAARC building. Further work can be done to apply this framework to buildings of various aspect ratios, slenderness ratios, or buildings with irregularities or entirely different characteristics.
- **Apply to additional analysis:** This study focuses entirely on wind load determination and includes analysis as per the NBCC and PBWD. Further analysis could be conducted to evaluate the frameworks performance under seismic loading, or under building codes across the world.

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