ENHANCING BUILDING FACADE RESILIENCE THROUGH MACHINE LEARNING

Improving Workflow for Seismic and Heat Wave resilience measures

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Abstract

With the increasing number of disruptive events impacting the built environment, identifying and enhancing the resilience of building facades has become crucial. This study focuses on improving the resilience of building facades against seismic and thermal hazards using machine learning techniques. A comprehensive methodology is developed, integrating thermal and seismic resilience analyses within a unified framework. The study utilizes extensive simulations and machine learning models to predict resilience metrics, such as thermal autonomy and seismic drift angles, based on various building parameters. The approach enables architects and engineers to optimize building designs for enhanced resilience efficiently.

The research is specifically applied to low-cost housing in New Delhi, India, an area prone to both extreme weather and seismic activity. Detailed simulations are conducted using data on building materials, geometries, and environmental conditions. The results are used to develop predictive models that inform design improvements and resilience strategies. The study demonstrates significant improvements in the accuracy and efficiency of resilience assessments, providing actionable recommendations to enhance building performance. This integrated methodology offers substantial benefits for both academia and practice, paving the way for more resilient and sustainable building designs in vulnerable regions.

Keywords: Façade Resilience, Multi-hazard Approach, Unsupervised Machine learning, Supervised Machine learning, Prediction model, Quantitative Resilience Assessment, Resilience-based Design, Multi-attribute decision making

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01

Introduction

This chapter addresses the context of the research, followed by the problem statement. Consequently, the research objectives, methodology and research questions will be explained, ending with the societal and scientific relevance of the research

1.1 Background Research

Sustainable Development: Building for Resilience

Climate change is leading to more frequent, intense, and longer-lasting extreme events such as heatwaves and earthquakes. This trend is making the living conditions for occupants inside buildings increasingly challenging and riskier. Such events are commonly defined as “a time and place in which weather, climate, or environmental conditions rank above a threshold value near the upper or lower ends of the range of historical measurements”.(Hong et al., 2023) A recent report by the world Meteoritical Organization(*State of the Global Climate 2022*, n.d.) stated that approximately 12,000 extreme events have occurred worldwide in the past 50 years. These events have resulted in over 2 million deaths and economic losses exceeding $4.3 trillion.

As the frequency of such hazards increases, designing structures that can withstand disturbances and recover quickly has become a priority in the construction industry. This approach not only secures the present but also safeguards future generations. The Sustainable Development 11.b target aims to ““By 2020, substantially increase the number of cities and human settlements adopting and implementing integrated policies and plans towards inclusion, resource efficiency, mitigation and adaptation to climate change, resilience to disasters, and develop and implement, in line with the Sendai Framework for Disaster Risk Reduction 2015-2030, holistic disaster risk management at all levels”. (*Goal 11 | Department of Economic and Social Affairs*, n.d.)

Resilience in Built Environment

The American Psychological Association (2014) defines resilience as ‘‘the process of adapting well in the face of adversity, trauma, tragedy, threats or even significant sources of stress”.(Southwick et al., 2014) The concept of resilience can also be applied to the built environment. It describes a building's ability to foresee and prepare for negative events, absorb and withstand their impact, and recover efficiently from these occurrences. Additionally, resilience includes the capacity to adapt more effectively to potential future adverse events.(Hong et al., 2023) The concept of resilience in buildings spans various domains such as structural, thermal, seismic, and fire resilience. However, the emphasis here will be on the domain that most critically affects the local context.

Resilience has become increasingly important in modern design and construction, influencing various aspects. In terms of thermal resilience, buildings can maintain a safe and comfortable indoor environment, thereby improving energy efficiency by minimizing the need for excessive heating or cooling. This efficiency not only reduces costs but also supports environmental sustainability. Additionally, thermal resilience extends the lifespan of a building by shielding its structure from damage due to temperature variations. It also prepares the building for emergencies, ensuring it stays liveable during power outages or heating system failures by maintaining a consistent indoor climate.

Regarding seismic resilience, maintaining a building's structural integrity during earthquakes is vital. This not only protects lives by preventing collapses but also mitigates economic losses from potential repairs and downtime. Furthermore, a seismically resilient building can play a pivotal role in community recovery post-disaster, serving as a safe haven or a base for emergency operations. In essence, seismic resilience is about safeguarding both the physical structure and the community it serves.

1.2 Problem statement

Our planet is currently confronting major challenges due to drastic climate change, which is causing various catastrophic events. Among these, earthquakes and heatwaves are particularly impactful, severely affecting infrastructure, public health, and the environment. This study highlights several critical issues arising from these events that demand urgent attention:

Narrow Emphasis on building Facade Resilience: While many initiatives are focused on evaluating resilience on larger scales, such as city-wide, district, and regional levels, there is still a significant lack of tools or methodologies designed specifically to assess resilience and performance at the building facade level during extreme events.(Kim, 2023)

Lack of Multi-Hazard Assessment: The absence of comprehensive multi-hazard assessment tools that account for both earthquake and heatwave impacts hinder a complete understanding of the related risks and vulnerabilities. Currently, no tool can correlate resilience loss with economic loss metrics for these events.(Daniels Faculty Of Architecture et al., 2022.)

Absence of a unified predictive analysis workflow in a single platform: By incorporating AI techniques, we can simplify the analysis process, eliminating the need for frequent transitions between different software platforms. Once adequately trained, a single, unified system can generate predictions and analyses, significantly boosting efficiency and reducing the time and complexity involved in coordinating multiple software tools. This integrated approach not only streamlines the workflow but also ensures more cohesive and consistent analysis results.

Lack of accuracy in the quantitative assessment: The necessity to optimize the digital workflow using AI techniques arises from the increasing complexity and volume of data involved in analysing environmental hazards. AI, especially machine learning, can efficiently process and analyse this vast amount of data, uncovering insights and patterns not readily apparent through traditional methods. This optimization leads to more accurate, faster, and cost-effective assessments, enhancing our ability to predict, prepare for, and mitigate the impacts of these hazards with greater precision and effectiveness.(Daniels Faculty Of Architecture et al., 2022.)

1.3 Research question

The Research aims to answer the following question –

"*How can machine learning techniques be effectively applied to improve the workflow of seismic and heat waves resilience analysis in building facades?*"

Further, the subsequent sub-questions are as follows –

- What simulation techniques can be utilized to achieve accurate results for façade resilience
- How can façade resilience be quantified?
- Which machine learning algorithms best predict building facade resilience to seismic activity and heat waves?
- How can machine learning enhance the detection and analysis of seismic and thermal risk factors for building facades?
- How can AI synthesize diverse data to provide a resilience score for building facades against heat waves and earthquakes?
- How can machine learning create a user friendly tool for architects and engineers to quickly assess facade resilience against hazards?

1.4 Objective

The aim of this research is to implement machine learning techniques to improve the workflow of existing seismic and heat wave resilience analyses in building facades. The primary objective is to enhance the efficiency and accuracy of the current digital workflow, which involves significant data transfer between platforms, leading to potential time delays and data loss. By introducing supervised and unsupervised learning, the research aims to achieve a more seamless and integrated process.

The outcome of this research will be a digital environment where façade parameters and hazard intensity data serve as input parameters. The tool's primary function is to collect user-provided inputs and utilize an underlying algorithm to predict a resilience score. Additionally, it will perform a correlation analysis between resilience loss due to heat waves and earthquakes, presenting the results in the form of a surrogate model. Ultimately, this tool aims to provide a quicker and more precise resilience score for building facades.

1.5 Methodology

The Study aims to deliver a digital tool for the assessment of the façade resilience in case of multi-hazard events (earthquakes and heatwave). The methodology of the research follows multiple steps as follows:

1. **Literature Review**: The initial phase of the thesis will involve a thorough literature review. This phase is essential for collecting foundational knowledge and current insights on AI techniques used to optimize buildings against heat waves and seismic hazards. The literature review will extend beyond general methodologies to focus on specific building archetypes in New Delhi. This analysis will include examining existing academic and industry research, case studies, and theoretical frameworks.

2. **Computational Simulation**: Following the literature review, the second phase involves conducting extensive computational simulations, which are essential for generating the data required for machine learning analysis. These simulations will be carried out separately for heat waves and seismic events to ensure accuracy and specificity in data collection. For seismic resilience analysis, several steps will be taken, including building modeling using the Grasshopper tool Alpacha4D. This tool will perform a linear static analysis to generate a building response chart. These steps will facilitate the calculation of critical measures such as inter-story drift and the development of fragility specifications, ultimately resulting in graphs that illustrate the resilience of building facades to seismic events. For the heat wave analysis, building models will be assembled using Grasshopper and plugins like Ladybug, Honeybee, and Dragonfly. This will be followed by thermal dynamic simulations using the EnergyPlus engine. The outcome will be spatial thermal autonomy data, linking functionality drop and recovery to standard effective temperatures, providing a clear visualization of the building's resilience to heat waves.(Kim, 2023)

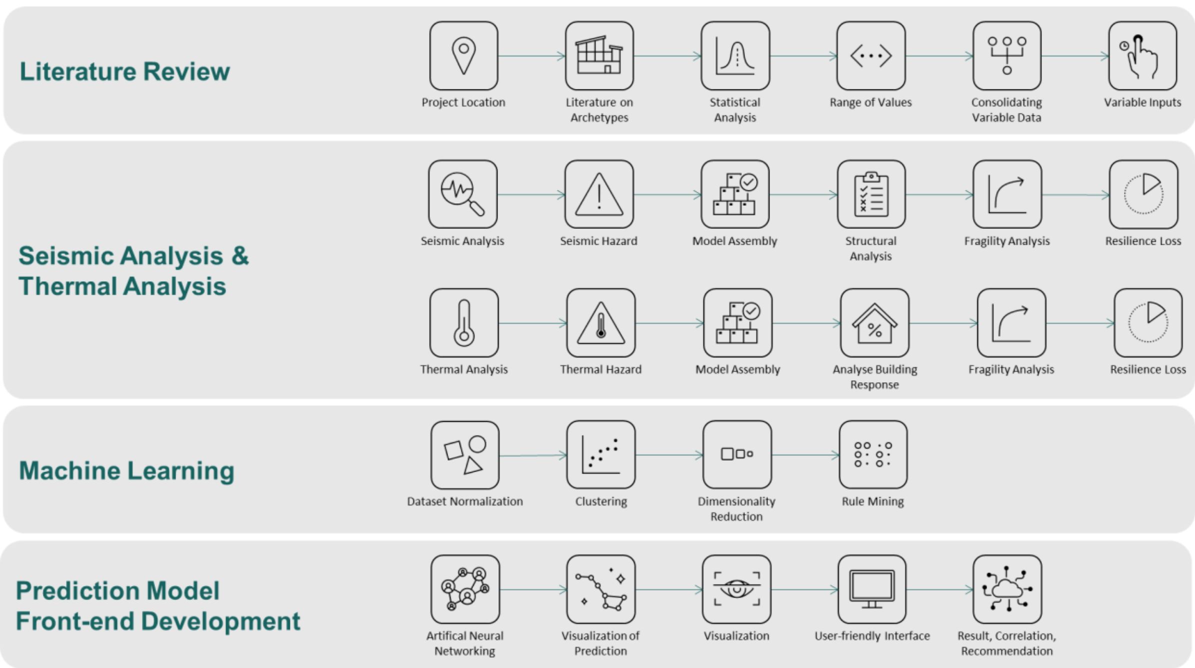
3. **Unsupervised machine learning implementation**: During the third phase of the thesis, unsupervised learning techniques will be implemented to analyze building facade resilience. This phase involves clustering algorithms such as K-means, DBSCAN, or hierarchical clustering to group similar building configurations.(Sun et al., 2021) By implementing these methods, the study seeks to identify hidden patterns and trends in the data that are crucial for understanding the factors contributing to resilience or vulnerability. Dimensionality reduction techniques such as Principal Component Analysis (PCA) and t-SNE will be used to visualize high-dimensional data in two or three dimensions, facilitating the identification of correlations and patterns. Additionally, association rule mining will be

applied to uncover significant relationships between variables within large datasets. For instance, this approach could highlight specific building features that frequently enhance resilience, offering valuable insights for future architectural design.

4. **Predictive modelling**: In the fourth phase, the focus shifts to predictive modeling. Advanced regression models, especially those designed for non-linear tasks, will be utilized to address the complex nonlinear relationships in the data. This step is crucial as it transitions the study from analysis to prediction, enabling the creation of models that can forecast building facade resilience under various scenarios of seismic and heat wave events. The effectiveness of these prediction models in processing and learning from large, multifaceted datasets is key to their success in this phase.

5. **Visualization of the results**: The fifth phase involves post-processing, where the results from the predictive models are interpreted and validated. Tools like SHAP (SHapley Additive exPlanations) will play a significant role in this phase. They will be used to interpret the machine learning model's outputs, particularly focusing on understanding which features most significantly impact resilience and economic loss. This interpretation is crucial for translating the complex model outputs into actionable insights.

6. **Recommendations:** The sixth and final phase of the thesis focuses on providing design recommendations to the user. This phase is dedicated to translating the complex data and insights gathered from the previous phases into a user-friendly interface. The objective is to create an accessible platform for architects, engineers, and other stakeholders to input data and receive comprehensive resilience assessments, predictions and finally recommendations to improve the design.



1.6 Societal and Scientific Relevance

The relevance of the thesis topic, "Enhancing Building Facade Resilience Analysis through Machine Learning: Optimizing Workflow for Seismic and Heat Wave Resilience Measures," extends across social, professional, and scientific domains. On a social level, the development of such a tool promises significant benefits in ensuring building safety and economic efficiency. By accurately assessing and enhancing building resilience, it contributes to public safety and can potentially reduce the economic impacts of environmental hazards. Professionally, the integration of AI techniques into the digital workflow of building analysis revolutionizes the field. It not only improves the accuracy of resilience assessments but also expedites the process, enabling quicker determinations of a building's resilience against hazards. This efficiency is paramount in fast-paced professional environments where timely decisions can have far-reaching consequences.

Scientifically, the application of AI opens new frontiers in understanding the complex interplay between various inputs and their impact on building resilience. The use of AI to identify hidden patterns and draw correlations, especially with indirect measures like standard effective temperature, paves the way for the development of more direct and precise resilience metrics. Furthermore, this research has the potential to yield a combined resilience score for both earthquakes and heat waves, a significant advancement in understanding and mitigating the impacts of these hazards. By analysing common inputs and their individual impacts on resilience, the study could lead to significant insights and methodologies in the field of building science.

02

Research

This section explores the concept of façade resilience, emphasizing the importance of designing facades that can withstand environmental hazards. It reviews existing resilience-based frameworks, discusses multi-hazard design approaches, and examines quantitative resilience assessment methods. The role of advanced machine learning techniques in enhancing façade resilience is also highlighted.

2.1 Literature Review

2.1.1 Concept of Façade Resilience

The escalating discourse surrounding resilience within the built environment is principally attributed to the heightened frequency and intensity of external environmental hazards, a consequence of ongoing climatic changes. This research centers on a particular element of building systems, namely the resilience of building facades. Situated at the interface between a building's exterior and interior, the facade fulfills a myriad of complex roles encompassing environmental, structural, and operational performance. Consequently, augmenting the resilience of the facade is inherently connected to enhancing the overall structural resilience of the building. (Kim, 2023)

(Patterson et al., 2017) To enhance building resilience through façade design, a holistic approach that balances durability, adaptability, and lifecycle considerations is paramount. Facades should be crafted using materials and structural elements robust enough to withstand extreme conditions, ensuring longevity and minimizing maintenance needs. This involves anticipating future uncertainties, such as climate change and evolving urban dynamics, to ensure that façade systems can adapt to a range of potential future scenarios rather than relying solely on historical data. Furthermore, the integration of standardized components within a customizable framework can streamline supply chains and reduce complexity while maintaining the system's ability to meet specific functional and aesthetic requirements. By focusing on these principles, the design not only enhances the resilience of the façade itself but also contributes to the sustainability and adaptability of the entire building, thereby supporting the resilience of the broader urban environment.(Patterson et al., 2017)

Despite its significant potential impact, facade resilience is frequently neglected in current discussions. According to the ASCE 7 building code, facade components are categorized as non-structural elements, with their seismic design criteria detailed in the section on Seismic Design Requirements for Non-Structural Components. (American Society of Civil Engineers, 2010). Non-structural elements are typically more susceptible to damage during disruptive events compared to the primary structure, as their design often lacks sufficient resilience. Damage to these elements can lead to significant economic losses. For example, a study of the 1994 Northridge earthquake showed that 75% of buildings experienced damage to non-structural components. (Charleson, 2008). Technical solutions, such as designing a proper connection between the facade and the primary structure, can significantly reduce earthquake damage by improving the interaction between the two systems (Baird et al., 2011).

Facade resilience enhances not only a single aspect of facade performance but also multiple performance domains. examine the resilience of building envelope design solutions in the face of long-term climate change impacts and the immediate effects of an earthquake. Their study shows that integrated resilience-enhanced solutions, including energy-efficient and earthquake-resistant systems, significantly reduce resilience loss. While facade resilience strategies can address multiple performance issues, not all solutions are complementary. Thus, a comparative analysis is crucial to balance performance and resilience aspects before making a final decision. (Kim, 2023)

2.1.2 Resilience-based Frameworks

Current research on assessing facades from a resilience perspective is limited, with only a few studies conducted. These studies primarily use qualitative assessments, which rely on conceptual frameworks and expert evaluations to measure resilience. However, a quantitative approach, utilizing numerical measurements, is needed to facilitate direct comparisons between buildings and to quantify potential improvements, thereby promoting the adoption of facade resilience in design processes. (Kim, 2023)

Favoino et al. (2022) introduced the Facade Resilience Evaluation Framework (FREF) to assess risks and identify mitigation strategies for facade designs in various contexts under climate change. Applied to a 41-story high-rise with a glazed facade in a high-risk area, the framework showed that early-stage resilience reviews greatly improved outcomes and reduced costs.

Attia et al. (2021) reviewed the performance of cooling technologies during extreme events and stressed the need for direct comparisons between technologies. They recommended future studies adopt a quantitative assessment approach with specific boundary conditions.

Analyzing different resilience-based frameworks reveals variations in focus, scale, and outcomes, either as resilience measurements or design solutions, as highlighted in Figure 2.2. For instance, the City Resilience Framework (Rockefeller Foundation & Arup, 2014) uses indicators to measure project resilience, the Resilient Cooling Strategies Assessment Framework (Zhang & Kazanci, 2021) evaluates cooling technology resilience, and FREF assesses facade stressor risks. The Resilience-based Engineering Design Initiative Framework (Almufti & Willford, 2013) results in design solutions meeting resilience-based criteria.

Arup’s REDi™ Rating System for resilience-based design (RBD) in building projects is categorized into four areas: Building Resilience (minimizing damage to structural, architectural, and MEP components), Organizational Resilience (contingency planning for utility disruptions and business continuity), Ambient Resilience (addressing external hazards), and Loss Assessment (evaluating financial losses and downtime).

Integrating the RBD approach into facade design enhances overall building resilience, especially regarding structural and economic impacts. Facades face multiple hazards, involve non-structural components, and significantly contribute to economic losses during disruptions. Expanding the RBD framework to include specific facade factors can promote a resilient built environment as illustrated in Figure 2.1 (Kim, 2023)

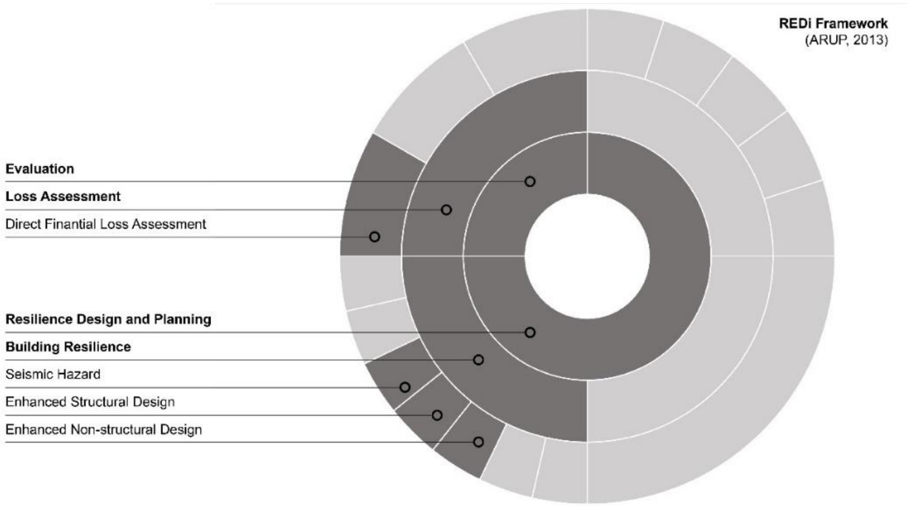


Figure 2.1: Resilience based Design for Facades

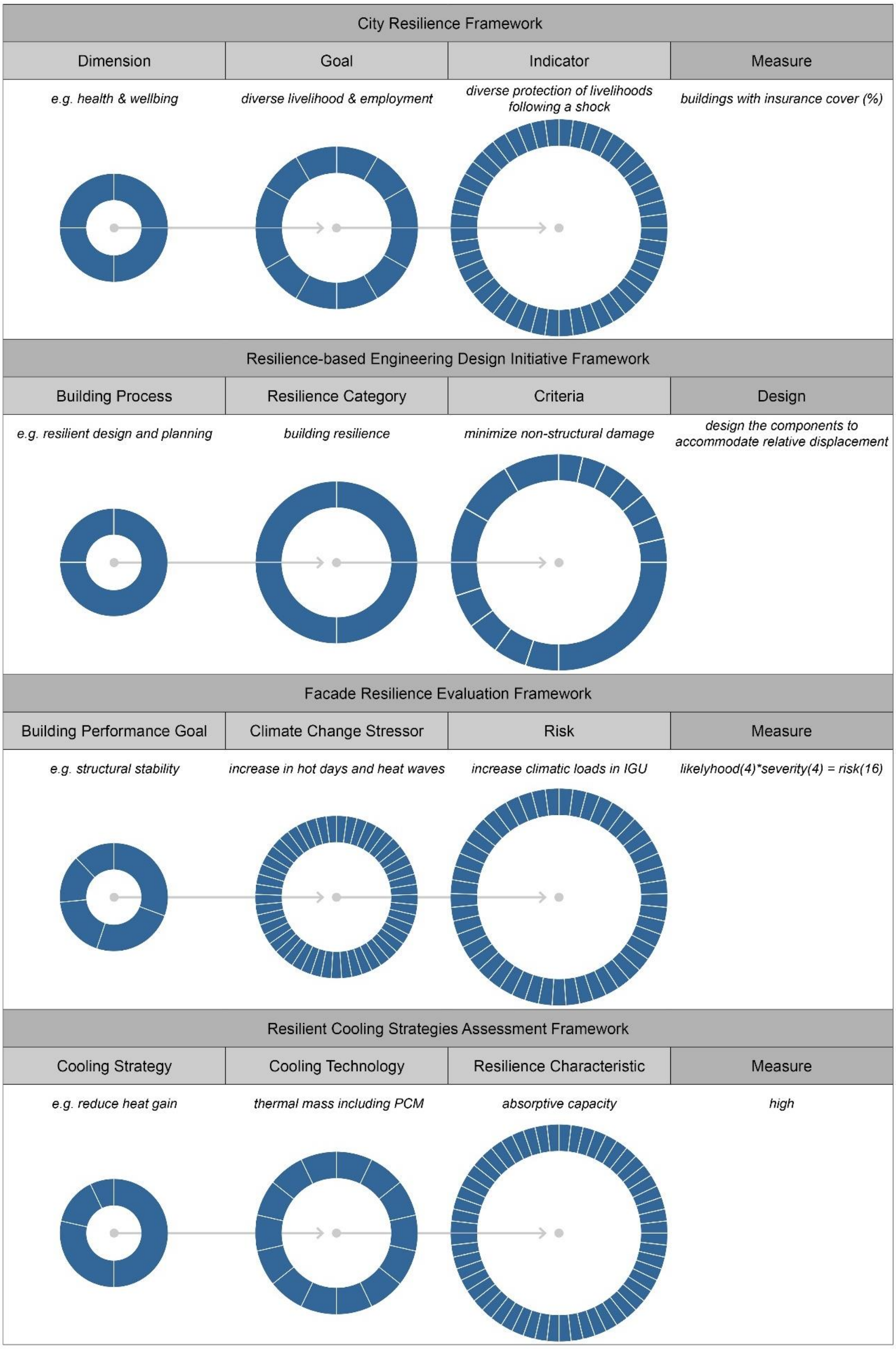


Figure 2.2: Comparison of Resilience Framework

2.1.3 Multi – Hazard Design of Facades

In structural engineering, a risk-based design approach evaluates the probability and intensity of potential risks to a structure and sets design criteria to mitigate these risks. Typically, risk assessments focus on a single hazard, determining the structural performance needed for that specific threat. However, designing exclusively for seismic performance does not ensure resilience against other hazards, such as wind. To address this, a multi-hazard approach is adopted to improve the dependability of structures in areas exposed to various threats. (Chiu & Chock, 1998).

When designing facades to withstand multiple hazards, various design criteria, which can occasionally clash, must be met. The best resisting behavior differs based on the specific hazard. The typical method compartmentalizes the design process by load case (illustrated in Figure 2.3). For each load case, the dimensions of all members and connections are identified in separate sequential steps. As a result, synergies and conflicts between load cases are frequently ignored, leading to unnecessary iterations in the final design. (McKay et al., 2015).

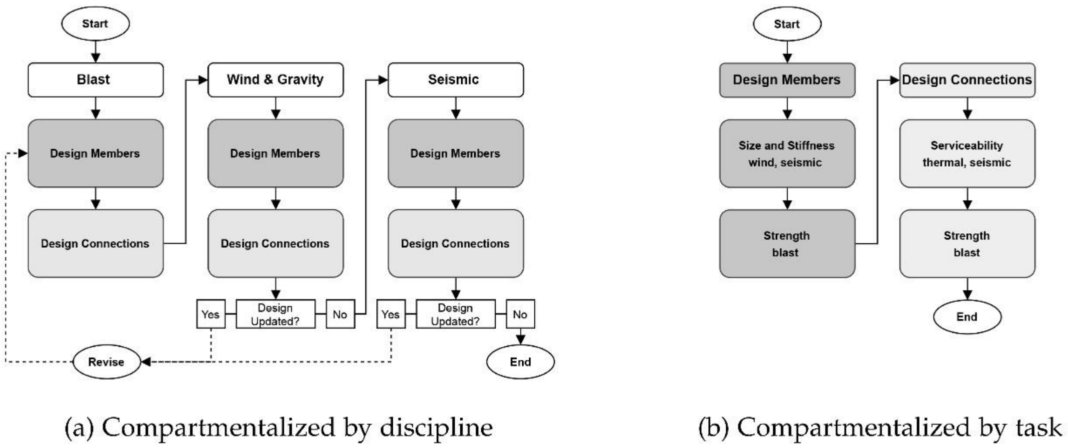


Figure 2.3: Façade design process for multiple hazards, adapted from Mckay et. Al. (2015)

A comprehensive approach can enhance this by incorporating all criteria and their interactions related to multiple hazards at each stage. When aligning design criteria for various hazards, it is essential to focus on facade system features, which may have contrasting effects depending on the load case. A design decision related to a specific building performance aspect can influence performance in other areas, requiring compromises in hazard resistance.

Table 2.2 presents a comparative analysis showing how specific features of the facade system require different design criteria based on the hazard. One debated feature is the weight of the facade system. Additional mass increases inertial resistance to blast loads and helps stabilize heat flow, resisting heat loads. However, it also imposes extra seismic loads on the supporting structure. By focusing on these features, it is possible to establish integrated design criteria that consider multiple hazards. This process includes facade system selection, design detailing, and the sizing of elements and connections, all determined through a reasonable consensus.

Multi-hazard design of facades necessitates a different process than single-hazard design, with decisions made under an objective that satisfies multiple design requirements. (Kim, 2023)

Design Criteria	Blast	Seismic	Wind	Heat
Weight of the System	Added mass provides increased inertial resistance to blast loads (Mckay et al., 2015)	Light weight systems result in lower connection forces and lower imposed loads on the supporting structure (Mckay et al., 2015)		Adding thermal mass locks the heat away and prevents overheating (H. Sun et al., 2022)
Flexural Strength and Stiffness	Reinforcement can lead to unnecessary high blast reations (Mckay et al., 2015)		Additional flexural stiffness provides resistance to wind loads (Mckay et al., 2015)	
Impact Resistance	Laminated lazing can transfer high reaction forces into supporting structural elements (Mckay et al., 2015)		Laminated glazing resist impact from a wind-borne debris missile (Mckay et al., 2015)	
Gap between panel and frame		Seismic gaps thus aim to prevent the infill panel from interacting with the frame (Baird et al., 2011)		Point thermal bridge effect can occur which can lead to a actual thermal loss from the envelope (Theodosiou et al., 2014)

Table 2.2: Influence on selection of design parameters as competing or complementary hazards, adapted from Kim (2023)

2.2 Quantitative Resilience Assessment

Resilience in a system can be achieved by lowering the likelihood of failure, lessening the impact of failures, and speeding up recovery time (Bruneau & Reinhorn, 2006). The resilience function, depicted in Figure 2.4, illustrates the variation in functionality over time and its connection to response and recovery processes. Engineering resilience involves improving the system's robustness and rapidity to reduce its susceptibility to loss. Robustness is the system's ability to endure a specific demand, which is mathematically represented by the residual functionality immediately following a disruptive event. Rapidity is the system's capacity to recover promptly, indicated by the slope of the functionality curve.

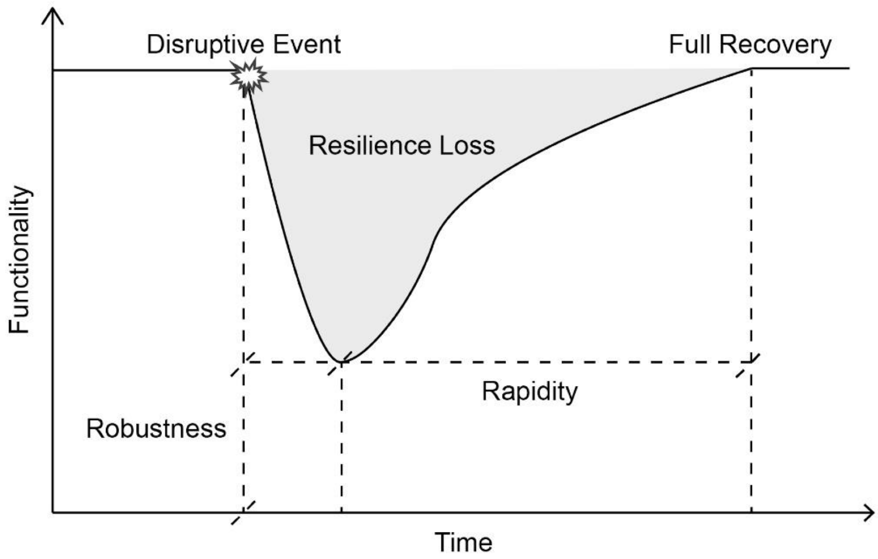


Figure 2.4: Engineering Resilience

The resilience assessment process closely aligns with the probabilistic risk assessment methodology. In this context, risk is defined as the combination of hazard, exposure, and vulnerability. A hazard represents a potential threat, typically depicted by a hazard curve that shows the likelihood of an event occurring within a specific timeframe. Exposure refers to the number of people, buildings, or the monetary value of assets at risk in a certain area. Vulnerability indicates the system's ability to withstand the impacts of hazards on these at-risk elements, given the hazard's intensity. The total expected loss is determined probabilistically as a function of hazard, exposure, and vulnerability. (Kim, 2023)

Probabilistic resilience assessment enhances risk analysis by accounting for the entire timeframe from the initial drop in functionality to complete recovery. This process is illustrated in Figure 2.5. The resilience function, also known as the functionality function, includes both functional loss, which is determined by the vulnerability function, and functional recovery. Vulnerability is evaluated by the average value of distributed functionality loss, which depends on the system's resistance to stressors and the extent of the damage incurred. The fragility function breaks down the building system into various limit states and measures the likelihood of exceeding these states. Data on the damage loss for each limit state is then combined to calculate the total loss. (Kim, 2023)

In summary, the hazard intensity measure (IM) of a specific facade system is determined by its location. Each system has its own unique fragility function, associated damage, and recovery trajectory, which together define a unique functionality function. (Kim, 2023)

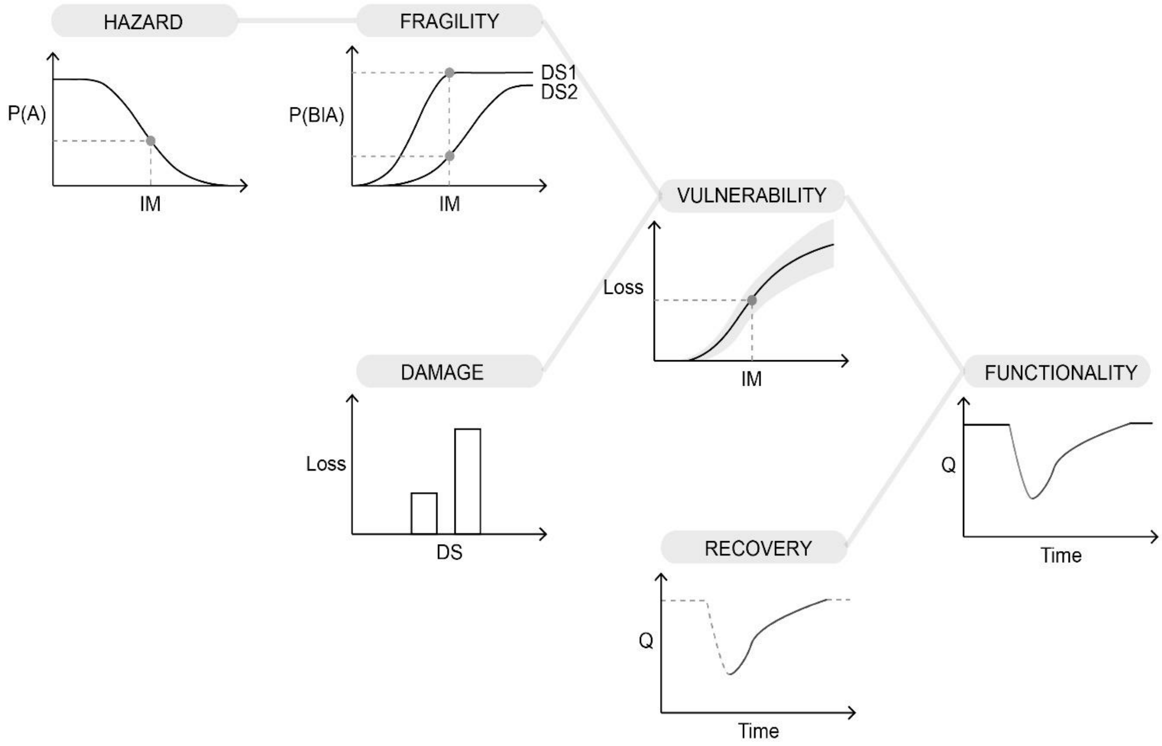


Figure 2.5: Probabilistic resilience assessment, adapted from Kim (2023)

2.3 Quantitative Resilience metrics

Seismic resilience can be assessed using the FEMA P-58 method, which relies on probabilistic seismic performance evaluations. This approach predicts building resilience metrics in terms of repair costs, repair time, life safety, occupancy, and environmental impacts. Thermal resilience in buildings is defined as the ability of a structure to withstand and adapt to thermal stresses caused by external temperature fluctuations, thus maintaining a habitable environment without relying on active energy inputs. This capability is particularly crucial in the face of climate change, which increases the frequency of harsh weather conditions such as severe heat waves and cold spells. By enhancing thermal resilience, buildings can reduce their dependency on mechanical systems, thereby optimizing energy use and minimizing environmental impact. Thermal resilience can be quantified using metrics like **Spatial Thermal Autonomy** and **Passive Survivability.** (Kesik et al., 2019)Spatial Thermal Autonomy measures the percentage of time a building can maintain comfort conditions autonomously, without mechanical heating or cooling. This is typically assessed through dynamic simulations that consider various passive design features. Passive Survivability evaluates a building's ability to continue providing safe conditions during extended periods of power outages or equipment failure, emphasizing the importance of passive heating, cooling, and ventilation strategies in maintaining thermal comfort. Table 2.3 outlines various other resilience metrics and their measurement scenarios in the literature, all assuming power outages during the inspection period. Active survivability involves correctly sizing batteries to maintain flexibility during power outages. Metrics such as the Discomfort Index (DI), Predicted Percent Dissatisfied (PPD), and Occupant Hours Lost (OHL) quantify the degree hours above the discomfort threshold. More complex metrics consider thermal behavior diversity and zone differences during the measurement period. The Indoor Overheating Degree

(IOD) accounts for thermal comfort limits across different zones, while the Weighted Unmet Thermal Performance (WUTP) applies varying weights to the pre-, during-, and post-heatwave periods. The Thermal Resilience Index (TRI) measures resilience by evaluating the relative improvement from the original indoor thermal conditions. (Kim, 2023)

Literature	Application Scenario	Resilience Metrics
Kesik et al., 2019	Power outage due to extreme weather	Thermal autonomy, Passive Habitability
Katal et al., 2019	Power outage due to historical snowstorm	Passive Survivability
O'Brien & Bennet, 2016	Power failure during winter and summer	Passive Survivability, Thermal Autonomy
Ozkan et al., 2019	Power outage during extreme weather	Passive Survivability, Thermal Autonomy
White & Wright, 2020	Power outage during resilience design week	Passive Survivability
Homaei & Hamdy, 2021a	Power outage during coldest and warmest periods	Active Survivability
Baniassadi & Sailor, 2018	Power outage during extreme heat episodes	Discomfort Index
Sailor, 2014	Global/local warming, Power outage, Failed AC operations	Predicted Percent Dissatisfied
Mathew et al., 2021	Power outage with 5 outdoor temperature conditions	Occupant Hours Lost Degree Hours
Hamdy et al., 2017	Historical and future climate scenario, Ventilative cooling	Indoor Overheating Degree
Ji et al., 2023	Heatwave during summertime, Natural ventilation	Thermal Resilience Index
Homaei & Hamdy, 2021b	Power failure during 5 days	Weighted Unmet Thermal Performance

Table 2.3: Thermal Resilience metrics in Literature

2.4 State-of-the-art Machine learning techniques

Recent advancements in the application of machine learning (ML) algorithms within civil engineering have significantly altered the methodologies used to predict and mitigate environmental stresses impacting building infrastructures. This innovation is particularly crucial in enhancing the resilience of building facades against seismic activities and heat waves. Machine learning's capacity to process complex and extensive datasets provides a solid foundation for the development of predictive models that not only bolster the safety of these structures but also their sustainability. (Tardioli et al., 2022)

The research conducted by Tardioli et al., (2022) investigates an innovative approach that integrates machine learning with building physics to enhance the prediction of indoor thermal comfort. This study is instrumental in demonstrating the utility of ML in building science. It showcases how a combination of Internet of Things (IoT) environmental sensors and ML algorithms can surpass traditional methods in predicting thermal comfort with greater accuracy. The methodology employs a hybrid model that melds data-driven techniques with dynamic building simulations, adaptable for evaluating the resilience of building facades against external environmental factors such as seismic shocks and thermal extremes.

Within the domain of facade resilience assessment, two primary categories of ML algorithms have been identified as particularly effective: ensemble methods and deep learning networks. Ensemble methods, including **Random Forests and Gradient Boosting Machines,** utilized in Tardioli et al.’s research for thermal comfort predictions, are aptly suited for modeling facade resilience. These methods enhance predictive accuracy through the amalgamation of multiple decision trees, thereby reducing variance and bias. Such algorithms are proficient in capturing the **non-linear relationships** and interactions amongst a multitude of features typical in datasets that include environmental stressors like temperature variations and seismic movements. Deep learning networks, specifically **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)**, play a critical role in modeling complex spatial and temporal data. For instance, CNNs are leveraged to analyze and interpret facade imagery and structural integrity data following seismic activities, identifying patterns of damage and stress markers. RNNs, known for their efficacy in sequence prediction tasks, are ideal for analyzing time-series data from seismic sensors, facilitating predictions of aftershock effects or the progression of facade deterioration under sustained heat waves.

The deployment of these ML algorithms necessitates the integration of various data sources, including real-time monitoring data from sensors embedded within the facades, alongside historical structural analyses and meteorological data. Through training on this comprehensive dataset, ML algorithms can ascertain the threshold limits of building materials and anticipate the likelihood of facade failure under specified environmental conditions. This predictive capability underscores the transformative potential of machine learning in enhancing the adaptive resilience of building structures to environmental challenges.

(Fang et al., 2022) has outlined a novel approach to utilizing machine learning (ML) in seismic analysis, focusing on a two-stage ML model within a multi-objective optimization framework. The first stage involves a classification model using **Light Gradient Boosting Machine (LightGBM)** to categorize structural samples into code-compliant and code-violated categories based on the maximum peak inter-story drift ratio (θmax). The second stage comprises various ML prediction models, including XGBoost, LightGBM, Random Forest, Gradient Boosting Decision Tree (GBDT), and Neural Networks (NN), to predict **engineering demand parameters** (EDPs) such as maximum peak inter-story drift ratio (θmax), average peak inter-story drift ratio (θavg), maximum peak floor acceleration (apmax), and average peak floor acceleration (apavg). Feature engineering and stacking techniques enhance the prediction accuracy by combining high-dimensional features extracted through neural networks with original features, demonstrating significant improvements in model performance. The framework also includes establishing a comprehensive sample database from the Pacific Earthquake Engineering Research (PEER) center's NGA-West database and training the ML models on this data. The Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is employed to optimize the design parameters of braces, balancing performance and cost. The cost processing module calculates the costs associated with different brace designs, aiding in determining cost-effective yet resilient structural solutions. (Fang et al., 2022)

Furthermore, ML facilitates the quantification and prioritization of risks using algorithms like Random Forests and Support Vector Machines, which assess risk levels associated with different facade materials and configurations under specific conditions. This capability allows for the prioritization of preventive measures, ensuring resources are directed towards the most vulnerable areas of the facade that require immediate attention. Additionally, ML's integration with simulation software can generate detailed models that simulate the impacts of seismic and thermal scenarios on building facades. This not only tests the resilience of materials and architectural designs but also aids in developing new building designs that are inherently more resistant to environmental stresses. Thus, ML enhances the detection and analysis of seismic and thermal risks and supports proactive building design and maintenance strategies, ultimately contributing to safer and more resilient urban infrastructure.

In conclusion, the application of machine learning (ML) in this research proves highly relevant, particularly through the use of prediction models for both thermal comfort levels, as demonstrated by Tardioli et al., (2022) and engineering demand parameters such as peak inter-story drift ratio for seismic analysis, as demonstrated by Fang et al., (2022). These predictive capabilities are essential for this study, enabling accurate assessments and interventions. Additionally, the cost processing module is instrumental in evaluating the economic feasibility of various design solutions. Although my research focuses on brick facades rather than steel bracing, the principles and methodologies can be effectively adapted to suit the specific requirements of brick facade analysis. Moreover, ML's integration with simulation software can generate detailed models that extracts the impacts of various seismic and thermal scenarios on building facades, providing valuable insights into the resilience of materials and architectural designs. Figure 2.6 highlights the pipeline that can be adopted for this research to integrate ML with simulated data and results.

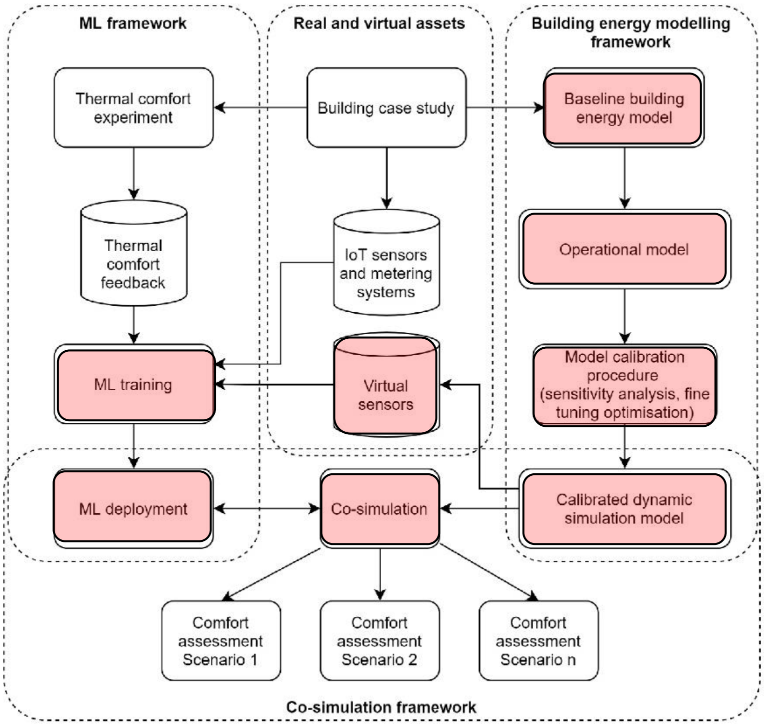


Figure 2.6: Workflow than can be adopted for this Research, Tardioli et al., (2022)

03

Dataset

This section outlines the criteria for selecting the study location, focusing on Delhi's multi-hazard exposure. It analyses housing typologies, emphasizing challenges faced by low-cost housing during power outages. The section also covers the development of Building Energy Models and seismic analysis, detailing the collection and evaluation of building materials from various regions in India.

3. Data collection Methodology

3.1 Location selection Criteria

Delhi falls within Seismic Zone IV, indicating a high level of seismic activity where moderate to severe earthquakes can occur, as classified in IS:1893:2002. Historical data reveal frequent low-magnitude earthquakes and several significant events, such as those in 1956, 1960, and 1966. The region has experienced at least ten notable earthquakes with magnitudes between 2.7 and 4.5 since 2001. These findings highlight Delhi's susceptibility to both seismic and climatic hazards, including intense heat waves during summer, making it an ideal location for studying building facade resilience under multiple hazards (BMTPC, 2010).

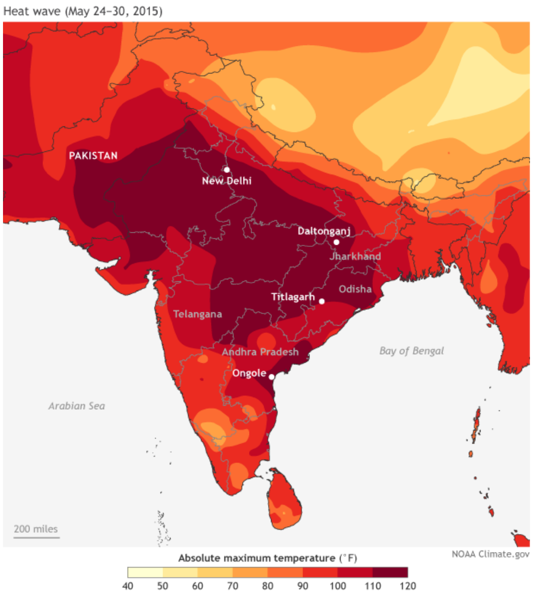


Figure 3.1 : Heat wave map

Figure 3.2 : Seismic zones

Choosing Delhi for this study is justified by its multi-hazard exposure, architectural diversity, high population density, and the availability of extensive historical and real-time data. As India's capital, Delhi's rich architectural landscape, from historical monuments to modern skyscrapers, offers a comprehensive dataset for resilience analysis. The city's large population increases the potential impact of natural disasters, emphasizing the need for robust building resilience measures. (BMTPC, 2010).

3.2 Housing typology analysis

In New Delhi, power outages are a significant issue, especially as temperatures soar beyond 45°C. A survey conducted by LocalCircles, which included over 28,000 responses from 364 districts, highlighted the severity of this problem. According to the survey, 38% of households experience daily power outages, with 18% enduring power cuts lasting between 2 to 12 hours. The primary causes of these outages were identified as poor supply infrastructure, mismanagement, and power thefts. (LocalCircles, 2024)

These frequent power outages have a particularly severe impact on residents of low-cost housing, who are disproportionately affected due to their limited financial resources. Unlike wealthier households, residents in these areas typically cannot afford inverters or photovoltaic (PV) charged cells for backup power. This lack of affordable backup options leaves them vulnerable during power cuts, affecting their daily lives and comfort, especially during extreme weather conditions.

Consequently, this study will focus on the unique challenges faced by low-cost housing residents in New Delhi. Budget constraints make it difficult to implement design interventions that could mitigate the effects of power outages. The study will aim to explore sustainable and cost-effective solutions that can provide comfortable indoor conditions for these vulnerable communities, improving their resilience against frequent power disruptions and enhancing their overall quality of life. By understanding the specific needs and limitations of low-cost housing residents, the study seeks to propose viable design interventions that can be realistically implemented within their financial constraints. This makes the design intervention particularly challenging due to budget constraints. Analyzing the base model and validating the need for enhancing resilience in these housing units is crucial.

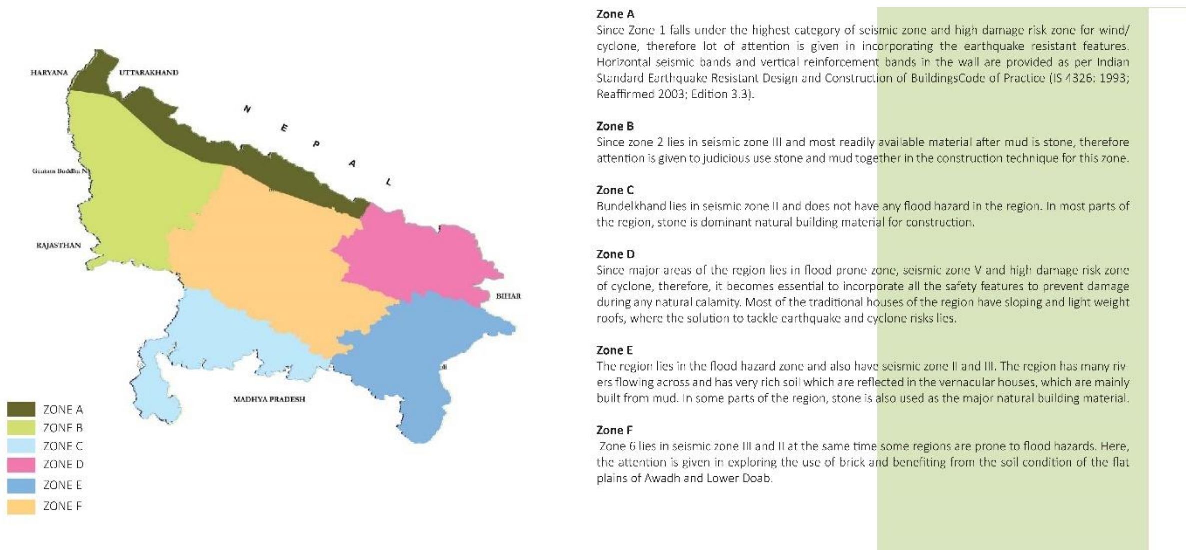


Figure 3.2 : Zone map of the state of Uttar Pradesh(Ministry of Rural Development, 2016)

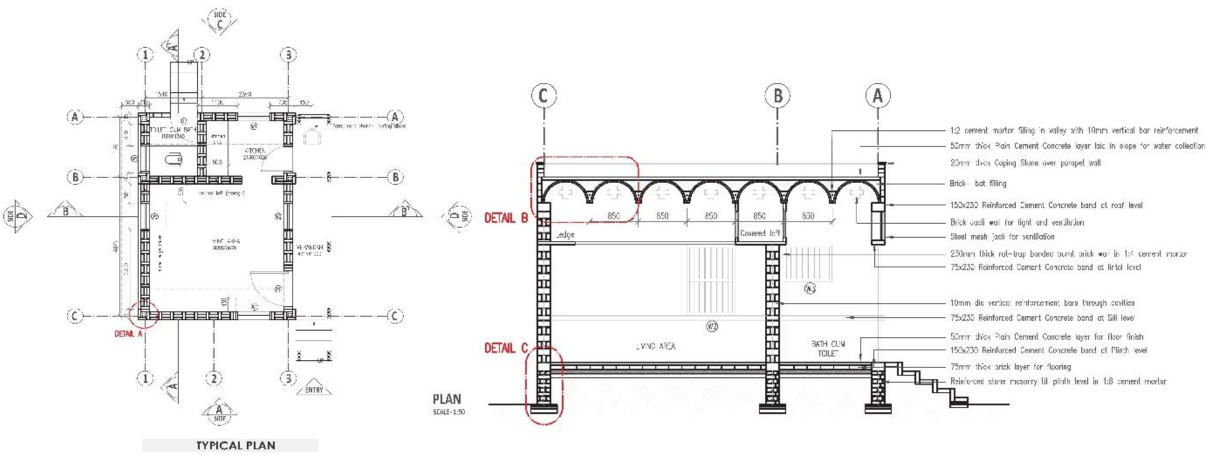


Figure 3.3 : Example of a house proposed by the government(Ministry of Rural Development, 2016)

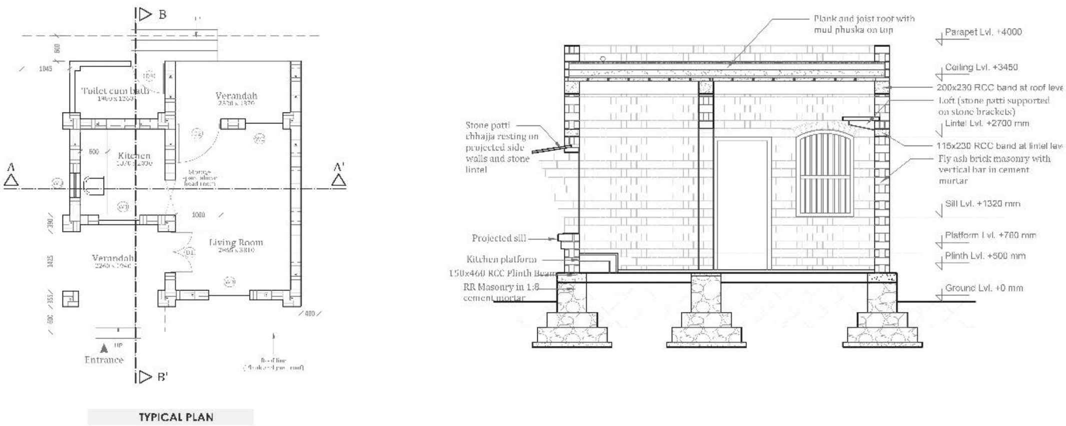


Figure 3.4: Example of a house proposed by the government (Ministry of Rural Development, 2016)

The Pradhan Mantri Awaas Yojana – Gramin (PMAY-G), restructured from the Indira Awaas Yojana, aims to provide assistance for the construction of 10 million houses in rural areas over three years from 2021-22 to 2024-25. The overall effort is to support poor households in developing functional, comfortable homes that meet the beneficiaries' aspirations rather than just constructing low-cost houses. To achieve this, PMAY-G proposes the creation of a menu of housing designs based on local typologies, incorporating local materials, traditional knowledge, and aesthetics. (Ministry of Rural Development, 2016) The states of Uttar Pradesh and Rajasthan, which experience extreme heat wave conditions, are geographically adjacent to the Indian capital, New Delhi, and therefore share similar climatic characteristics.

The architectural details of twelve different houses, as illustrated in Figures 3.3 and 3.4, were extracted from relevant documents and utilized to create twelve distinct base models. A statistical analysis of all the building dimensions inside the document is also done, figure 3.5, to identify the range of lengths, widths and total heights of all the low-cost housings. These building dimensions will be used to create multiple geometric configurations for the seismic analysis. These base models served as the foundation for building energy simulations, incorporating varied inputs to generate multiple scenarios. This approach facilitated the creation of an extensive dataset. (Ministry of Rural Development, 2016)

These detailed inputs are crucial for accurately simulating building performance under different conditions, thereby enabling a comprehensive analysis of thermal and seismic resilience. (Ministry of Rural Development, 2016)

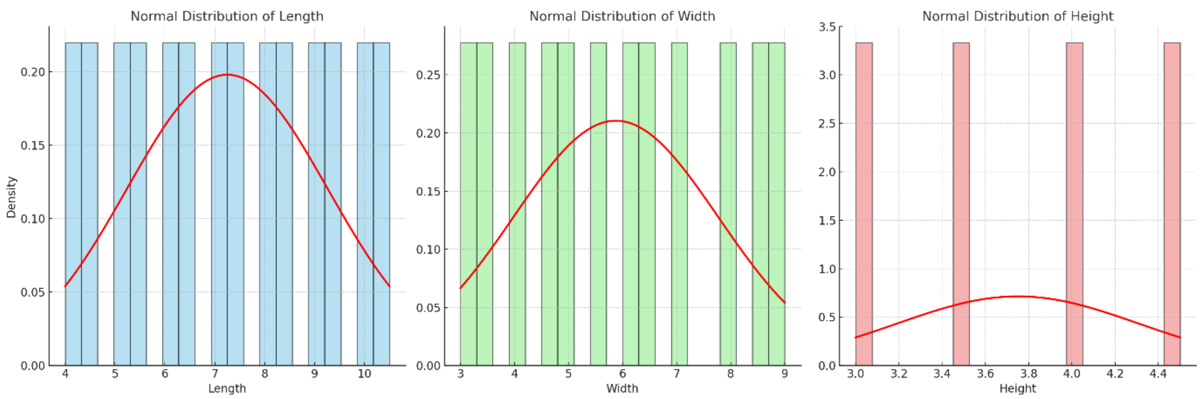


Figure 3.5: Statistical analysis of building dimensions to extract range of values

3.3 Energy Modelling key factor

When developing a Building Energy Model (BEM) to assess thermal resilience, several key considerations must be addressed. Firstly, it is essential to accurately determine the effective thermal resistance (R-values) of various building enclosure components and assemblies. These values serve as critical inputs to energy simulation models and must reflect the climate zone of the building's location. The ASHRAE Climate Zones, for example, categorize regions based on their thermal characteristics, guiding the selection of suitable weather files for modeling purposes (Kesik et al., 2019). Additionally, the overall airtightness of the building should be considered, as this affects the building's ability to maintain indoor temperatures during power outages or extreme weather events (Kesik et al., 2019).

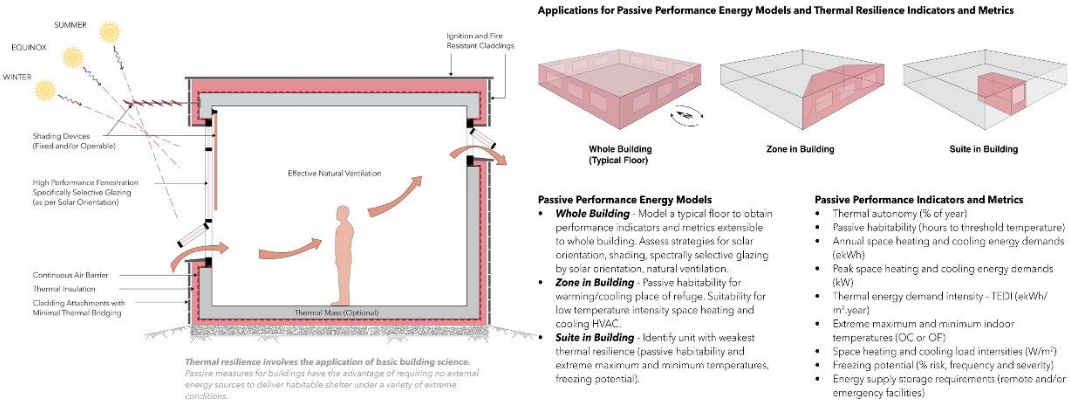
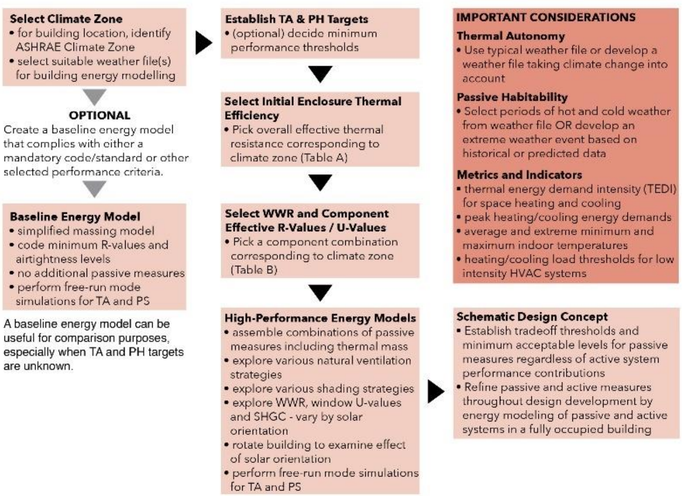


Figure 3.6: Guidelines for creating a thermal model, (Kesik et al., 2019).

Building physics plays a significant role in modeling, including the thermal mass of the structure, natural ventilation strategies, and shading mechanisms. Passive measures such as solar orientation, spectrally selective glazing, and natural ventilation must be optimized during the design phase to enhance the building's thermal autonomy and passive habitability (Kesik et al., 2019). Thermal autonomy measures the fraction of the year when the building remains within a comfortable temperature range without active heating or cooling, while passive habitability assesses the duration a building can maintain livable conditions during power failures (Kesik et al., 2019). Both metrics are crucial for understanding and improving the building's resilience to heat waves and cold spells. Simulation tools like EnergyPlus can be used to create baseline and high-performance energy models, adjusting parameters such as window-to-wall ratios, U-values, and shading devices to test various scenarios and identify the most effective passive strategies (Kesik et al., 2019).



When conducting simulations, it is also important to consider occupant behavior. Modeling both passive and active occupant interactions with the building's features, such as the use of shading devices and operable windows, can significantly impact the accuracy of the thermal resilience assessment (Kesik et al., 2019). The use of typical meteorological year (TMY) weather files for thermal autonomy simulations and extreme weather event files for passive habitability simulations ensures that the model reflects realistic and worst-case scenarios (Kesik et al., 2019). Ultimately, these simulations help to establish design criteria for resilient buildings that can withstand the challenges posed by climate change and energy infrastructure disruptions.

3.4 Seismic analysis Overview

To conduct a valid seismic analysis, acquiring earthquake data is crucial to understand the reaction of buildings. Six different earthquake datasets were collected from the official website of IIR Roorkee. The magnitudes of these earthquakes range from 5.5 to 7.8, and all ground accelerations are recorded in m/s² with a time step of 0.005 seconds. The performance of buildings under seismic activity is assessed by examining the damage state of various components. The extent of functionality loss is determined based on the damage state resulting from the seismic event. Finally, the seismic resilience of brick facades will be evaluated using seismic resilience metrics.

3.4.1 Damage Intensity Measure

As outlined in FEMA P58-1 (2018), the term "damage state" denotes the extent of damage associated with specific consequences for a particular component or the entire building. Different levels of damage for a component are represented by discrete damage states. Each of these states corresponds to various performance measures, as different damage levels lead to different performance outcomes. For example, an exterior cladding component might reach damage state 1, where the sealant joint cracks, necessitating minimal repair time and cost. On the other hand, damage state 2, involving panel cracking, requires replacement, which incurs greater repair time and expense. The average damage state (DS) is calculated by weighting the number of damaged components on a specific floor in a certain direction (i.e., performance group) against the severity of their damage, using the following equation (FEMA, 2013a):

$$DS=\sum i=1ni\cdot \mathrm{DS}i \tag{3.1}$$

The extent of damage to a component is assessed by determining the probability of reaching a specific damage state using a fragility function, given a certain demand. Consequently, performance measures such as necessary repair actions, estimated repair costs, and repair times for each damage state can be derived.

3.4.2 Seismic Resilience Metrics

The seismic performance of a building is expressed using metrics such as casualties, repair cost and time, unsafe placarding, and environmental impact. Replacement becomes necessary in the case of total loss, where a new structure of comparable design and construction must be built. This study focuses on repair cost and repair time as metrics to assess the impact of earthquakes on the facades of low-cost housing. The aim is to analyze the structural performance of the facade component in the event of an earthquake.

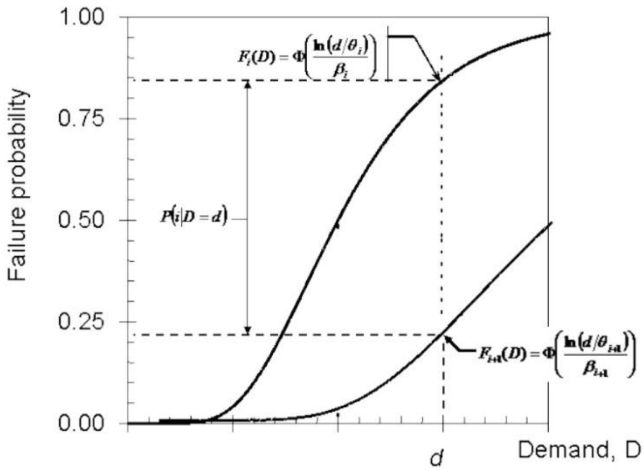
3.4.3 Fragility Function

In vulnerability assessments of structural systems, the fragility function is employed to determine the type and severity of damage a component is likely to sustain. It is assumed that the probability of experiencing damage at various demand levels follows a lognormal distribution. The mathematical expression for a fragility function is as follows:

$$F_i(D)=\Phi(\ln(D/\vartheta_i)/\beta_i) \qquad (3.2)$$

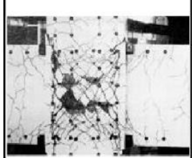
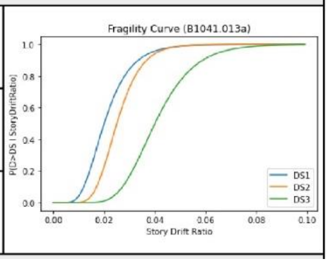
where $Fi(D)$ is the conditional probability that the component will be damaged to damage state ii as a function of a demand parameter D; Φ denotes the standard normal cumulative distribution function; θi denotes the median value of the probability distribution; and βi denotes the logarithmic standard deviation. Both $\theta$and β are established for each component type. Figure 3.7 illustrates the fragility curve for sequential damage states. This curve can be used to determine the failure probability for damage state "i" and a more severe damage state "i+1", given a demand parameter equal to "d". (Kim, 2023)

Figure 3.7: Fragility curve for sequential damage state (FEMA P-58, 2018)



3.4.4 Structural and Non-Structural Fragility Specifications

FEMA P-58 Volume 3 offers a fragility database that includes over 700 individual fragility specifications. When a component is not found in this database, custom components can be added through the PACT Fragility Specification Manager. As shown in Figure 3.8, fragility specifications for structural components and a fragility curve based on the database can be visualized. This visualization can be created with a Python script to estimate repair costs and times Reinforced concrete moment-resisting frames (B1041.013) are engineered to endure seismic loads to a certain degree. In such frames, beam-column joints transfer forces through reinforcement. Structural failures typically occur due to the crushing or cracking of concrete, or the yielding or fracturing of the reinforcement. For this analysis, non-structural fragility specifications for masonry infill walls are necessary. The FEMA database lacks information on facade materials like masonry or concrete. To fill this gap, additional data was sourced from the literature. Specifically, information on masonry infill walls (B2011.301) was derived from Cardone and Perrone (2015). This data will be utilized to forecast the damage state of masonry infill walls based on the reaction of the concrete portal frame to seismic activity. (Kim, 2023)

B1041.013a	MF with SMF-conforming beam and column flexural and confinement reinforcement but weak joints , Conc Col & Bm = 36” x 36”, Beam one side				
	DS1	No significant spalling. No fracture or buckling of reinforcing.	0.02	0.4	
	DS2	Spalling of cover concrete exposes beam and joint transverse reinforcement.	0.025	0.3	
	DS3	Fracture or buckling of reinforcing requiring replacement may occur.	0.04	0.3	

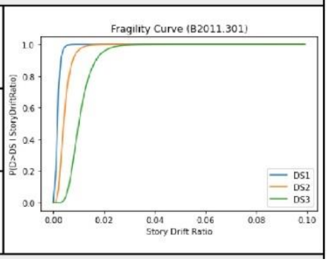
B2011.301	Exterior Wall - Masonry infills with French window and Partitions with door				
 int ext	DS1	Detachment of infill, Light diagonal cracking	0.0015	0.5	
	DS2	Extensive diagonal cracking	0.004	0.5	
	DS3	Corner crushing and sliding of mortar joints	0.01	0.4	

Figure 3.8: Structural and non-structural components fragility curves

3.5 Sample collection Methodology

A comprehensive dataset on the properties of various building blocks commonly used in Indian housing was collected. Notably, a significant majority of houses in India are constructed using bricks. Therefore, samples of these building materials were gathered from diverse locations across the country to ensure a representative dataset (Rawal et al., 2020)

	Firedclay Brick	Flyash Brick	Concrete Brick	Concrete Block	Calcium Silicate Block	AAC	CLC	CSEB
Tamil Nadu	4	1	-	-	-	-	-	-
Telangana	1	-	-	-	-	-	-	-
Andhra Pradesh	1	-	-	1	-	-	-	-
Maharashtra	2	2	-	-	1	1	1	-
Gujarat	2	1	-	-	-	-	-	-
Bihar	1	1	-	-	-	-	-	-
Delhi & NCT	-	1	-	-	-	-	-	1
Uttar Pradesh	3	-	-	-	-	-	-	-
Madhya Pradesh	1	1	-	-	-	-	-	-
West Bengal	1	1	-	-	-	-	-	-
Haryana	3	1	-	-	-	1	-	-
Karnataka	2	-	-	1	-	-	-	1
Punjab	2	1	1	-	-	-	-	-
Total	23	10	1	2	1	2	1	1

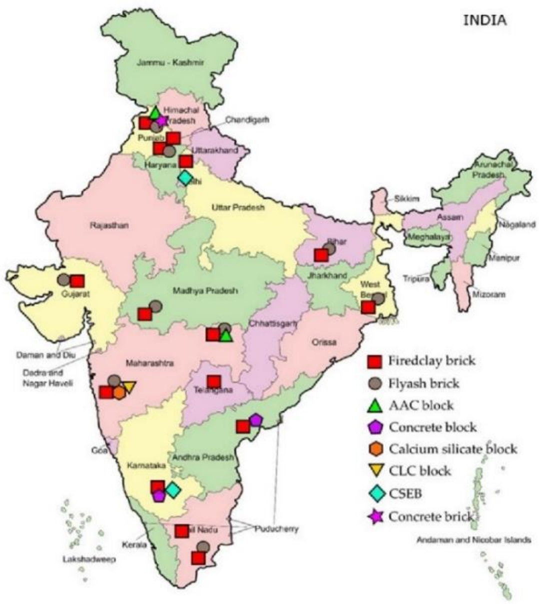


Figure 3.9: Map of India illustrating collection points of samples, Rawal et al., 2020)

The properties of the collected samples were meticulously extracted through a series of experiments, including measurements of thermal conductivity, bulk density, specific heat, and compressive strength. Additionally, correlations between these properties were analyzed to understand the interdependencies and behavior of materials under different conditions (Rawal et al., 2020). Each block sample was meticulously labeled and accompanied by detailed property measurements. This systematic labeling and documentation provide a robust dataset essential for conducting Building Energy Modeling (BEM) and structural analysis. The gathered data ensures that the thermal and physical characteristics of the materials are accurately represented, facilitating reliable and precise modeling outcomes.

S. N.	Sample	Bulk Density ρ (kg/m^3)	Thermal conductivity λ (W/m.K)	Specific heat C_p (J/kg.K)	Compressive strength (MPa)	Water absorption (%)
Hand-moulding						
1	RB01	1599	0.48	907.8	14.83	21
2	RB02	1777	0.60	921.6	16.54	15
3	RB04	1654	0.57	917.5	23.08	19
4	RB06	1887	0.76	927.0	20.23	12
5	RB07	1738	0.53	960.4	7.21	16
6	RB09	1604	0.39	909.0	6.1	23
7	RB10	1512	0.42	926.5	5.32	26
8	RB11	1447	0.50	936.6	10.01	24
9	RB14	1503	0.42	935.9	4.88	26
10	RB15	1264	0.38	927.8	4.16	32
11	RB20	1780	0.55	952.9	18.68	15
12	RB21	1716	0.54	923.1	17.8	17
13	RB23	1819	0.74	978.6	25.8	13

Figure 3.10: Illustration to explain sample tag(top) and photograph of tagged bricks, Rawal et al., 2020

The collected data and subsequent analyses form a critical foundation for evaluating the thermal resilience and structural integrity of buildings, particularly in the context of multi-hazard scenarios involving heat waves and earthquakes. This approach ensures that the findings and recommendations are grounded in empirical evidence, enhancing the reliability and applicability of the study's outcomes (Rawal et al., 2020).

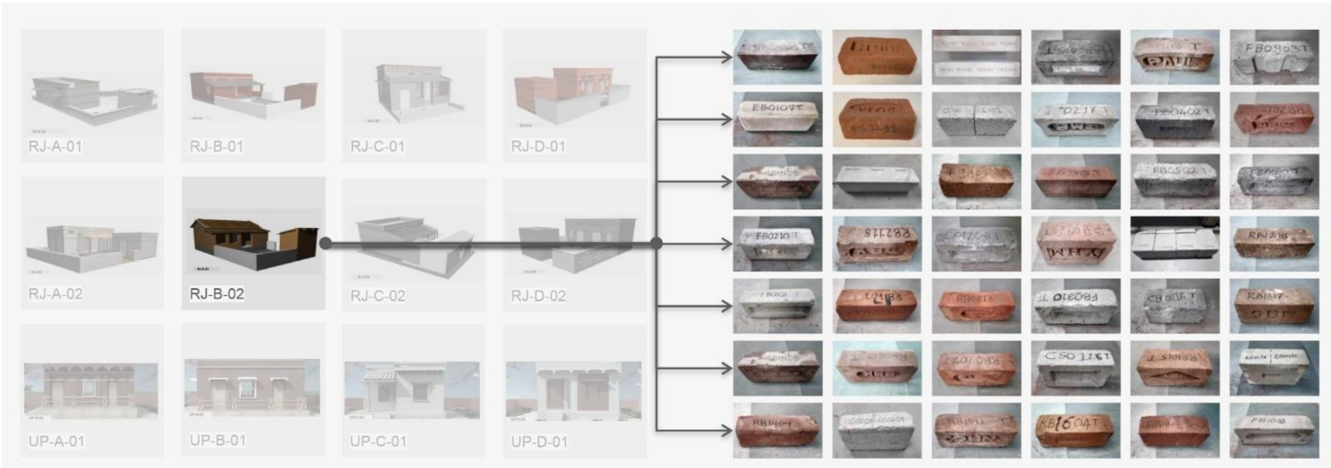


Figure 3.11: Illustration showing housing architectural data and brick properties combined for dataset

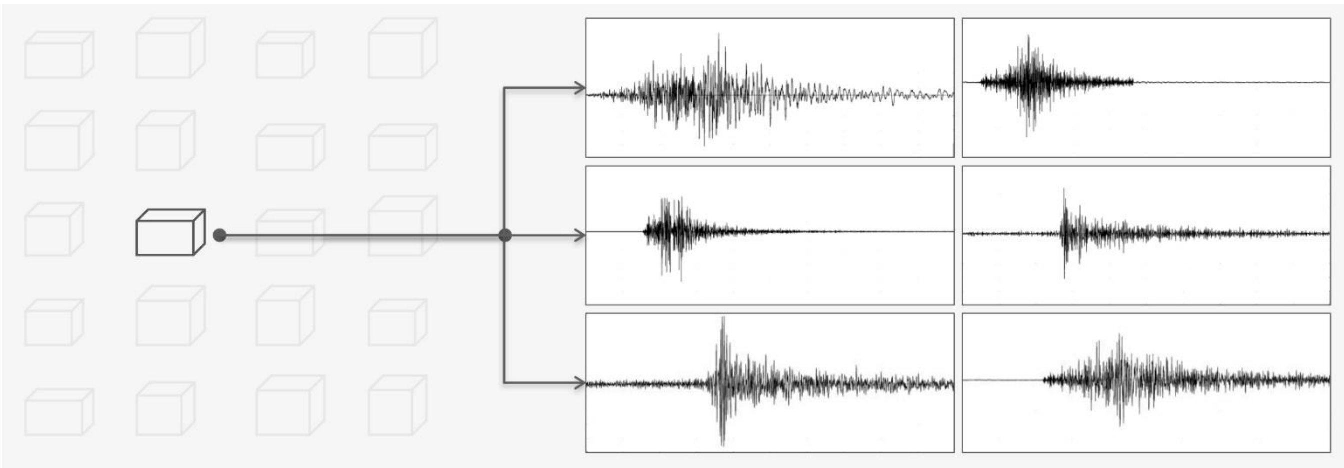


Figure 3.12: Illustration showing housing architectural data and earthquake data combined for dataset

04

Simulations

This section details the methodologies for simulating Building Energy Models (BEM) and seismic analysis of housing structures. It covers data collection, model setup using Grasshopper and EnergyPlus, and the evaluation of thermal and seismic resilience. The approach includes comprehensive datasets, automated scripts, and simulation tools to assess building performance under various scenarios.

04. Computational Simulations for RBD

4.1 Building Energy Model Simulation

A comprehensive dataset on the properties of various building blocks commonly used in Indian housing was collected.

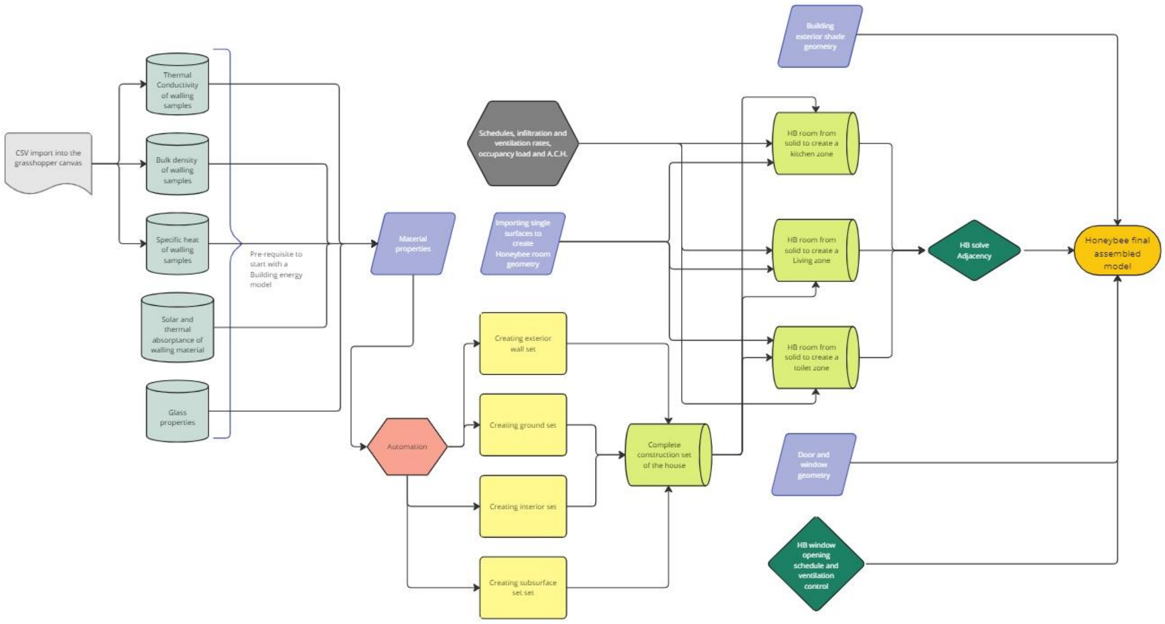


Figure 4.1: Flowchart explaining the grasshopper script for thermal simulations

The dataset is compiled into a CSV file containing the material properties of 43 different building blocks, as detailed in Section 3.5. This CSV file is imported into the Grasshopper canvas. An automation script is employed to feed these properties into the materials component. The properties include thermal conductivity, bulk density, and specific heat of each walling sample, as well as glass properties for various combinations. The window used throughout the design remains constant. The dataset also includes fractional values for solar absorptance and thermal absorptance, ranging from 0 to 1, which denote the extent to which a building material absorbs heat. The default value is 0.8, and four scenarios with values of 0.2, 0.4, 0.6, and 0.8 are created to analyze the impact of thermal absorptance on the results and its significance in the machine learning model.

After setting the material properties, construction set are created where these properties are assigned to the walls, floor, and roof. For running building energy simulations, a Honeybee room set is created by defining single surface closed geometries in Rhino, which are imported into the Grasshopper canvas. These geometries are interpreted as rooms by the component. As described in Section 3.2, 12 different housing plans were selected and converted into Rhino models. These models are used sequentially in the script to generate numerous combinations of houses, material properties, and other crucial features.

Three room sets are defined for the kitchen, toilet, and living room, each with distinct air change rate (ACH) values, occupation rates, and occupancy schedules, significantly affecting the results. Given the absence of an HVAC system in the model—reflecting scenarios without power—the ACH value is calculated based on a standard formula: the ventilation rate in m^3/hr divided by 20, a common professional assumption. Once the Honeybee rooms are established, adjacency is solved to avoid double-counting overlapping wall values. External shadings, their angles, windows, and doors are added as subsurface. To enhance realism, a ventilation control component is added. It operates on the principle that if the outdoor temperature exceeds 28 degrees Celsius, windows are shut to prevent hot air entry; otherwise, they remain fully open for fresh air, contingent on the occupancy schedule.

With these elements, a detailed building energy model is constructed and used for simulations. This model is connected to the thermal simulation component, which requires additional critical inputs, such as the EnergyPlus weather data file, as illustrated in figure 4.2

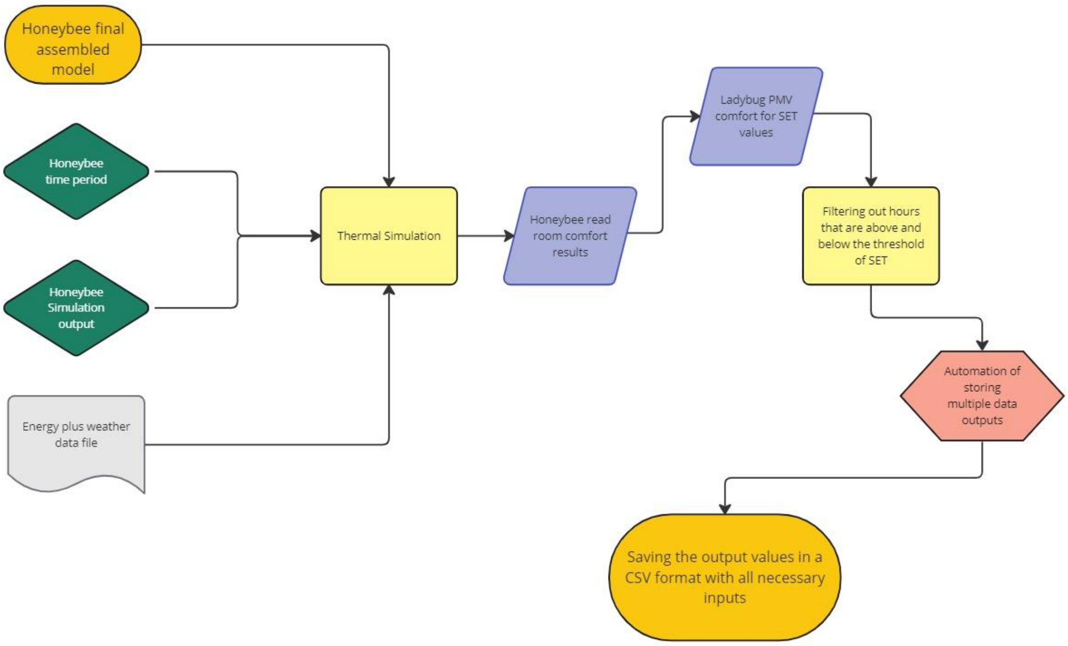


Figure 4.2: Flowchart explaining the grasshopper script for thermal simulations

To simulate real-life scenarios, a Typical Meteorological Year (TMY) weather data file for New Delhi is used, specifically from the year 2022, the hottest recorded year of this century. Another crucial input is the Honeybee time period. Since winter results are not required, the analysis period is set to six months, from mid-March to mid-September, encompassing a total of 4380 hours.

Once the model setup is complete, the visual script is run, initiating the EnergyPlus engine in the background to execute the simulations. The EnergyPlus engine generates various outputs, among which the indoor operative temperature, relative humidity, and indoor air temperature are particularly relevant for this research. These values are then used to calculate the Standard Effective Temperature (SET) for each hour.

A Python script is subsequently utilized to bifurcate the data into two sets: hours with an SET score below 28 degrees Celsius and hours with an SET score above 28 degrees Celsius. Finally, spatial thermal autonomy is calculated by dividing the number of hours within the acceptable thermal comfort threshold (SET less than 28 degrees) by the total number of analysis hours. This result is stored in a CSV file for each of the 2563 simulations, encompassing different permutations and combinations as illustrated in Figure 4.2. This comprehensive approach ensures a detailed understanding of how different material properties and design scenarios impact the thermal performance of buildings, aiding in the development of a robust machine learning model capable of predicting thermal comfort in varied conditions.

4.2 Seismic Model Simulation

A comprehensive dataset on the properties of various building blocks commonly used in Indian housing was collected.

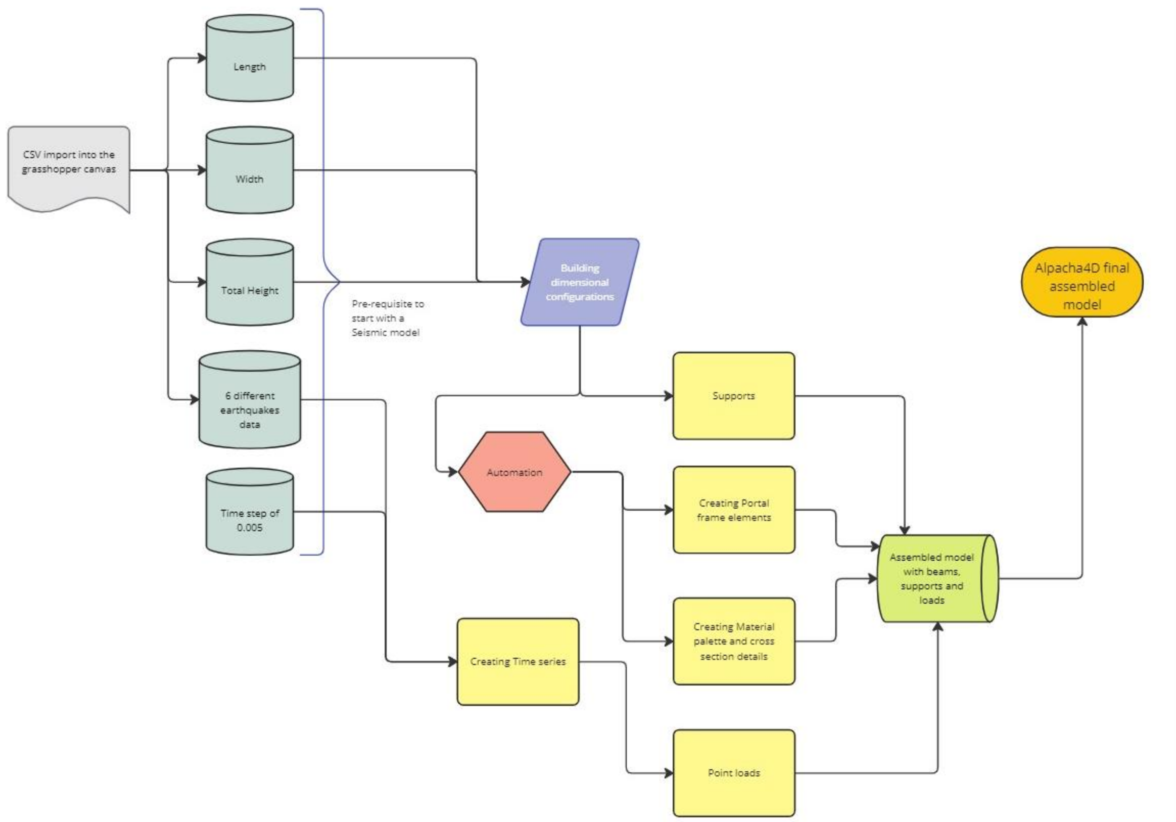


Figure 4.3: Flowchart explaining the grasshopper script for seismic simulations

The seismic analysis begins with a linear static analysis of the structure performed using Alpacha4D. The essential inputs for this analysis include the length, width, and height of the house, the type of structure (whether it is a portal frame or load-bearing structure), material properties, type of support, type of load, and earthquake data. After conducting statistical analysis on various dimensional values, a list of 643 different combinations of length, width, and height configurations is generated. This CSV file is imported into the Grasshopper canvas, where an automation script sequentially feeds the length, width, and height values to create the grid for each house configuration.

Research on house plans revealed that the heights range from 3 meters to 4.5 meters. A script was developed to adjust the section size based on the height, varying from 0.25 to 0.35 meters to create realistic scenarios. Concrete portal frames are selected as the material, reflecting common construction practices in India. Additionally, earthquake data is crucial for the analysis. Six different sets of earthquake data, with magnitudes ranging from 5.5 to 7.8, are used. These are historical records from India, with acceleration units in m/s^2 and a time step of 0.005 seconds. A time series is created for each earthquake magnitude, and simulations are run sequentially for each dataset. This time series helps calculate the point loads acting on the portal frame.

The Alpacha4D model is then assembled, incorporating dimensional configurations, material and section size, point loads, and earthquake data. This model is prepared for simulation, which includes force and displacement analysis. Once the displacement values are obtained, the inter-story drift angles are calculated using a Python script. These angles, measured in radians, are then evaluated to find the maximum drift angle for each simulation. The maximum drift angle is stored in a CSV file using an automation script, which systematically saves the drift angles for all simulations, as illustrated in figure 4.4

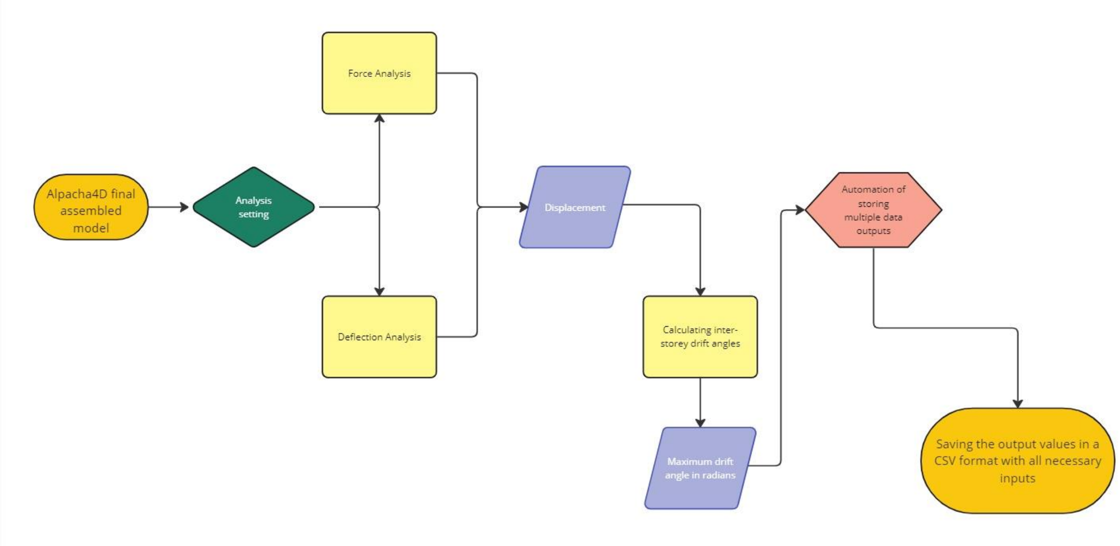
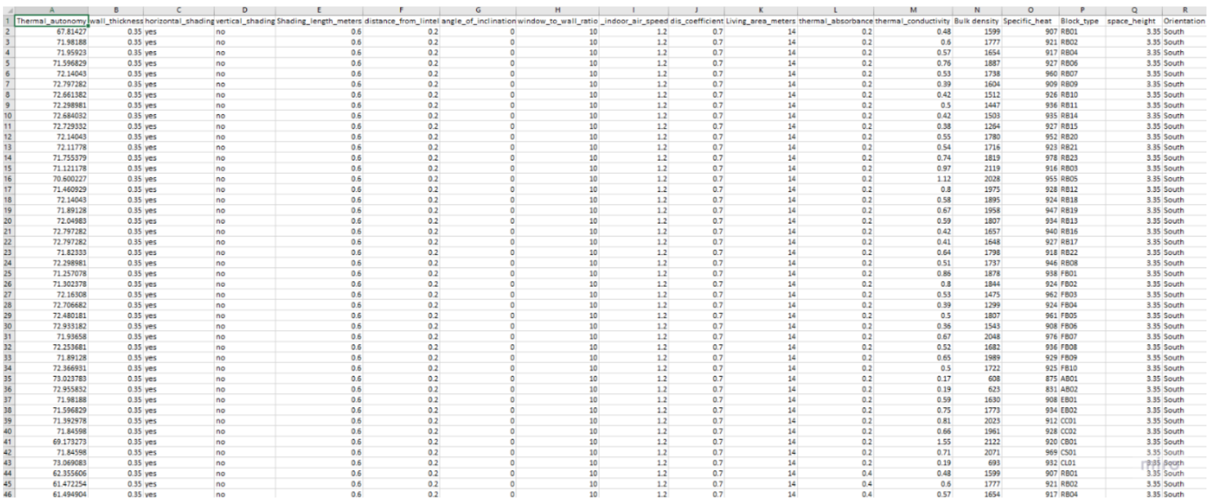


Figure 4.4: Flowchart explaining the grasshopper script for seismic simulations



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	Thermal_autonomy	wall_thickness	horizontal_shading	vertical_shading	Shading_length_meters	distance_from_lintel	angle_of_inclination	window_to_wall_ratio	_indoor_air_speed	dis_coefficient	Living_area_meters	thermal_absorbance	thermal_conductivity	Bulk density	Specific_heat	Block_type	space_height	Orientation
2	67.81427	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.48	1599	907	RB01	3.35	South
3	71.98188	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.6	1777	921	RB02	3.35	South
4	71.95923	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.57	1654	917	RB04	3.35	South
5	71.596829	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.76	1887	927	RB06	3.35	South
6	72.14043	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.53	1738	960	RB07	3.35	South
7	72.797282	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.39	1604	909	RB09	3.35	South
8	72.661382	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.42	1512	926	RB10	3.35	South
9	72.298981	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.5	1447	936	RB11	3.35	South
10	72.684032	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.42	1503	935	RB14	3.35	South
11	72.729332	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.38	1264	927	RB15	3.35	South
12	72.14043	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.55	1780	952	RB20	3.35	South
13	72.11778	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.54	1716	923	RB21	3.35	South
14	71.755379	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.74	1819	978	RB23	3.35	South
15	71.121178	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.97	2119	916	RB03	3.35	South
16	70.600227	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	1.12	2028	955	RB05	3.35	South
17	71.460929	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.8	1975	928	RB12	3.35	South
18	72.14043	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.58	1895	924	RB18	3.35	South
19	71.89128	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.67	1958	947	RB19	3.35	South
20	72.04983	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.59	1807	934	RB13	3.35	South
21	72.797282	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.42	1657	940	RB16	3.35	South
22	72.797282	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.41	1648	927	RB17	3.35	South
23	71.82333	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.64	1798	918	RB22	3.35	South
24	72.298981	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.51	1737	946	RB08	3.35	South
25	71.257078	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.86	1878	938	FB01	3.35	South
26	71.302378	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.8	1844	924	FB02	3.35	South
27	72.16308	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.53	1475	962	FB03	3.35	South
28	72.706682	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.39	1299	924	FB04	3.35	South
29	72.480181	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.5	1807	961	FB05	3.35	South
30	72.933182	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.36	1543	908	FB06	3.35	South
31	71.93658	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.67	2048	976	FB07	3.35	South
32	72.253681	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.52	1682	936	FB08	3.35	South
33	71.89128	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.65	1989	929	FB09	3.35	South
34	72.366931	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.5	1722	925	FB10	3.35	South
35	73.023783	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.17	608	875	AB01	3.35	South
36	72.955832	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.19	623	831	AB02	3.35	South
37	71.98188	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.59	1630	908	EB01	3.35	South
38	71.596829	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.75	1773	934	EB02	3.35	South
39	71.392978	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.81	2023	912	CC01	3.35	South
40	71.84598	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.66	1961	928	CC02	3.35	South
41	69.173273	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	1.55	2122	920	CB01	3.35	South
42	71.84598	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.71	2071	969	CS01	3.35	South
43	73.069083	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.2	0.19	693	932	CL01	3.35	South
44	62.355606	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.4	0.48	1599	907	RB01	3.35	South
45	61.472254	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.4	0.6	1777	921	RB02	3.35	South
46	61.494904	0.35	yes	no	0.6	0.2	0	10	1.2	0.7	14	0.4	0.57	1654	917	RB04	3.35	South

Figure 4.5: Example showing how the final dataset was arranged for Machine Learning

05

Machine Learning

This section details the use of Python scripts to streamline thermal and seismic resilience assessments in low-cost housing. It covers data preparation, machine learning model training, and performance predictions, emphasizing efficiency and enhanced decision-making. Key processes include data pre-processing, dimensionality reduction, clustering, and supervised model training, aimed at predicting resilience metrics and improving design optimization.

05. Machine learning

5.1 Scripting

The Python script is designed to streamline and enhance the process of evaluating thermal and seismic resilience in low-cost housing projects, with a specific focus on New Delhi, India. Traditionally, assessing resilience requires the creation of detailed 3D models and the execution of extensive simulations, both of which are time-consuming and resource-intensive. By utilizing machine learning (ML) techniques, this script allows architects and engineers to predict resilience metrics more efficiently. The script processes simulation data, applies both unsupervised and supervised learning methods, and provides tailored recommendations based on user inputs. The primary advantages of this approach include significant reductions in the time and effort needed for resilience assessment, improved decision-making capabilities, and enhanced design optimization.

5.1.1 Data preparation

The first step in the analysis involves loading the datasets for thermal and seismic resilience. The thermal data, containing various building features and thermal autonomy, is sourced from 'BEM_data_for_ML_2.csv'. The seismic data, detailing structural dimensions and earthquake-related parameters, is obtained from 'Formatted_Residence_Dimensions.csv'. These datasets form the foundation for the machine learning models. Preprocessing ensures the data is suitable for training machine learning models. For thermal resilience, the features are scaled using '**StandardScaler**' to normalize the data. For seismic resilience, the relevant features are extracted and split into training and testing sets. This step is crucial for standardizing the data, thereby improving the model's performance.

5.1.2 Dimensionality Reduction and Clustering

Principal Component Analysis (PCA) is applied to the scaled thermal features to reduce dimensionality. This reduction simplifies the data while retaining most of the variance, facilitating easier visualization and clustering. n_components is set as 2 to reduce the data to two principal components. The choice of two components is significant because:

- Visualization: Reducing the data to two dimensions allows for easy visualization in a 2D plot, making it simpler to interpret and understand the data distribution. This is particularly useful for identifying patterns and clusters in the data.
- Sufficient Variance Retention: While higher components might retain more variance, two components often capture the majority of the essential variance in the data. This balance between simplicity and information retention ensures that the main features of the data are preserved while making the data easier to handle and visualize**.**

K-means clustering is performed on the PCA-reduced features to identify distinct clusters within the thermal data. The optimal number of clusters is determined empirically. Clustering helps in categorizing the data into meaningful groups based on similar characteristics. random_state is set at 42 to ensure reproducibility. The specific choice of 42 is arbitrary, but it has become a convention in the machine learning community due to its frequent use in examples and tutorials (Pedregosa et al., 2012). The significance of this setting includes:

- Consistency: Setting a random state ensures that the initial positions of the centroids are the same each time the code is run, leading to consistent clustering results. This is crucial for validating the results and ensuring that they are not influenced by the random initialization of centroids.
- Comparability: Using a fixed random state allows results to be compared across different runs. This facilitates validation, debugging, and comparison with other models or datasets.

5.1.3 Supervised Model training and Evaluation for both Analyses

A variety of machine learning models are selected to predict thermal autonomy. These include Linear Regression, Random Forest Regressor, Support Vector Regressor (SVR), and Gradient Boosting Regressor. Each model is chosen for its unique strengths in handling different types of data and relationships.

1. **Linear Regression**:

- A fundamental statistical method that models the relationship between a dependent variable and one or more independent variables by fitting a linear equation.
- Utilized here to understand the basic linear relationships influencing the drift angle.

2. **Decision Tree Regressor**:

- A non-linear model that splits the data into subsets based on the value of input features.
- This model is advantageous for capturing complex interactions between variables without requiring prior data transformations.

3. **Random Forest Regressor**:

- An ensemble learning method that constructs multiple decision trees during training and outputs the mean prediction of the individual trees.
- Known for its robustness and ability to improve predictive accuracy by reducing overfitting.

4. **Support Vector Regression (SVR)**:

- An extension of the Support Vector Machine (SVM) that performs regression analysis.
- Effective in high-dimensional spaces and suitable for cases where the relationship between the independent and dependent variables is non-linear.

The models are trained on the pre-processed training data and evaluated on the test data using metrics such as Mean Squared Error (MSE) and R-squared. Visualization of actual vs. predicted values provides insight into the models' accuracy and reliability.

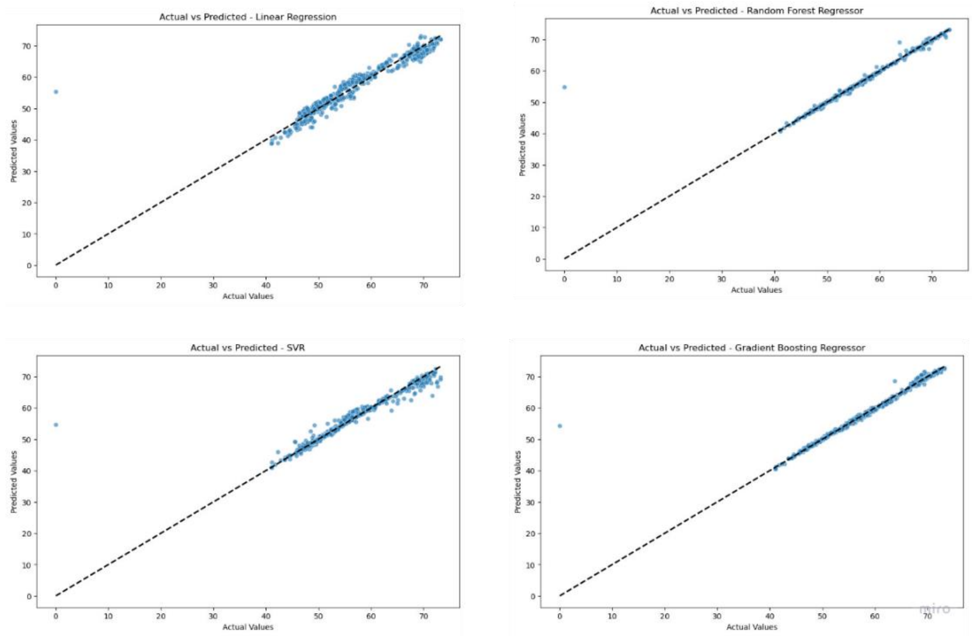


Figure 5.1 : Actual vs Predicted thermal Autonomy

For seismic resilience, models including Linear Regression, Decision Tree Regressor, Random Forest Regressor, and SVR are trained to predict the drift angle, a critical parameter in seismic analysis. These models are evaluated based on their predictive accuracy using MSE and R-squared metrics. Plots of actual vs. predicted drift angles are generated to visualize the models' performance.

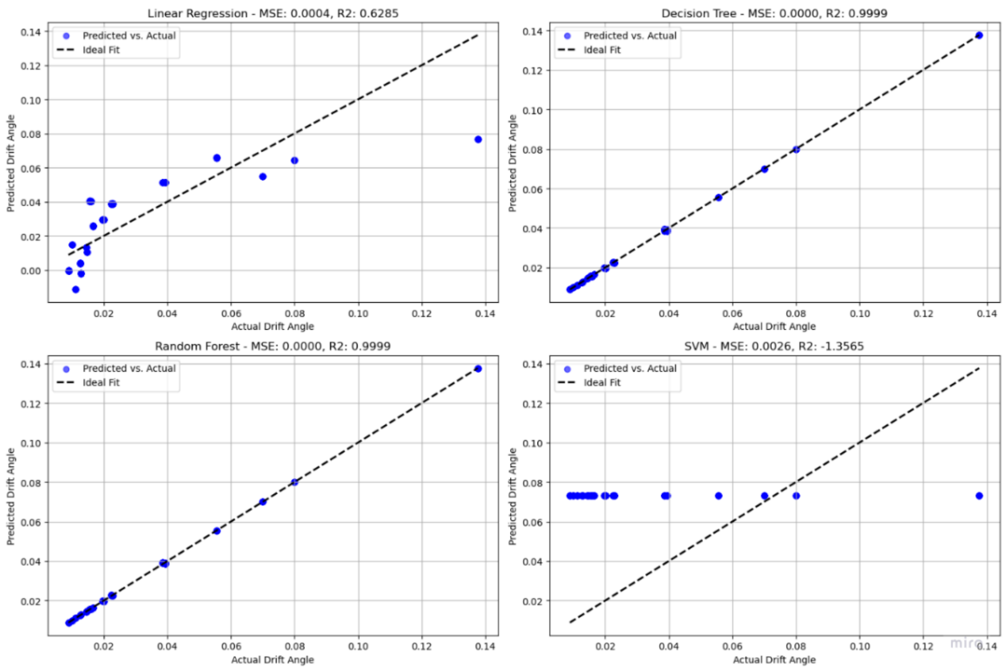


Figure 5.2 : Actual vs Predicted Drift Angles

The graphs titled "Actual vs. Predicted Thermal Autonomy" and "Actual vs. Predicted Drift Angles" is a scatter plot used to compare the actual values against the predicted values derived from various predictive models.

Key Elements of the Graph:

- X-axis (Actual Values): Represents the true values of thermal autonomy from the dataset.
- Y-axis (Predicted Values): Represents the values predicted by the model for thermal autonomy.
- Points: Each point represents a specific observation. The position of a point indicates its actual value along the x-axis and its predicted value along the y-axis.
- Diagonal Dashed Line: This line represents the line of perfect prediction, where the predicted values exactly match the actual values. Points that lie on this line are perfect predictions.

5.1.4 Input-Based Performance Predictions

To enhance the thermal autonomy and seismic resilience of buildings, a multifaceted approach is undertaken involving the prediction of key parameters through machine learning models. For thermal autonomy, the process begins by collecting a comprehensive set of input features from the user, including wall thickness, shading parameters, window-to-wall ratio, indoor air speed, thermal properties, and building orientation. These inputs are crucial as they directly impact the thermal performance of a building. Once the data is collected, it is fed into a pre-trained **Random Forest Regressor** model to predict the thermal autonomy. This prediction helps in understanding how well a building can maintain comfortable indoor temperatures without relying on mechanical heating or cooling systems. The Resilience metric here is Spatial thermal Autonomy.

On the seismic resilience front, the focus is on predicting the drift angle, a critical parameter that indicates how much a building will sway during an earthquake. The user is prompted to enter specific structural and seismic parameters, including the length, width, total height of the building, magnitude of the potential earthquake, and section size. These inputs are then formatted and processed using **Random Forest Regressor**, which is known for its accuracy and ability to handle complex, non-linear relationships between input variables. By predicting the drift angle, engineers and architects can assess the potential structural performance and stability of buildings under seismic loads, allowing for better-informed design and retrofitting decisions.

The integration of both thermal and seismic prediction models into a single system provides a holistic tool for evaluating building performance. By seamlessly switching between thermal and seismic analysis, this system ensures that both comfort and safety are addressed comprehensively. Predictive models are trained and evaluated using key metrics like Mean Squared Error (MSE) and R-squared (R^2), ensuring their reliability and accuracy. Visualization tools, such as plots of actual versus predicted values, further aid in understanding model performance and identifying areas for improvement.

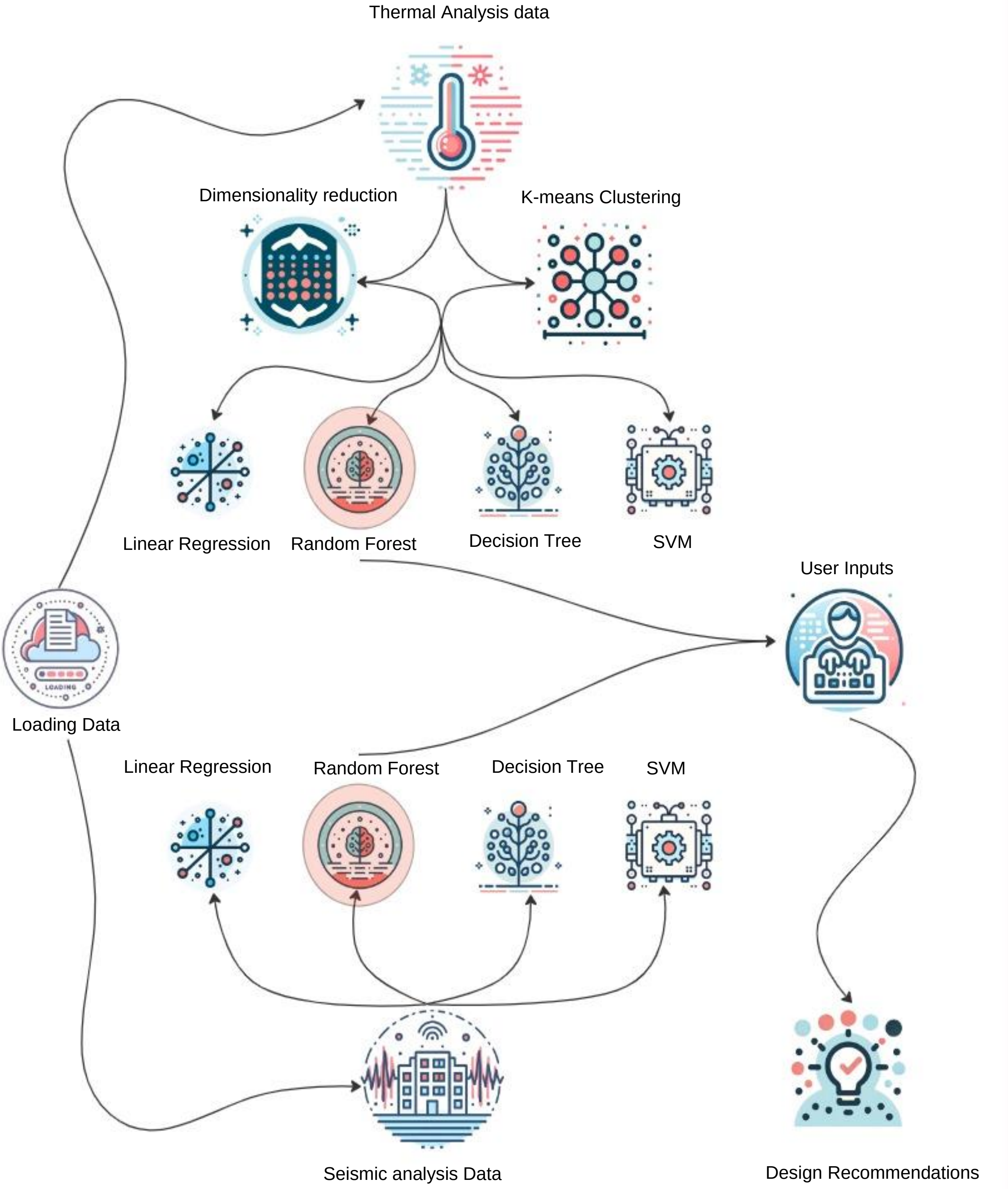


Figure 5.3: Illustration explaining the flow of data within the python script

5.2 Visualization of Energy model results

The results are divided into four subsections: Principal Component Analysis (PCA) results, correlations heat map results, feature importance results, and fragility curves results. Each subsection provides a detailed examination of the respective analysis, offering insights into the underlying patterns and relationships within the data. The PCA results highlight the key components that capture the most variance, while the correlations heat map illustrates the relationships between different variables. Feature importance results identify the most significant predictors, and the fragility curves results assess the vulnerability of the system under various conditions.

5.2.1 Principal Component Analysis results

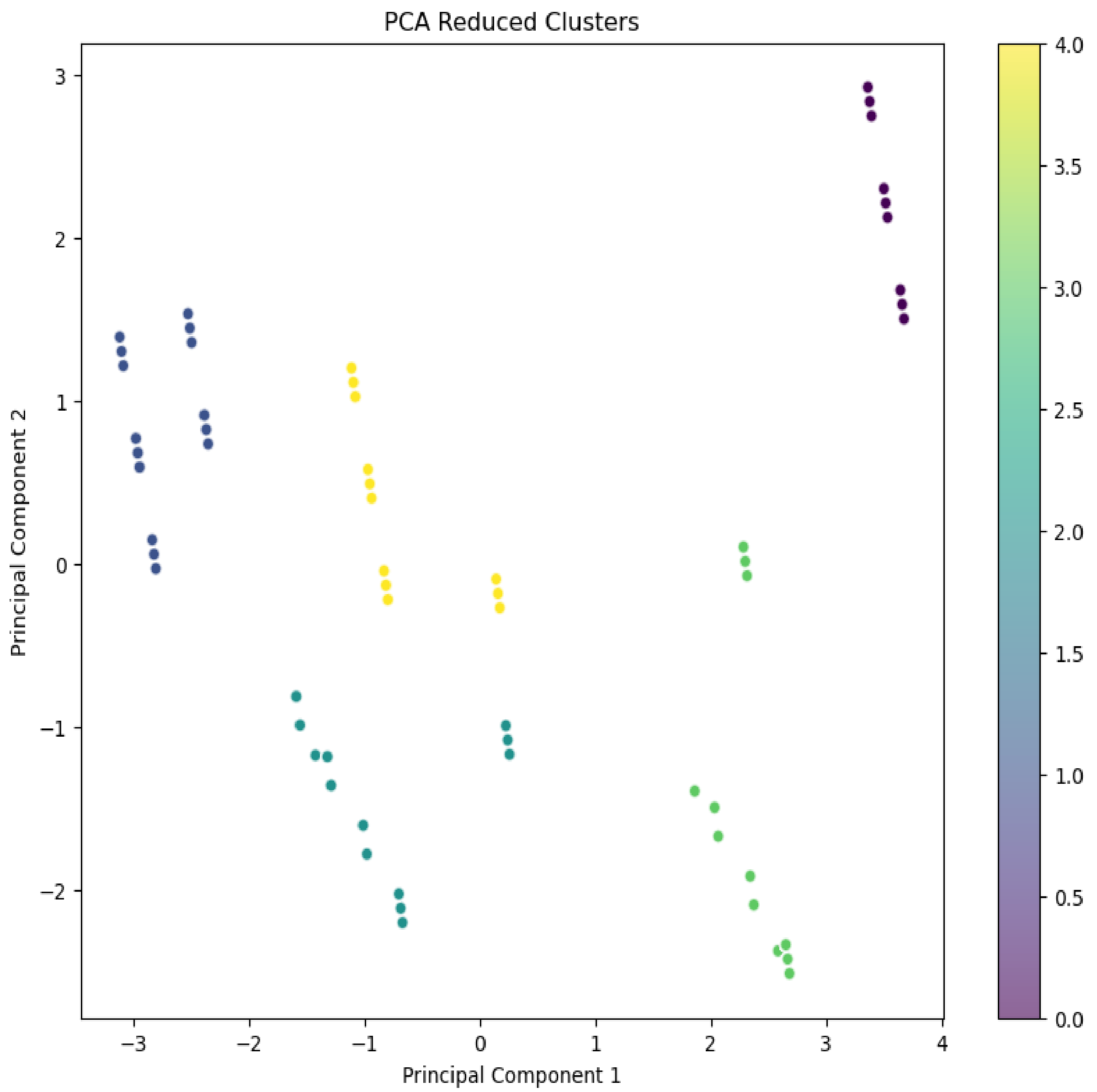


Figure 5.4 : Principal Component Analysis Plot

Figure 5.4 is a PCA (Principal Component Analysis) plot that illustrates the clustering of data points after dimensionality reduction. PCA is a statistical technique used to simplify the complexity of high-dimensional data while retaining most of the variability present in the dataset. This plot helps in visualizing the clustering structure of the data in a reduced two-dimensional space.

Axes:

- X-Axis (Principal Component 1): This axis represents the first principal component, which captures the largest possible variance in the data.
- Y-Axis (Principal Component 2): This axis represents the second principal component, orthogonal to the first, and captures the second highest variance in the data.

Colors:

The colors in the plot represent different clusters of data points. Each color corresponds to a unique cluster, which groups data points that share similar characteristics. The color bar on the right side of the plot ranges from 0 to 4, indicating the cluster index or label assigned to each data point. The specific colors do not have inherent meanings but serve to visually distinguish between the clusters.

Cluster 0:

Parameter	Value
Thermal Autonomy	54.58
Wall Thickness	0.23 meters
Horizontal Shading	Present
Vertical Shading	Absent
Shading Length	0.60 meters
Distance from Lintel	1.20 meters
Angle of Inclination	11 degrees
Window to Wall Ratio	5%
Indoor Air Speed	1.00 m/s
Discharge Coefficient	0.70
Living Area	12 square meters
Thermal Absorbtance	0.40
Thermal Conductivity	0.595 W/mK
Bulk Density	1683.64 kg/m3
Specific Heat	929.64 J/kgK
Space Height	3.60 meters
Orientation	270 degrees

Table 5.2.1 : Cluster 0

Interpretation: Cluster 0 represents houses with moderate thermal autonomy, thin walls, horizontal shading, and no vertical shading. The houses in this cluster have a significant distance from the lintel, higher angle of inclination, lower window-to-wall ratio, and higher discharge coefficient. The orientation is predominantly west (270 degrees).

Cluster 1:

Parameter	Value
Thermal Autonomy	52.79
Wall Thickness	0.302 meters
Horizontal Shading	Absent
Vertical Shading	Absent
Shading Length	0.00 meters
Distance from Lintel	0.00 meters
Angle of Inclination	0 degrees
Window to Wall Ratio	10%
Indoor Air Speed	0.96 m/s
Discharge Coefficient	0.45
Living Area	14 square meters
Thermal Absorbtance	0.40
Thermal Conductivity	0.595 W/mK
Bulk Density	1683.64 kg/m3
Specific Heat	929.64 J/kgK
Space Height	3.35 meters
Orientation	90 degrees

Table 5.2.2 : Cluster 1

Interpretation: Cluster 1 houses have the lowest thermal autonomy, thicker walls, and no shading (horizontal or vertical). The absence of shading and zero distance from the lintel likely contribute to the lower thermal autonomy. The houses also have the highest window-to-wall ratio. The orientation is predominantly east (90 degrees).

Cluster 2:

Parameter	Value
Thermal Autonomy	60.69
Wall Thickness	0.322 meters
Horizontal Shading	Present
Vertical Shading	Somewhat Present (23%)
Shading Length	0.83 meters
Distance from Lintel	0.20 meters
Angle of Inclination	9.23 degrees
Window to Wall Ratio	9.42%
Indoor Air Speed	1.20 m/s
Discharge Coefficient	0.51
Living Area	14 square meters
Thermal Absorbtance	0.38
Thermal Conductivity	0.595 W/mK
Bulk Density	1683.64 kg/m3
Specific Heat	929.64 J/kgK
Space Height	3.35 meters
Orientation	90 degrees

Table 5.2.3 : Cluster 2

Interpretation: Cluster 2 houses have the highest thermal autonomy, thick walls, horizontal shading, and some vertical shading. The longer shading length and higher discharge coefficient likely contribute to the higher thermal autonomy. The orientation is predominantly east (90 degrees).

Cluster 3:

Parameter	Value
Thermal Autonomy	60.91
Wall Thickness	0.23 meters
Horizontal Shading	Present
Vertical Shading	Mostly Present (75%)
Shading Length	0.56 meters
Distance from Lintel	0.45 meters
Angle of Inclination	12.5 degrees
Window to Wall Ratio	5%
Indoor Air Speed	1.20 m/s
Discharge Coefficient	0.45
Living Area	12 square meters
Thermal Absorbtance	0.37
Thermal Conductivity	0.595 W/mK
Bulk Density	1683.64 kg/m3
Specific Heat	929.64 J/kgK
Space Height	3.35 meters
Orientation	270 degrees

Table 5.2.4 : Cluster 3

Interpretation: Cluster 3 houses have high thermal autonomy, thin walls, significant horizontal and vertical shading, and moderate shading length. The higher angle of inclination and moderate discharge coefficient contribute to the high thermal autonomy. The orientation is predominantly west (270 degrees).

Cluster 4:

Parameter	Value
Thermal Autonomy	59.23
Wall Thickness	0.32 meters
Horizontal Shading	Present
Vertical Shading	Absent
Shading Length	0.60 meters
Distance from Lintel	0.45 meters
Angle of Inclination	0 degrees
Window to Wall Ratio	9.38%
Indoor Air Speed	1.05 m/s
Discharge Coefficient	0.64
Living Area	14 square meters
Thermal Absorbtance	0.40
Thermal Conductivity	0.595 W/mK
Bulk Density	1683.64 kg/m3
Specific Heat	929.64 J/kgK
Space Height	3.35 meters
Orientation	157.5 degrees

Table 5.2.5 : Cluster 4

Interpretation: Cluster 4 houses have high thermal autonomy, thick walls, horizontal shading, and no vertical shading. The moderate shading length, zero angle of inclination, and high discharge coefficient contribute to the high thermal autonomy. The orientation is predominantly southeast (157.5 degrees).

An in-depth analysis of cluster characteristics is provided based on several thermal performance metrics. Thermal autonomy, wall thickness, shading, and other factors are examined to understand their influence on building resilience. Visualizations and cluster plots offer insights into the performance of different clusters, highlighting areas for improvement and optimization.

Analysis of Cluster Characteristics

Thermal Autonomy:

- Clusters 2 and 3 have the highest thermal autonomy, indicating better thermal resilience.
- Cluster 1 has the lowest thermal autonomy, suggesting potential areas for improvement.

Wall Thickness:

- Clusters 1, 2, and 4 have relatively thicker walls, which correlates with higher thermal autonomy.
- Cluster 0 and 3 have thinner walls but still maintain high thermal autonomy due to other factors.

Shading (Horizontal and Vertical):

- Horizontal shading is present in most clusters except Cluster 1.
- Vertical shading varies, with Cluster 3 having the highest proportion of vertical shading.

Shading Length and Distance from Lintel:

- Longer shading lengths in Clusters 2 and 4 contribute to higher thermal autonomy.
- Distance from the lintel is significantly higher in Cluster 0, which might be affecting thermal performance.

Angle of Inclination:

- Clusters with higher angles of inclination (Cluster 3) show better thermal autonomy.
- Cluster 1 has an angle of inclination of 0 degrees, which could be a factor in its lower thermal autonomy.

Window to Wall Ratio:

- Clusters 0 and 3 have lower window-to-wall ratios, which helps in maintaining better thermal autonomy.
- Cluster 1 has the highest window-to-wall ratio, contributing to its lower thermal autonomy.

Indoor Air Speed and Discharge Coefficient:

- Higher indoor air speed and discharge coefficients in Clusters 2 and 3 correlate with better thermal autonomy.

Living Area, Thermal Absorbance, Thermal Conductivity, Bulk Density, Specific Heat, and Space Height:

- These features show relatively consistent values across clusters, suggesting their impact is less significant compared to other features.

Orientation:

- Clusters 0 and 3 have west orientation (270 degrees), and Cluster 1 has east orientation (90 degrees).
- Orientation seems to play a role, with mixed orientations providing varying thermal autonomy results.

Clusters 2 and 3: Superior Thermal Autonomy

Buildings classified under Clusters 2 and 3 exhibit the highest levels of thermal autonomy. This means these houses maintain comfortable indoor temperatures without relying heavily on external cooling systems. The key characteristics that contribute to this superior thermal resilience include:

- Significant Shading: Both horizontal and vertical shading elements are prominently used in these houses. These shading features help to reduce direct solar gain, thereby minimizing the amount of heat entering the building during hot periods.
- Thicker Walls: The walls in these houses are notably thicker compared to others. Thicker walls provide better thermal mass, which helps in regulating indoor temperatures by absorbing heat during the day and releasing it during cooler periods.
- Higher Discharge Coefficients: Houses in these clusters have higher discharge coefficients, indicating more efficient natural ventilation systems that enhance the removal of warm air and the intake of cooler air, thus contributing to better thermal comfort.
- Specific Orientations: These houses are primarily oriented towards the east and west. Such orientations are beneficial as they help in optimizing the exposure to sunlight, allowing for maximum natural heating during the morning and evening while minimizing overheating during the peak afternoon hours.

Cluster 1: Inferior Thermal Autonomy

In stark contrast, houses in Cluster 1 show the lowest thermal autonomy. This cluster is characterized by several features that make these houses less effective in maintaining thermal comfort:

- No Shading: Houses in this cluster lack any form of shading, leaving them fully exposed to direct sunlight, which significantly increases indoor temperatures.
- High Window-to-Wall Ratio: These houses have a high ratio of window area to wall area. While windows are essential for natural lighting, an excessive window-to-wall ratio can lead to higher heat gains and losses, making it harder to maintain stable indoor temperatures.

The characteristics of the clusters vary significantly, particularly in aspects such as shading, wall thickness, window-to-wall ratio, and building orientation as shown in figure 5.5. These factors are crucial in determining the thermal autonomy of a building. Understanding these characteristics is essential for designing buildings that are not only energy-efficient but also capable of maintaining thermal comfort in varying climatic conditions. By addressing these critical factors, architects and builders can enhance the thermal autonomy of these low-cost housing units, leading to more sustainable and comfortable living environments.

Figure 5.5: Clusters analysis for each feature

5.2.2 Feature importance

After plotting the clusters, a feature importance chart was generated to identify which features most significantly affect thermal autonomy. The chart highlights the relative importance of various factors in determining the thermal resilience of these houses. The most influential feature is thermal absorptance, followed by indoor air speed and thermal conductivity, with other features like wall thickness and bulk density also playing notable roles.

This analysis underscores the complexity of creating a comprehensive building energy model in software like Rhino Grasshopper. Architects and engineers need to account for a multitude of variables, each impacting the overall thermal performance of the building. Balancing these features can be quite taxing, as even minor changes can lead to significant variations in thermal autonomy.

Understanding feature importance is crucial for professionals in the field. It allows architects and engineers to pinpoint the areas where improvements can yield the most significant benefits. For example, focusing on enhancing thermal absorptance and optimizing indoor air speed could lead to better thermal performance. By prioritizing these critical factors, professionals can design the housing blocks that are not only energy-efficient but also offer improved thermal comfort for occupants.

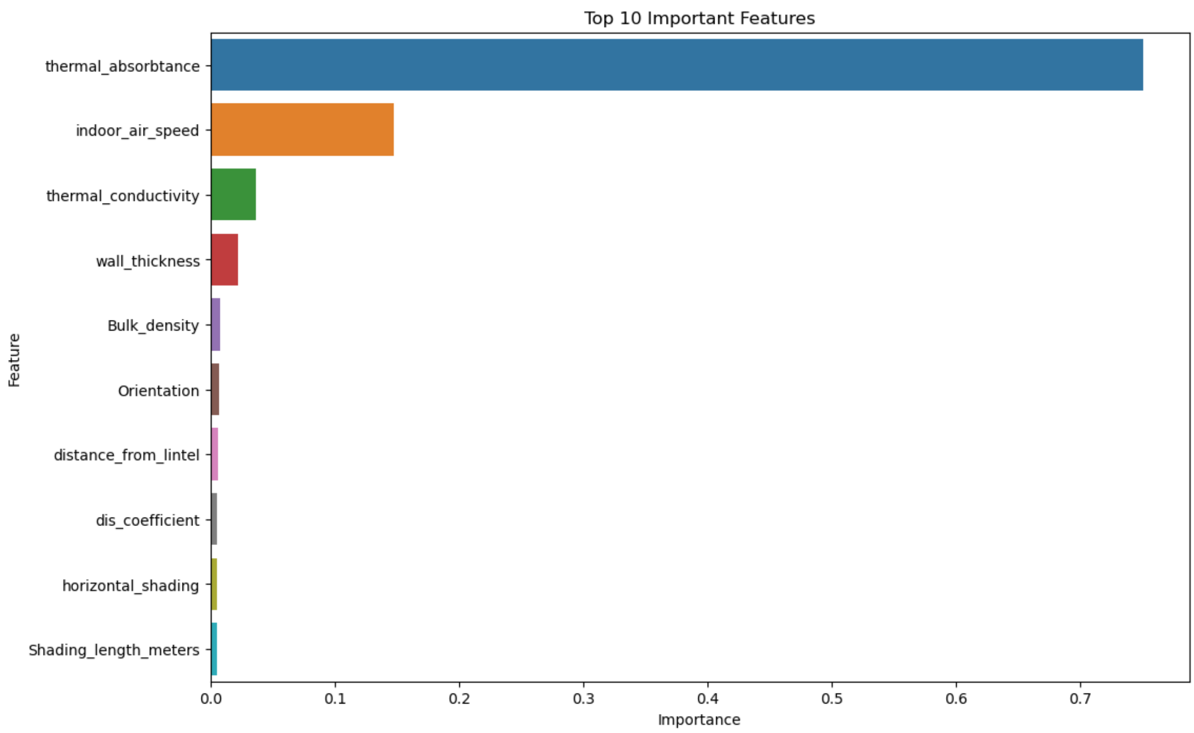


Figure 5.6: Feature Importance

5.2.3 Correlation Heat-map

The correlation heatmap analysis of features related to thermal autonomy reveals significant insights into how various building characteristics impact thermal performance. Notably, thermal autonomy is negatively correlated with thermal absorbance (-0.85),figure 5.7, indicating that materials with higher absorbance might contribute to increased heat gain, reducing thermal efficiency. Conversely, thermal autonomy is positively influenced by horizontal shading (0.31), suggesting that the presence of shading can mitigate heat gain and enhance thermal performance. Cluster analysis also shows a moderate positive correlation with thermal autonomy (0.28), underscoring the importance of categorizing buildings based on their thermal characteristics for targeted improvements.

Wall thickness exhibits a strong positive correlation with the window-to-wall ratio (0.78), as shown in figure 5.2.4, implying that structural requirements necessitate thicker walls for buildings with larger windows. This correlation highlights the trade-off between structural integrity and thermal performance, as thicker walls generally improve thermal autonomy. Additionally, wall thickness has a negative correlation with the distance from the lintel (-0.52), suggesting that buildings with thicker walls have shorter distances from the lintel, potentially impacting their shading and thermal characteristics. Horizontal shading also shows a moderate positive correlation with both thermal autonomy (0.31) and shading length (0.49), indicating that effective shading strategies can significantly enhance thermal resilience. The presence of vertical shading, although less pronounced, correlates with longer shading lengths and contributes to the overall shading effectiveness.

Distance from the lintel has a high negative correlation with wall thickness (-0.52) and the window-to-wall ratio (-0.55), highlighting the interplay between these structural features and their impact on thermal performance. A greater distance from the lintel generally corresponds to a lower window-to-wall ratio, which can improve thermal autonomy by reducing heat transfer through windows. Angle of inclination exhibits a positive correlation with both thermal autonomy (0.12) and the discharge coefficient (0.24), indicating that optimal angles can enhance air circulation and thermal performance. Indoor air speed also positively correlates with thermal autonomy (0.42) and shading length (0.37), emphasizing the role of ventilation and shading in maintaining comfortable indoor temperatures.

The discharge coefficient shows a moderate positive correlation with shading length (0.43) and angle of inclination (0.24), suggesting that buildings with longer shading and higher angles have better airflow management, contributing to improved thermal autonomy. Living area, while showing consistent values across clusters, has a high positive correlation with the window-to-wall ratio (0.95) and a strong negative correlation with clustering (-0.93), indicating that larger living spaces often feature more extensive windows, affecting thermal performance. Lastly, the orientation of buildings shows a significant influence on clustering (0.55), underscoring the importance of strategic orientation in optimizing thermal performance.

Overall, the correlation heatmap highlights key areas for improving thermal resilience in buildings. Reducing thermal absorbance through the use of materials with lower absorptive properties can significantly enhance thermal autonomy. Implementing effective shading strategies, both horizontal and vertical, along with optimizing the window-to-wall ratio, can further improve thermal performance. Maintaining adequate indoor air speed and leveraging cluster characteristics for targeted interventions can also contribute to better thermal efficiency. By addressing these factors, housing designs can be optimized to achieve higher thermal resilience and comfort for occupants.

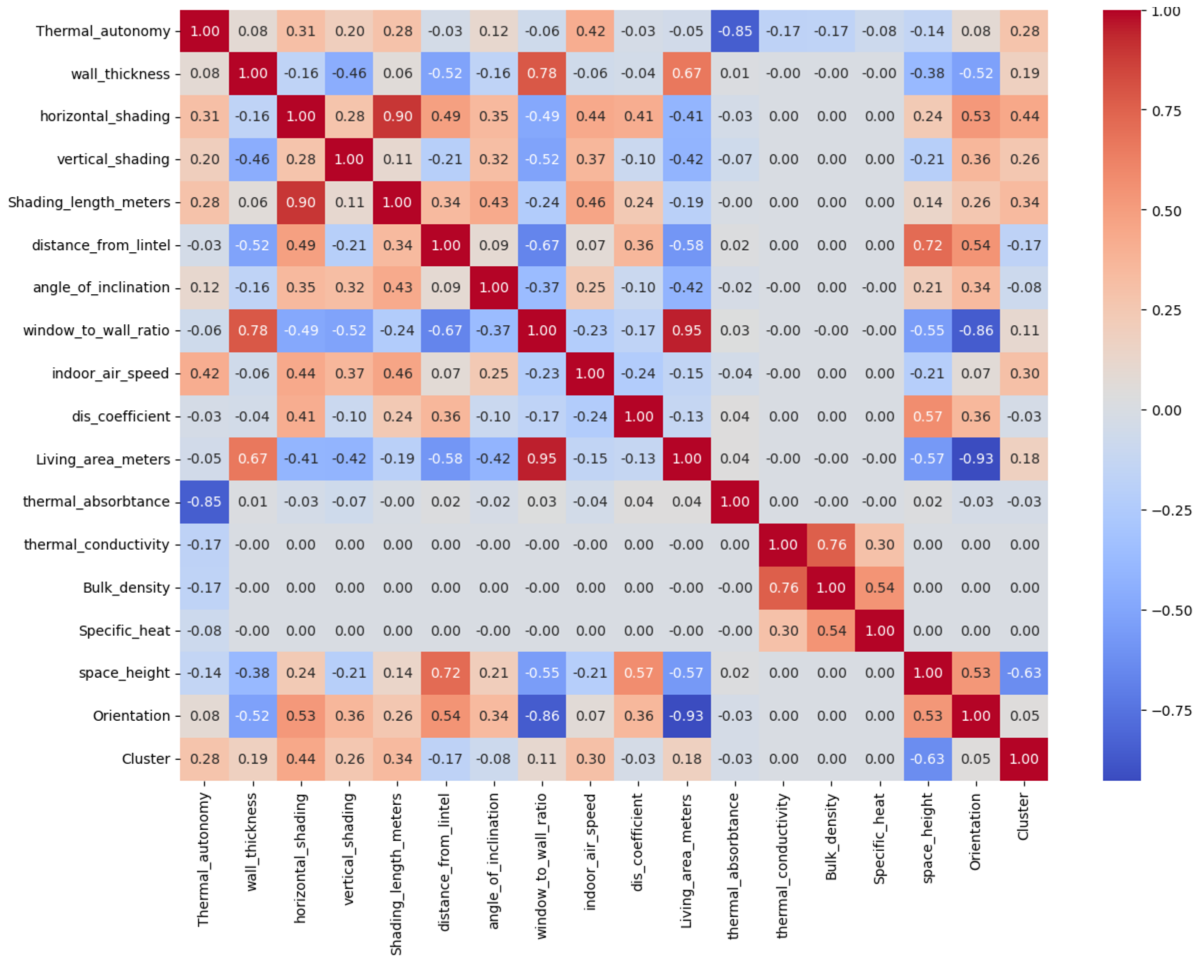


Figure 5.7: Correlation heat-map of all features

5.2.4 Comparison of Spatial thermal Autonomy

The analysis chart (figure 5.8) illustrates various Thermal Autonomy values for each archetype under distinct conditions to assess the impact of indoor air speed and thermal absorbance. The chart includes five key bars for each archetype:

- Lowest STA for Lowest Air Speed and Absorbance 0.6: This bar represents the minimum STA achieved when the indoor air speed is at its lowest and the thermal absorbance is 0.6, highlighting the effect of low air speed with high absorbance on thermal autonomy. Here the assumption made is that no fans are present inside the house that leads to minimum indoor speed.
- Highest STA for Highest Air Speed and Absorbance 0.6: This bar shows the maximum STA when the indoor air speed is at its highest and the thermal absorbance is also 0.6, indicating the best possible thermal autonomy under moderate air speed and high absorbance conditions. Here the assumption made is that a small fan is provided inside the house that provides minimum indoor air speed for acceptable conditions.
- Lowest STA for Lowest Air Speed and Absorbance 0.2: This bar illustrates the minimum STA when the indoor air speed is at its lowest and the thermal absorbance is 0.2, providing insight into how a lower absorbance value affects STA under minimal air speed conditions.
- Baseline Lowest STA (≥ 30, no filter): This bar represents the general minimum STA for each archetype without any specific filtering, ensuring that the value is not less than 30, serving as a baseline for comparison against conditioned STA values.
- Baseline Highest STA (no filter): This bar shows the highest possible STA for each archetype without any specific filtering, providing an upper limit of thermal autonomy under general conditions.

Comparing the bars highlights several key insights:

Impact of Indoor Air Speed: Significant differences between the STA values for high and low air speed conditions (bars 1 and 2) indicate that indoor air speed notably impacts STA. Higher air speed (bar 2) often results in significantly higher STA compared to lower air speed (bar 1), suggesting that increased air speed enhances thermal autonomy under these conditions. (Figure 5.8)

Effect of Absorbance: Differences between the STA values for thermal absorbance levels of 0.6 and 0.2 (bars 1 and 3) highlight the impact of absorbance changes on STA. A higher absorbance (bar 1) typically leads to higher STA compared to lower absorbance (bar 3), indicating that increased absorbance improves thermal autonomy under low air speed conditions. (Figure 5.8)

Baseline Comparison: Comparing the baseline STA values (bars 4 and 5) with the conditioned STA values (bars 1, 2, and 3) shows how specific conditions affect STA relative to general scenarios. If conditioned scenarios achieve comparable or superior STA values, it suggests that those specific conditions (e.g., high air speed and absorbance 0.6) are beneficial for optimizing thermal autonomy. (Figure 5.8)

This comprehensive comparison reveals how varying indoor air speed and thermal absorbance levels influence thermal autonomy across different archetypes, providing valuable insights for optimizing building performance.

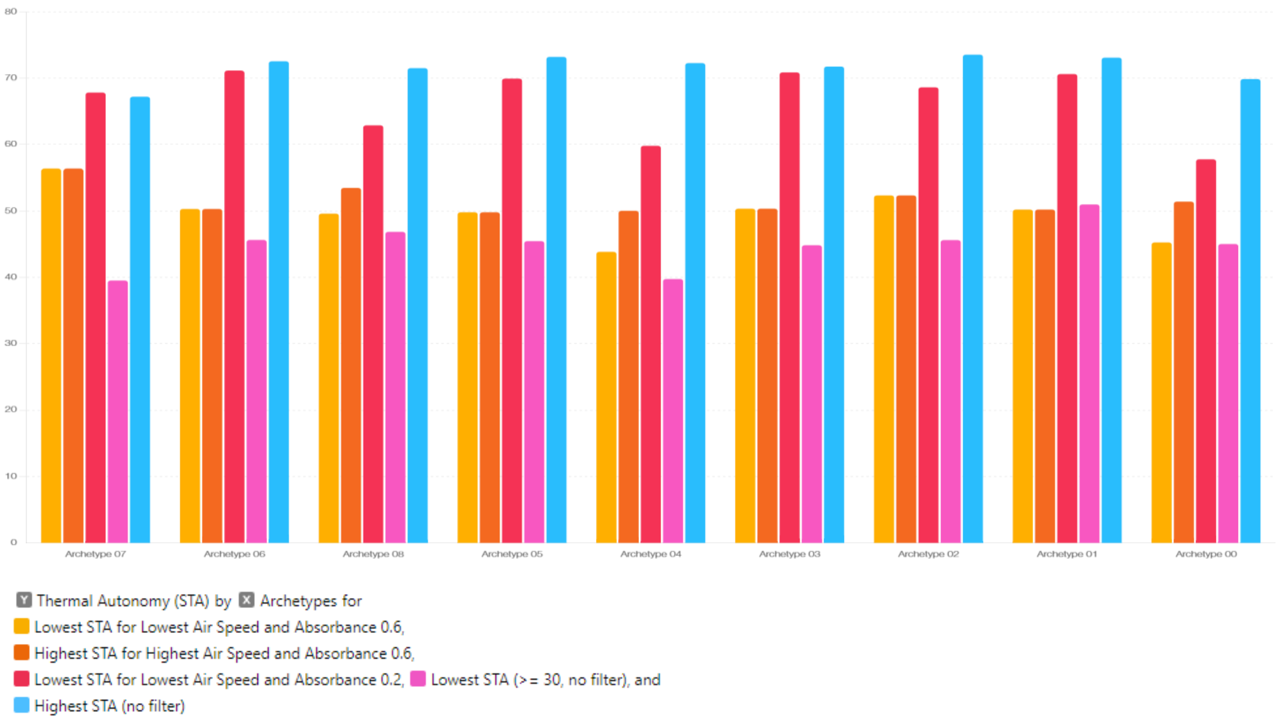


Figure 5.8: Impact Of Indoor Air Speed On STA For Each Archetype

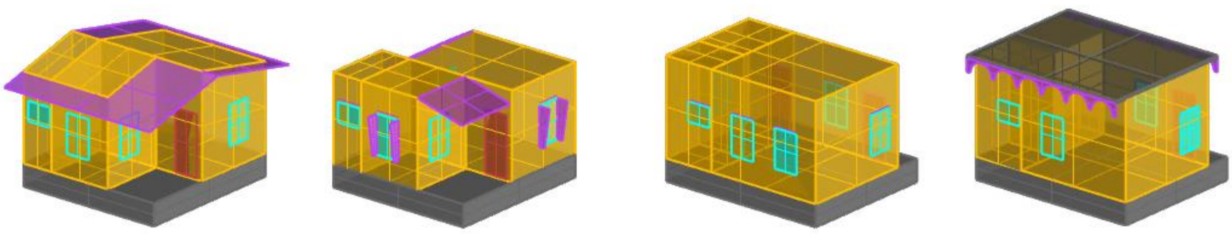


Figure 5.9: Archetype 1-4

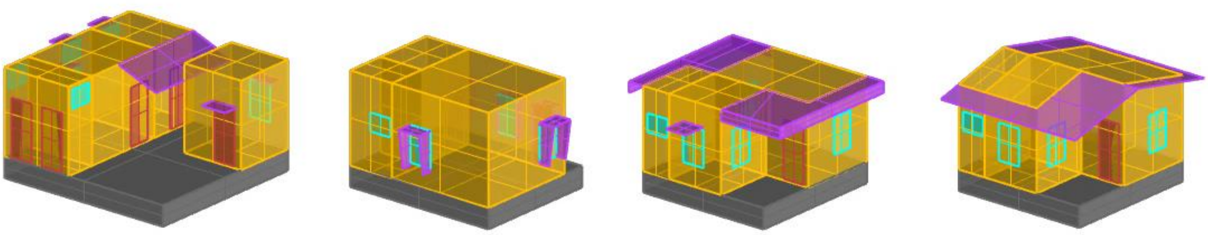


Figure 5.10: Archetype 5-8

5.3 Visualization of Structural model results

The results are divided into three subsections: Feature Importance Results, Correlation Heatmap Results, and Residual Plot Results. Each subsection provides a detailed examination of the respective analysis, offering insights into the underlying patterns and relationships within the data. The feature importance results identify the most significant predictors, the correlation heatmap illustrates the relationships between different variables, and the residual plot results assess the accuracy and bias of the predictive model.

5.3.1 Residual Plot for Random Forest Model

The residual plot shows the residuals (differences between actual and predicted drift angles) versus the predicted drift angles for the Random Forest model. Key points to note:

- The residuals are mostly scattered around zero, indicating that the model predictions are unbiased and generally accurate across the range of predicted values.
- There is some spread in residuals for lower predicted drift angles (around 0.02 to 0.04), which may suggest slightly higher prediction errors in this range.
- The residuals do not display any obvious patterns or trends, which is good as it indicates that the model does not systematically overestimate or underestimate the drift angles.

From this plot, we can infer that the Random Forest model performs well in predicting drift angles without significant bias. The absence of patterns in the residuals suggests that the model captures the underlying data distribution effectively. However, the spread at lower drift angles might be an area for further model refinement or data exploration.

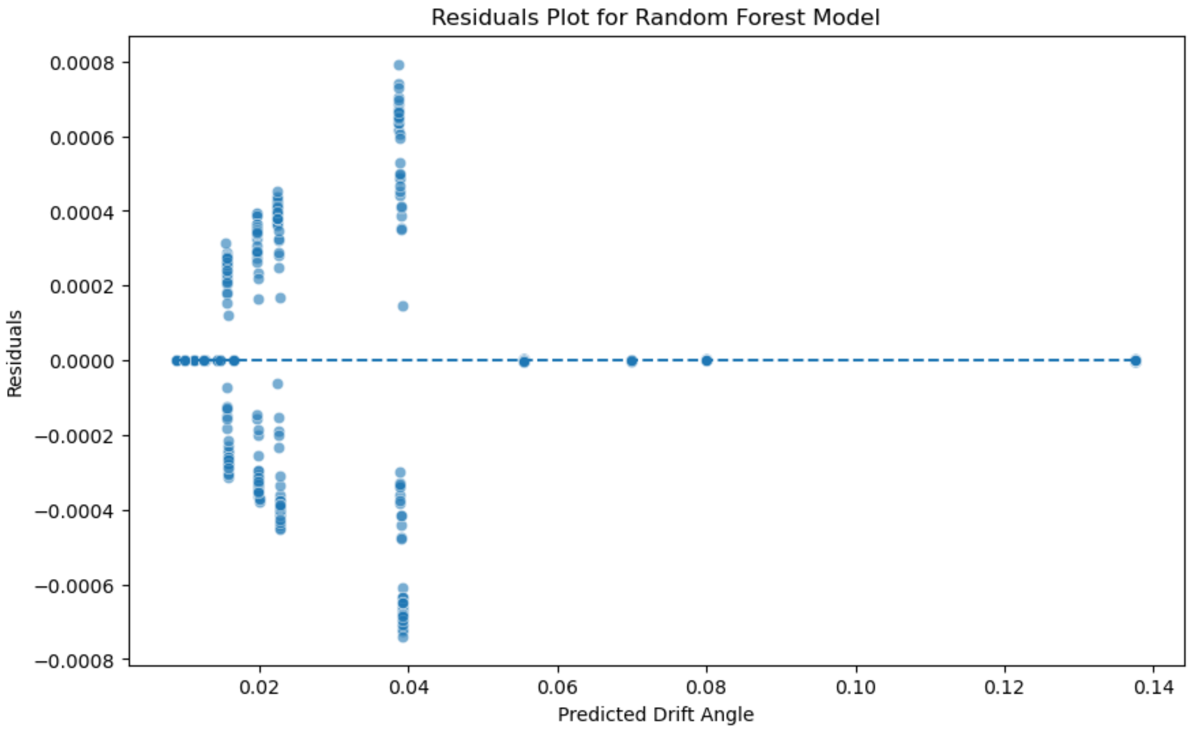


Figure 5.8: Residual plot for Random Forest Model

5.3.2 Feature importance

The feature importance plot highlights the relative importance of different features in predicting the seismic resilience (drift angle) using a Random Forest Regressor. In this plot, we observe:

- **Magnitude_earthquake** has the highest importance, significantly higher than all other features. This indicates that the magnitude of the earthquake is the most critical factor in determining the drift angle, which makes intuitive sense as stronger earthquakes typically cause more significant structural displacements.
- **Section_size** and **Total_Height** follow, showing that the size of the building's sections and the total height also play substantial roles. Larger section sizes and heights likely contribute to higher vulnerability during seismic events.
- **Length** and **Width** have negligible importance. This suggests that, for the given model and data, these dimensions do not significantly affect the drift angle compared to the other features.

From this plot, we can infer that focusing on improving structural design elements like section size and total height might be more beneficial for enhancing seismic resilience compared to modifying the building's length and width.

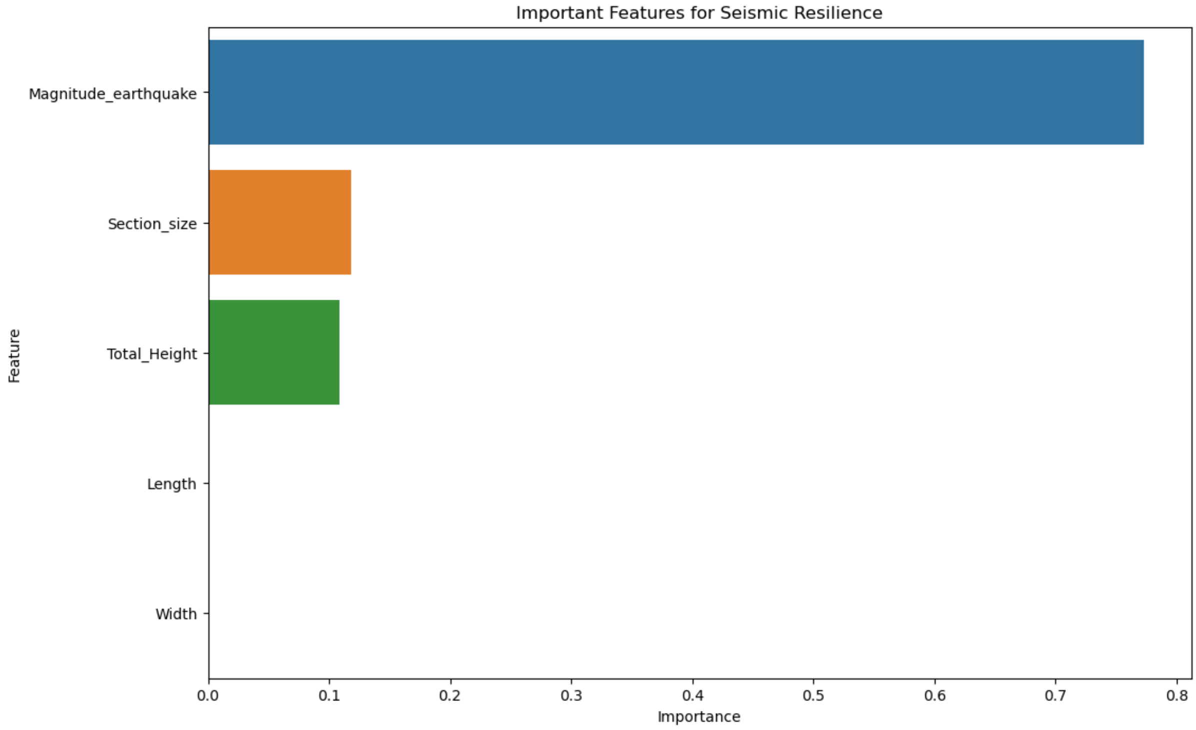


Figure 5.9: Feature importance for Seismic Resilience

5.3.3 Correlation Heatmap of Seismic Features

The correlation heatmap shows the pairwise correlations between the seismic features and the target variable, drift angle. Key observations include:

- **Magnitude_earthquake** and **Drift_angle** have a strong positive correlation (0.74), reinforcing the earlier finding that the earthquake's magnitude is a crucial predictor of drift angle.
- **Section_size** also shows a moderate positive correlation with **Drift_angle** (0.23), which aligns with its feature importance.

- There is a high correlation between **Total_Height** and **Section_size** (0.94). This suggests that taller buildings often have larger section sizes, potentially indicating a design pattern or structural code requirement.
- **Width** and **Length** show very low correlations with the other features and drift angle, confirming their lower importance in the feature importance plot.

The heatmap allows us to see how different features interact and their collective impact on the target variable. It provides a clearer understanding of the relationships within the data, suggesting that improving certain features could mitigate seismic risks.

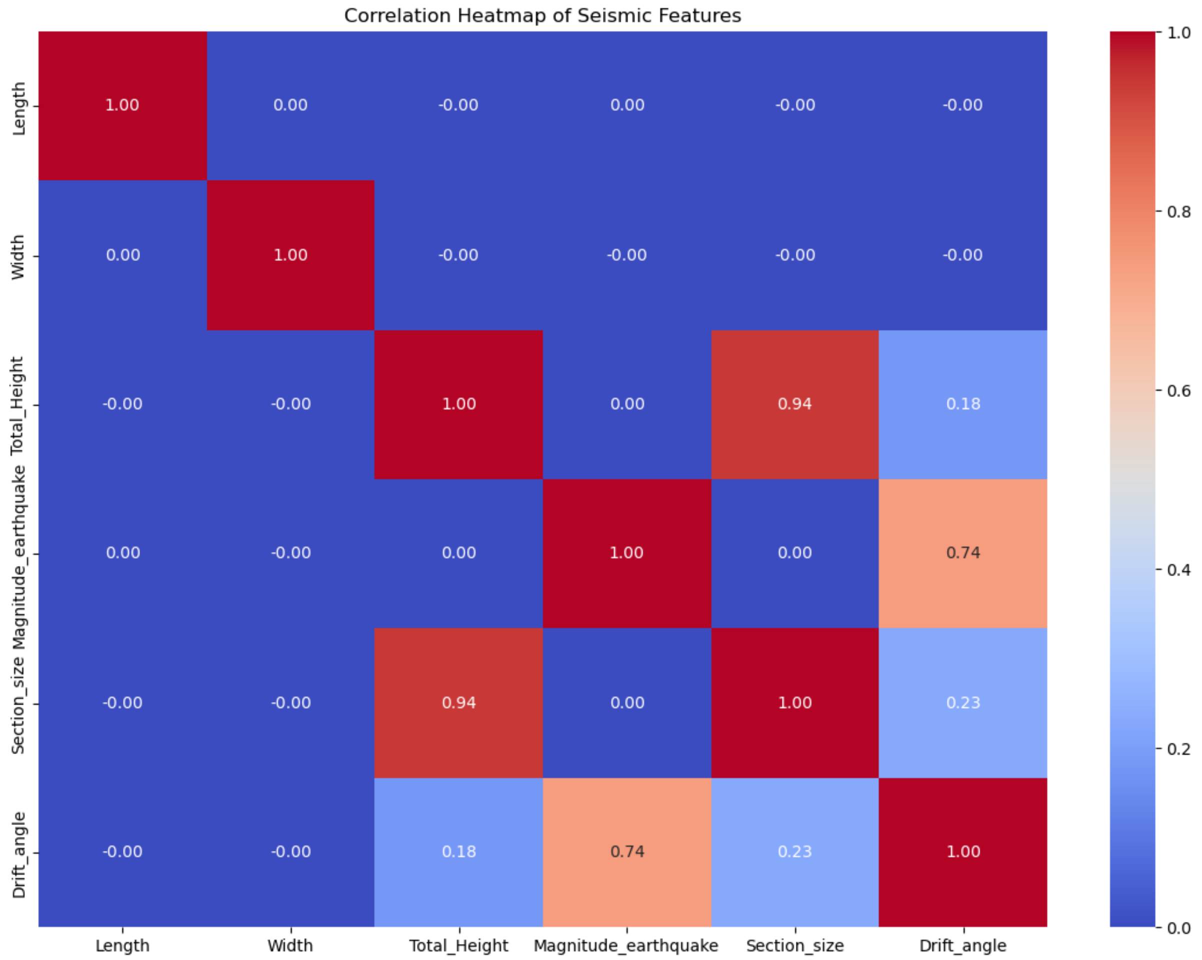


Figure 5.10: Correlation heat map for Seismic features

06

Results and Recommendations

This section describes the developed script that integrates both thermal and seismic resilience analyses for low-cost housing projects. Users can input specific parameters, and the script provides detailed resilience assessments and tailored recommendations. The analysis covers thermal properties such as wall thickness, shading, and thermal conductivity, and seismic factors including building dimensions and earthquake magnitude. Comprehensive results include resilience metrics, fragility curves, and economic loss estimates, guiding users towards optimized building designs for improved resilience.

06. Multi-attribute Decision Making

The developed script effectively integrates both thermal and seismic resilience analyses, allowing users to obtain comprehensive results from a single script without switching between different tools. Users can provide inputs, and the script outputs detailed resilience analyses and recommendations for both thermal and seismic resilience.

6.1 Thermal Resilience

The script prompts the user to input several parameters related to the building's thermal properties. These parameters include:

- Wall thickness
- Horizontal shading (presence or absence)
- Vertical shading (presence or absence)
- Shading length
- Distance from shading
- Angle of inclination
- Window to wall ratio
- Indoor air speed
- Discharge coefficient
- Living area
- Thermal absorbance
- Specific heat
- Thermal conductivity
- Bulk density
- Space height
- Orientation (relative to north)

The **provide_recommendations** function, Appendix x.x, is a crucial component of the thermal resilience analysis, designed to offer targeted suggestions based on the predicted spatial thermal autonomy of a building. The function operates by first checking if the thermal autonomy value falls within the range of 40% to 60%. If so, it identifies specific areas for improvement by creating a dictionary of suggestions, each addressing different aspects of thermal resilience such as thermal absorptance, indoor air speed, thermal conductivity, and wall thickness. These suggestions are tailored to enhance the building's insulation and energy efficiency. The function then prints these suggestions, ensuring they align with the top important features identified in the feature importance analysis. Furthermore, the function recommends the best block with optimal thermal properties by selecting the block with the lowest thermal conductivity from a predefined dataset. This dataset includes various blocks with detailed properties such as thermal conductivity, bulk density, specific heat, and block names. On the other hand, if the thermal autonomy exceeds 60%, the function provides general recommendations for further improvements. These include applying reflective coatings, adding a second layer of cladding, providing a green facade, using passive techniques to improve indoor air speed, and selecting blocks with better thermal properties. By integrating these recommendations, the function guides users towards making informed decisions to enhance the thermal resilience of their building designs, thereby ensuring better energy efficiency and sustainability.

Example Input and Output:

After testing the script with specific inputs, the following results were obtained:

User Inputs:

- Wall thickness: 0.35 meters
- Horizontal shading: 1 (present)
- Vertical shading: 0 (absent)
- Shading length: 0.6 meters
- Distance from shading: 0.2 meters
- Angle of inclination: 0 degrees
- Window to wall ratio: 10%
- Indoor air speed: 0.8 m/s
- Discharge coefficient: 0.6
- Living area: 14 square meters
- Thermal absorbance: 0.8
- Specific heat: 950
- Thermal conductivity: 0.48 W/mK
- Bulk density: 1599 kg/m3
- Space height: 3.35 meters
- Orientation: 180 degrees (relative to north)

Predicted Thermal Autonomy: 47.27%

Based on this prediction, the script provided the following recommendations to improve thermal resilience:

Suggestions for Improvement (40-60% Thermal Autonomy):

- Thermal Absorbance: Apply reflective coating to reduce thermal absorbance, add a second layer of cladding, or provide a green facade. Reflective coating is the cheapest option.
- Indoor Air Speed: Use passive techniques like evaporative cooling, providing more Jaali(Perforated) walls, and installing heat vents to improve indoor air speed and quality.
- Thermal Conductivity: Use blocks with better thermal properties.
- Wall Thickness: Increase wall thickness to enhance insulation and reduce energy loss.

Recommended Block for Better Thermal Properties:

- Thermal Conductivity: 0.17 W/mK
- Bulk Density: 608 kg/m3
- Specific Heat: 875
- Block Name: AB01

These recommendations are derived from a dataset of blocks with better thermal properties. The script identifies the most suitable materials and design adjustments to enhance the building's thermal resilience based on the predicted thermal autonomy and the critical factors identified in the feature importance analysis. A detailed explanation has been provided in section 6.3

6.2 Seismic Resilience

The script prompts the user to input parameters related to building dimensions, earthquake magnitude, and section size. Based on these inputs, the machine learning model predicts the drift angles, which are then used to plot the fragility curves. The fragility curves represent the probability of reaching or exceeding various damage states as a function of drift angle. To plot the fragility curves, the script uses predefined median and dispersion values taken from the literature provided in Section 3.4.3. The fragility function utilizes the cumulative distribution function (CDF) of the normal distribution to calculate the probability of collapse. Specifically, the function **fragility_function(drift_angle, median_da, sigma_lnda)** computes the probability based on the formula:

$$P(Collapse) = \Phi\left(\frac{\ln(drift\_angle) - \ln(median\_da)}{\sigma\_lnda}\right) \tag{6.1}$$

where Φ is the CDF of the standard normal distribution, **drift_angle** is the observed drift angle, **median_da** is the median drift angle for the damage state, and **σ_lnda** is the logarithmic standard deviation (dispersion). The fragility curves are then plotted for an extended range of drift angles to visualize the probability of collapse for different damage states.

Once the probability of collapse is determined, the script calculates the economic losses or repair costs associated with the different damage states shown in the fragility curves. The repair costs, denoted as **Lr_ci**, are predefined for each damage state. The script calculates the economic loss using the formula:

$$Economic\_Loss = \sum \left[(P_i - P_{i+1}) \times Lr\_ci[i] \times V_t\right] \tag{6.2}$$

where Pi and Pi+1 are the probabilities of collapse for consecutive damage states, and Vt is typically set to 1. This calculation accounts for the incremental repair costs as the building transitions through different damage statesFollowing the calculation of economic loss, the script computes the resilience loss using the predicted repair costs and downtime. The resilience curve illustrates the building's functionality over time, considering the downtime and subsequent repair periods. The total downtime is calculated by summing various delays due to impeding factors and repair times, using the function **calculate_downtime().** This function incorporates inspection delay, financing delay, contractor mobilization delay, permitting delay, and actual repair times. The initial functionality drop is determined by the ratio of economic loss to the total replacement cost of the building. The resilience curve is plotted to show the functionality drop and recovery over an extended period, with specific markers indicating the end of downtime, structural repair, and facade repair periods.

The calculation of downtime assumes many variables as constants, following a simplified methodology explained in Section A4.3 of the REDi report (Almufti Arup et al., 2013). For instance, variables like HVAC repair time and gas disruption are set to zero, reflecting the context of low-cost housing in India where individual gas cylinders are used, and HVAC systems are typically absent. Assumptions for electrical and water disruption times are based on typical values, while structural and facade repair times are sourced from the PACT database. The replacement cost represents the total cost of the house. The script ultimately provides detailed insights into the building's seismic resilience by calculating the repair time, repair cost, functionality drop, and estimated repair duration. These comprehensive results guide users in improving their building designs to enhance seismic resilience effectively.

Example inputs and outputs:

Please enter the following parameters for drift angle prediction:

- Enter Length: 4
- Enter Width: 4
- Enter Total Height: 3.35
- Enter Magnitude of Earthquake: 5.5
- Enter Section Size: 0.35

Predicted Drift Angle: 0.0105

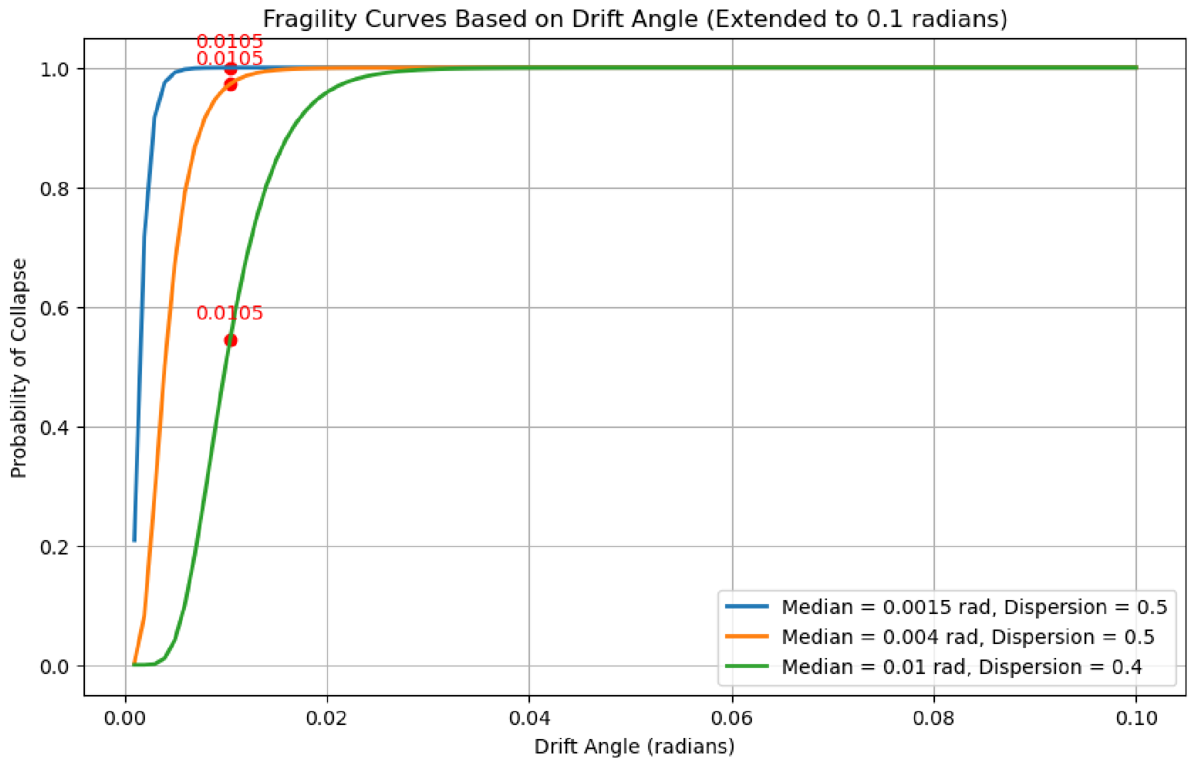


Figure 6.1: Fragility curves extracted after the user inputs

- Damage state 1 - Detachment of infill, Light diagonal cracking
- Damage state 2 - Extensive diagonal cracking
- Damage state 3 - Corner crushing and sliding of mortar joints

Estimated Economic Loss: 859751.05 INR

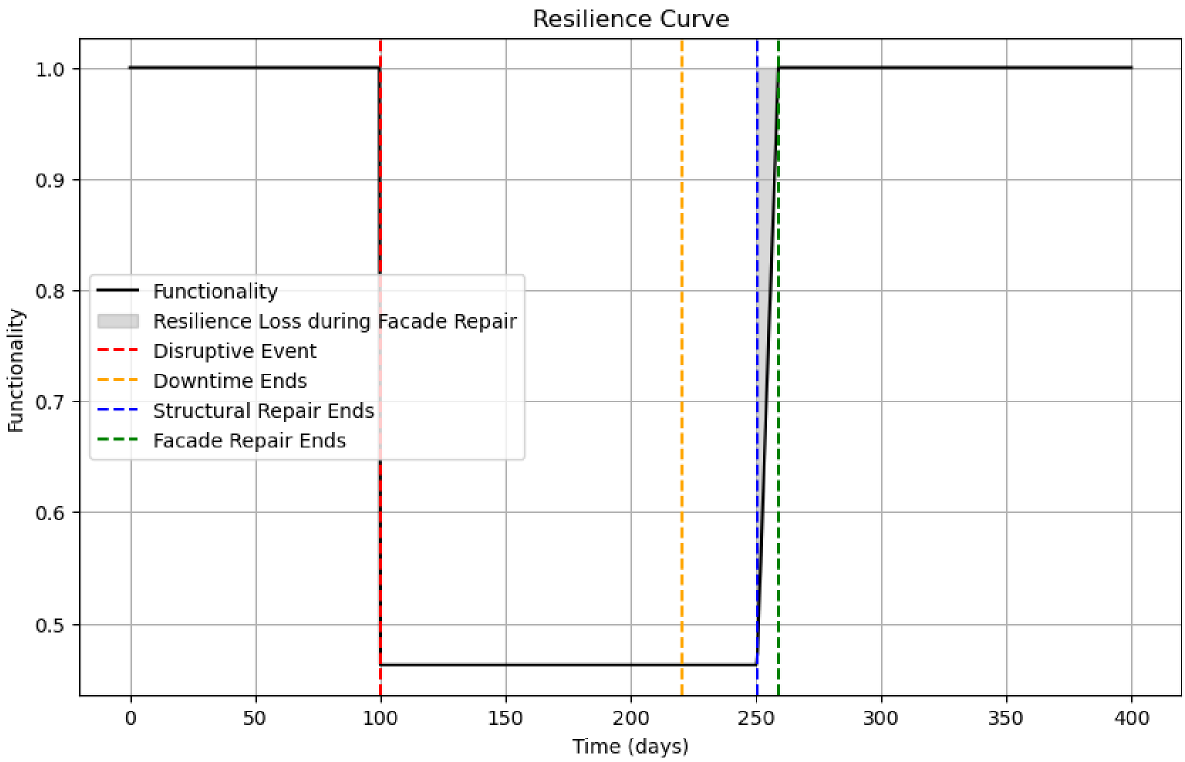


Figure 6.2: Façade Seismic Resilience

Total estimated downtime: 120.5 days

Initial functionality drop: 0.54

6.3 Recommendations for thermal Resilience

The script provides the user with various design recommendations outlined in section 6.1. These suggestions are derived from an analysis of correlation heat maps, feature importance charts, and the impact of features on spatial thermal autonomy and drift ratios, as illustrated in figure 6.3. Given that this design intervention targets low-cost housing in India, budget constraints pose a significant challenge. To overcome this, the recommendations emphasize local or indigenous practices to enhance the building's thermal and seismic performance. The primary metric for thermal performance is spatial thermal autonomy—the higher the percentage, the better the living conditions. This section details the recommendations and their impact on the outcomes.

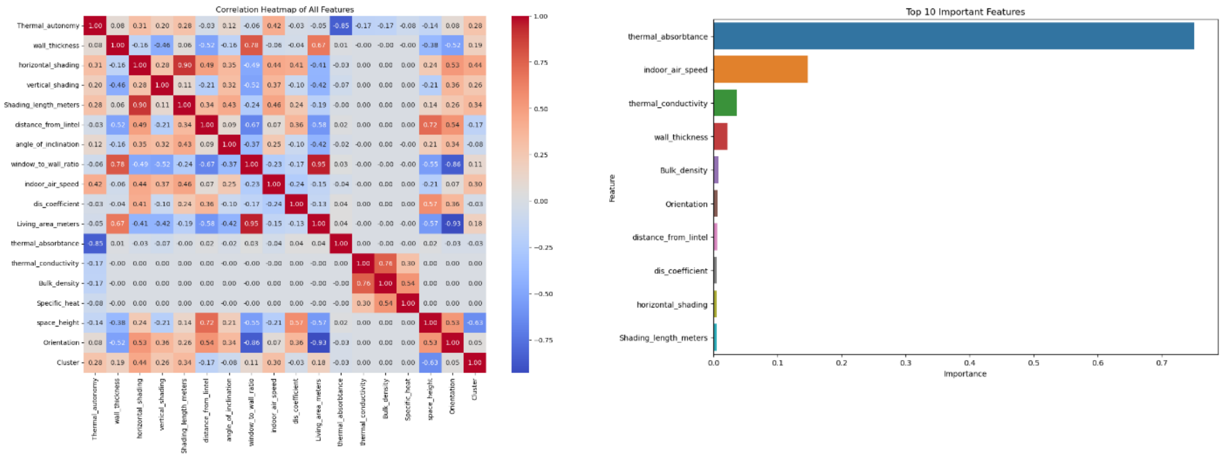


Figure 6.3: Correlation heatmap and feature importance

The charts clearly indicate that thermal absorbance is crucial in mitigating SET values within the house. Various passive techniques can be implemented to enhance this, either during the design stage or through retrofitting

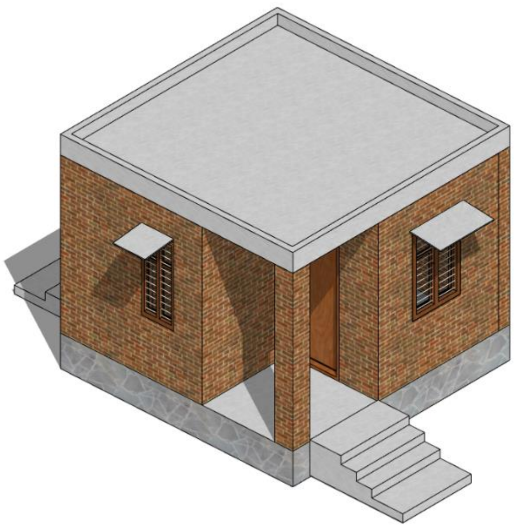


Figure 6.4: Typical design of a low-cost housing in India

Figure 6.4 shows a typical house design extracted from the PMAY document of the government of India. The thermal performance of this house in terms of Spatial thermal autonomy ranges from 40-45% which is quite low to provide comfortable indoor conditions for people inside.

Recommendation 1: Thermal performance can be enhanced by reducing the thermal absorbance of exterior walls and the roof. One effective method is the indigenous technique known as Mud Phuska coating. This involves applying a mixture of clay and Bhusa (hay) sand as a waterproofing solution on the walls. The final layer is plastered with a mixture of cow dung and mud, with proper curing to ensure it remains waterproof. This technique was recently implemented by the Indian architecture firm Envisage in one of their projects. Thermal readings inside the space revealed that the coating reduced thermal absorption by almost 70%, lowering the thermal absorbance feature to 0.3. This method not only improves the overall U-value of wall construction but also utilizes local materials and labour.

Figure 6.5: Mud Phuska design option

Recommendation 2: Green walls, also known as living walls or vertical greenery systems, significantly enhance the thermal performance of buildings. They reduce the amount of solar radiation hitting the building's surface, providing natural insulation that lowers indoor temperatures during summer and retains heat during winter. This results in reduced energy consumption for heating and cooling, with studies showing potential reductions of up to 16.5% in heating and 51% in cooling energy demand (Susca et al., 2022). This can be done by installing a wooden Trellis or planters with a variety of plants that can be both creepers as well as potted plants. or low-cost options that can be installed by individuals from low-economic backgrounds, it's important to focus on plants that are inexpensive, easy to propagate, and require minimal maintenance. Here are some of the cheapest indigenous plants suitable for small planters on external walls in North India:

Plant Name	Description
Money Plant (Epipremnum aureum)	Hardy climber with heart-shaped leaves
Indian Ivy (Hedera nepalensis)	Evergreen climber with dense foliage
Sweet Potato Vine (Ipomoea batatas)	Vigorous climber with attractive foliage
Spider Plant (Chlorophytum comosum)	Produces baby plants, easy to propagate
Aloe Vera (Aloe barbadensis miller)	Medicinal uses, minimal watering
Jade Plant (Crassula ovata)	Easy to propagate from cuttings
Basil (Ocimum sanctum)	Culinary and medicinal uses
Marigold (Tagetes spp.)	Bright flowers, easy to grow from seeds
Purslane (Portulaca oleracea)	Edible, thrives in full sun
Snake Plant (Sansevieria trifasciata)	Low maintenance, tolerates low light

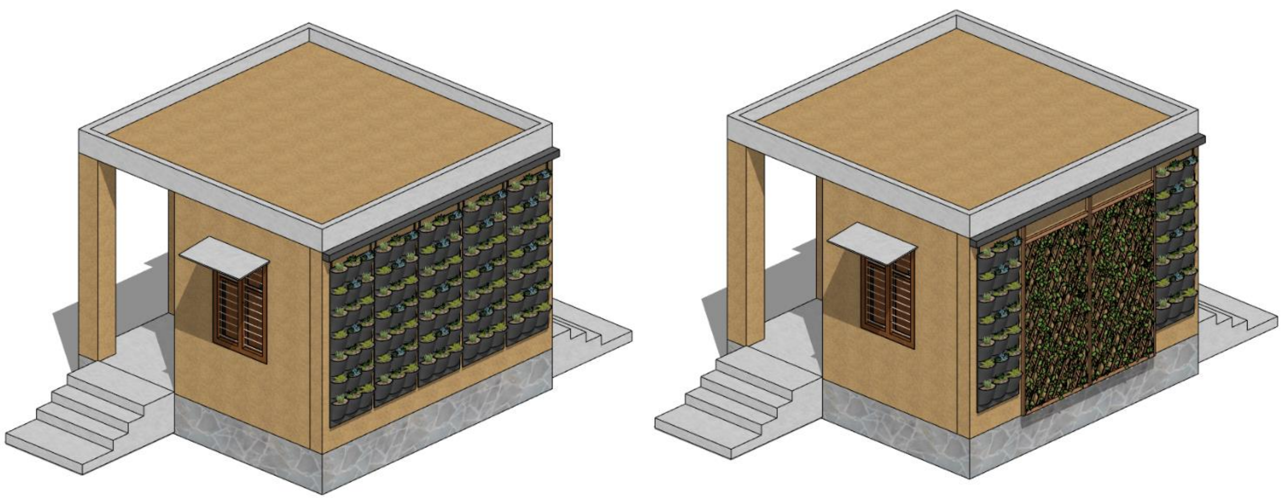


Figure 6.6: Green Facade design option

Recommendation 3: Terracotta is an excellent material choice for low-cost housing cladding due to its outstanding thermal properties and cost effectiveness. Terracotta exhibits remarkable heat resistance and thermal regulation capabilities, primarily due to its porous nature. The porosity of terracotta allows for effective water diffusion, which can enhance its thermal properties (P.Signanini,2014). When wet, terracotta’s ability to retain water and subsequently evaporate it helps to cool the material, thereby reducing the overall heat transfer and maintaining a cooler indoor environment. An Additional coating with cool materials significantly reduce heat absorption, enhancing energy efficiency. This makes terracotta an ideal choice for reducing thermal stress on occupants in hot climates.(Pisello et al., 2014).

For low-cost housing, terracotta's affordability and ease of production make it a viable material. Its durability and low maintenance requirements further add to its suitability, ensuring long-term cost savings. Therefore, integrating terracotta in architectural designs can effectively mitigate thermal stress, enhance occupant comfort, and contribute to sustainable and cost-efficient building solutions. Figure 6.7 showcases one of the ways how terracotta cladding can be integrated with green facades.

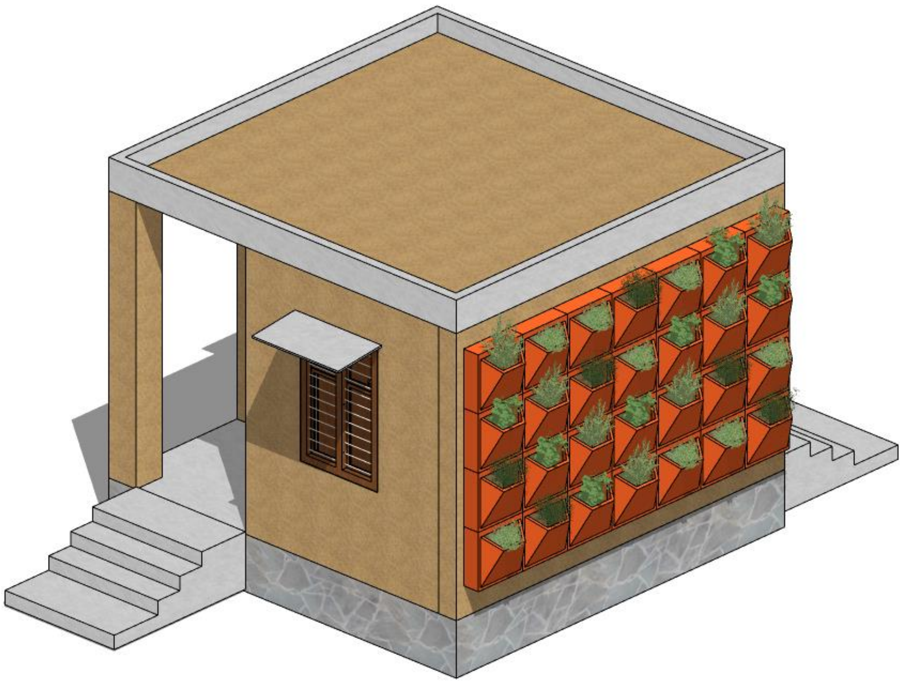


Figure 6.7: Terracotta cladding with Green Facade design option

Recommendation 4: The cSNAP technology, developed by the Wyss Institute at Harvard University, represents a significant advancement in eco-friendly air conditioning. Utilizing advanced materials science and design, cSNAP leverages evaporative cooling to achieve up to 75% energy savings compared to traditional vapor-compression air conditioning systems. This efficiency is particularly beneficial for sustainable building designs, such as low-cost housing projects, where budget constraints are critical. By avoiding the use of synthetic refrigerants, cSNAP also minimizes the release of harmful greenhouse gases, contributing to a reduced global warming potential and promoting environmental sustainability. (CSNAP: Eco-Friendly Air Conditioning, 2024)

One of the key advantages of cSNAP is its versatility and adaptability. Unlike conventional evaporative cooling systems that struggle in high humidity, cSNAP performs efficiently in both hot and humid climates. The system can be integrated into existing evaporative coolers or directly into building façades, providing flexibility in application and enhancing the overall design of the structure. The use of nanoscale hydrophobic materials isolates water vapor from the air, preventing excess humidity and ensuring comfortable indoor environments. This feature improves air quality and stabilizes indoor temperatures, significantly enhancing occupant comfort.

The cost-effectiveness of cSNAP makes it an ideal solution for low-cost housing developments (Figure 6.8). Its low production costs, combined with substantial energy savings, result in lower operational expenses and long-term financial benefits for residents. Additionally, the technology's successful real-world testing at Harvard’s HouseZero has demonstrated its effectiveness in extremely hot conditions, providing empirical support for its practical application

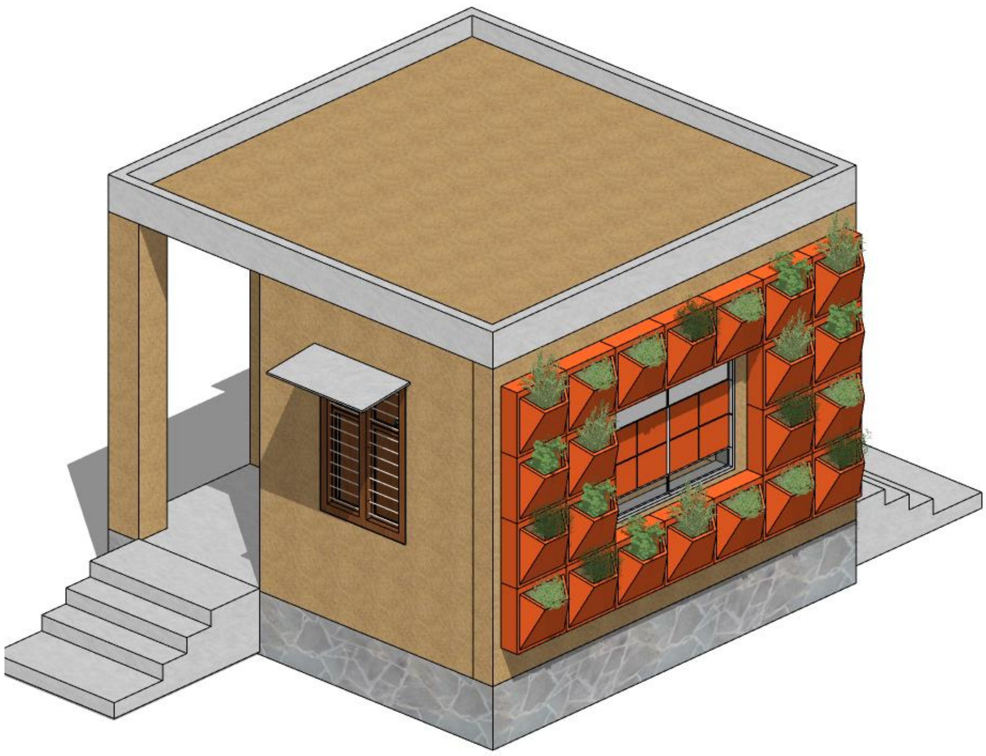


Figure 6.8: Terracotta cladding with cSNAP façade element

Recommendation 5: Implementing a rat trap bond for increasing wall thickness is an effective approach to improving a building's thermal efficiency (Figure 6.9). The rat trap bond involves placing bricks on edge to form a cavity within the wall, creating an insulating air gap that reduces heat transfer. This technique enhances the wall's thermal mass, contributing to better temperature regulation within the building.

This method not only offers excellent thermal insulation but also uses fewer bricks compared to traditional solid brick walls, leading to material savings and reduced construction costs. The air cavities created by the rat trap bond also aid in sound insulation, improving overall comfort for occupants. Adopting the rat trap bond construction technique can result in more energy-efficient buildings, lower heating and cooling costs, and a more sustainable living environment. (Figure 6.9).

Choosing building blocks with superior thermal properties from available materials can greatly improve a building's energy efficiency and occupant comfort. Options such as autoclaved aerated concrete (AAC), lightweight concrete blocks, and stabilized earth blocks are ideal due to their excellent thermal insulation characteristics. These materials have low thermal conductivity, which means they effectively resist heat transfer, helping to maintain consistent indoor temperatures. Using these advanced building blocks can significantly enhance a building's thermal performance, reducing the need for artificial heating and cooling. This leads to lower energy consumption and costs while promoting sustainability. Incorporating these materials into construction can help create energy-efficient, comfortable, and environmentally friendly buildings suitable for modern housing needs.

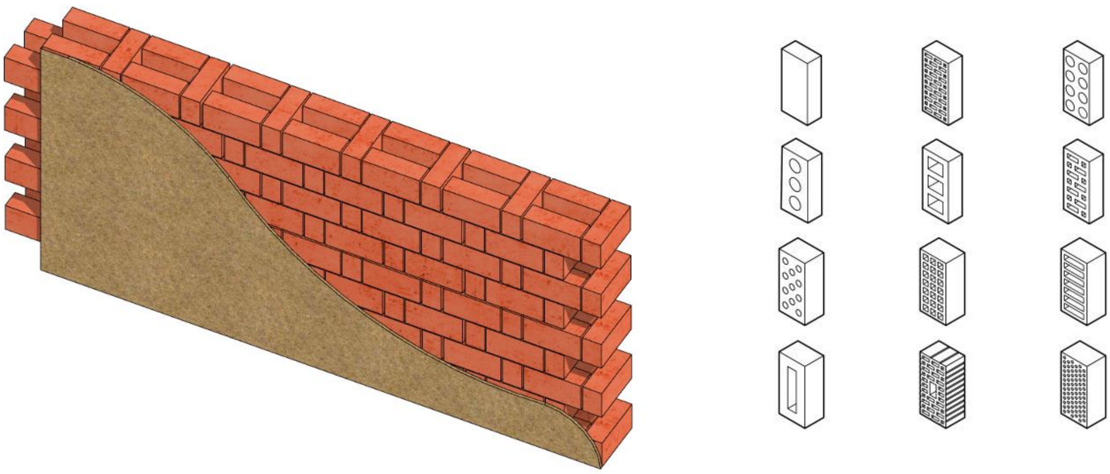


Figure 6.9: Rat trap bond and various building blocks

6.4 Recommendations for Seismic Resilience

Based on the prediction made by the Machine learning model, the script provided the following recommendations to improve Seismic resilience as per Indian Standard Earthquake Resistant Design and Construction of Buildings Code of Practice (IS 4326: 1993). As it has been identified that drift angles have a direct impact on the functionality drop of the façade. Therefore, the aim of these recommendations is to improve the drift angle values which in turn will reduce the economic losses and repair time. (Figure 6.10)

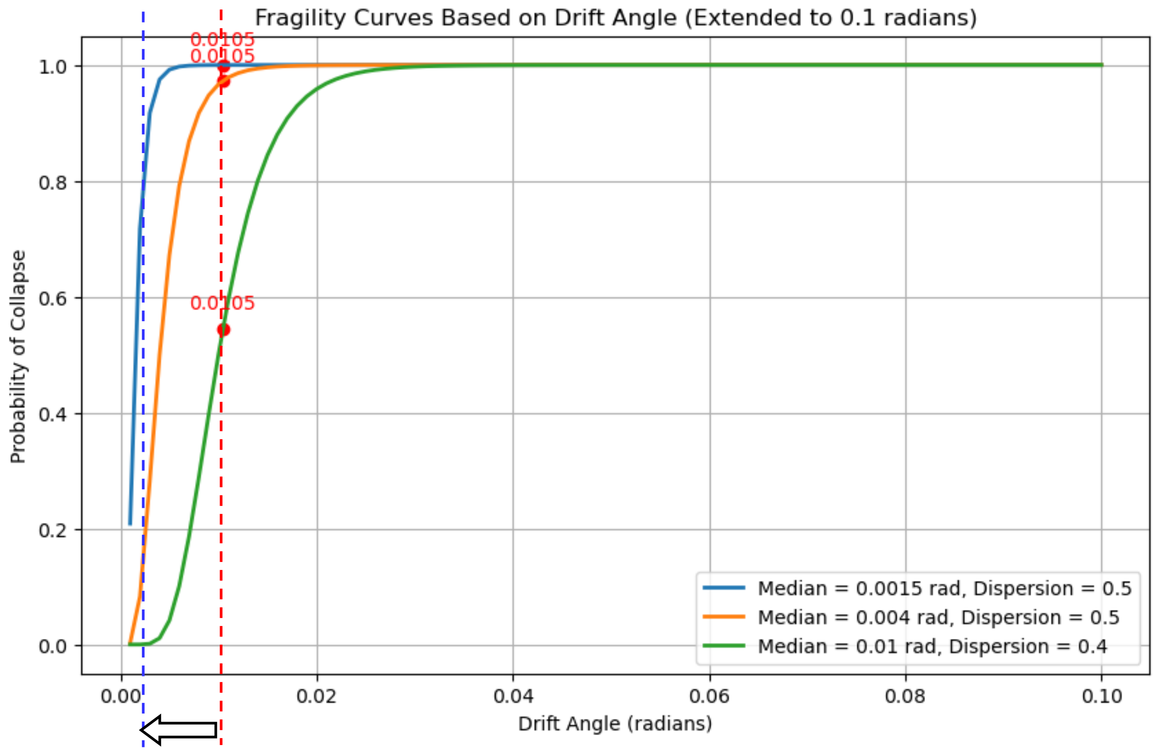


Figure 6.10: Improving the drift angle values

Recommendation 1: Horizontal Seismic Bands with Bamboo Reinforcement

Horizontal seismic bands reinforced with bamboo leverage the high tensile strength and flexibility of bamboo. Case studies and structural analyses of bamboo-reinforced elements have shown improvements in energy dissipation and crack control during seismic events. This reinforcement can improve the drift angle by about 10-15%, reflecting the benefits observed in structures that utilized bamboo in seismic reinforcement strategies, enhancing their overall stability and resilience. (Figure 6.11)

Vertical Seismic Bands with Steel Reinforcement

Incorporating vertical seismic bands with steel reinforcement significantly enhances the lateral load resistance of buildings. Research and case studies have shown that adding vertical steel reinforcements can improve the structural ductility and load-bearing capacity. This method can improve the drift angle by approximately 15-20%, based on studies where similar reinforcements were implemented in masonry and concrete structures, showing marked improvements in their ability to withstand lateral seismic forces. (Figure 6.11)

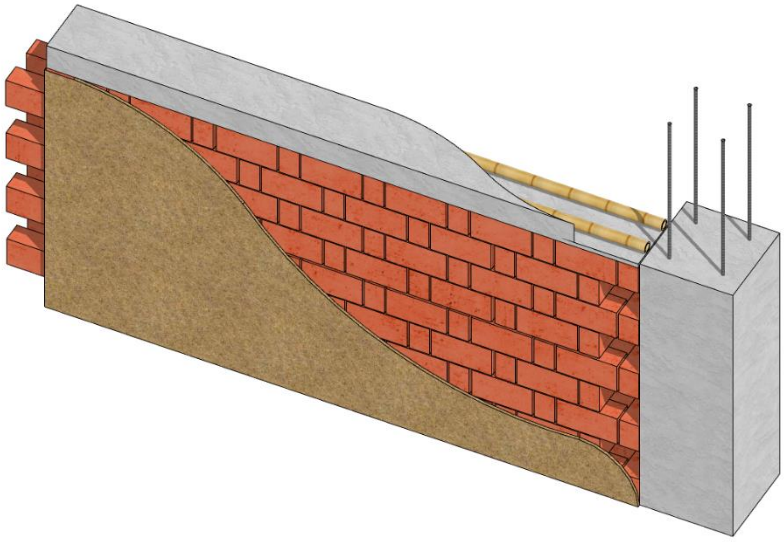


Figure 6.11: Horizontal and vertical Seismic Bands

Recommendation 2: 2 Brick Thick Rat Trap Bonded Wall with Corner Reinforcement

Constructing walls using a 2-brick thick rat trap bond method with corner reinforcement increases the wall's load-bearing capacity and stability. Structural tests and empirical data from buildings using this method demonstrate better performance under lateral loads. This construction method can improve the drift angle by around 15-20%, as reinforced walls provide enhanced structural continuity and load distribution, which are critical for seismic resilience (Figure 6.12)

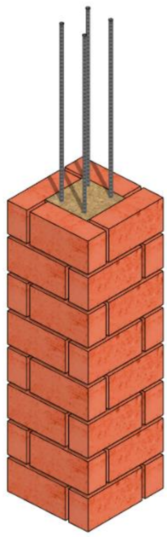


Figure 6.12: 2 Brick Thick Rat Trap Bonded Wall with Corner Reinforcement

Recommendation 3: Minimum 10 mm Reinforcing Bars Embedded in Brick Masonry

Embedding a minimum of 10 mm reinforcing bars within brick masonry adds significant tensile strength to the walls. Research on reinforced masonry structures has shown substantial improvements in their ability to resist seismic forces. The addition of reinforcing bars can improve the drift angle by approximately 15-20%, based on studies where masonry walls reinforced with steel bars exhibited increased ductility and reduced damage during seismic events (Figure 6.13)

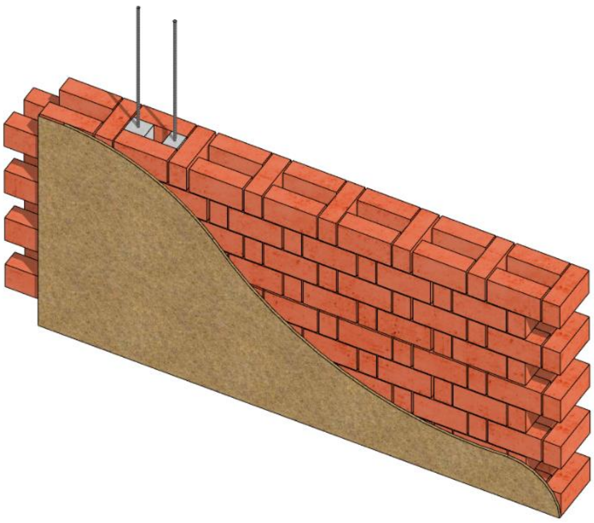
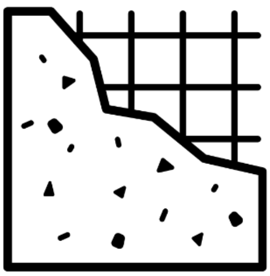


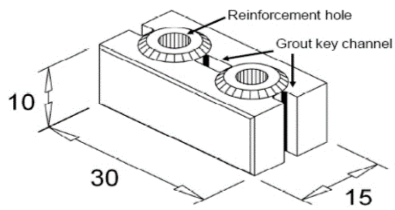
Figure 6.13: Minimum 10 mm Reinforcing Bars Embedded in Brick Masonry

Recommendation 4: Ferrocement Roof and Hollow Interlocking CSEB block wall

Using a ferrocement roof, which is 60% lighter than conventional concrete roofs, reduces the overall mass of the building. Studies on lightweight roofing materials in seismic zones indicate a significant reduction in seismic forces acting on the structure. A lighter roof reduces inertia during an earthquake, thereby improving the drift angle by approximately 20-25%. This estimation is based on comparative analyses of buildings with conventional concrete roofs versus lightweight alternatives, which showed substantial improvements in seismic performance.

Using hollow interlocking Compressed Stabilized Earth Blocks (CESB) for wall construction provides better interlocking and stability while reducing the overall weight of the structure. Case studies and experimental research on CESB blocks indicate improvements in seismic performance due to better interlocking and reduced mass. The use of CESB blocks can improve the drift angle by about 10-15%, reflecting the enhanced stability and reduced seismic vulnerability observed in structures utilizing interlocking blocks.





07

Conclusion

This section outlines the findings and recommendations based on the integration of advanced thermal efficiency and sustainability strategies for low-cost housing. The analysis incorporates innovative approaches such as the cSNAP eco-friendly air conditioning technology, the rat trap bond technique for wall construction, and the selection of building blocks with superior thermal properties. By examining these methods, the report provides comprehensive insights into their impact on reducing energy consumption, enhancing thermal comfort, and promoting sustainable building practices. Detailed evaluations highlight the effectiveness of these strategies in various climatic conditions, offering practical solutions for optimizing low-cost housing designs to achieve improved thermal performance and sustainability

7.1. Discussion

In recent years, the world has experienced an increase in the number of disruptive events, which have significantly impacted the built environment. These disruptions underscore the importance of considering system resilience from the early stages of design. Quantifying resilience is crucial as it enables effective preparation, recovery, and adaptation to future uncertainties.

This study specifically focuses on the resilience of building facades, which play a vital role in maintaining a comfortable indoor environment. The facade serves as the barrier between the indoor and outdoor environments and acts as a protective layer. Therefore, its resilience needs to be prioritized during the design phase. However, resilience analysis requires architects and engineers to be proficient in various software tools, which can be time-consuming to learn, resource-intensive, and often involves trial and error to achieve optimal results. The primary research question of this study addresses this gap:

"How can machine learning techniques be effectively applied to improve the workflow of seismic and heat waves resilience analysis in building facades?"

To address this research question, a methodology with two main objectives was developed:

Simulation of Various Models: To achieve resilience scores of facades and create a comprehensive dataset for machine learning models.

Application of Machine Learning Techniques: To identify the most critical features and predict outcomes based on user inputs.

The following sections will discuss the effectiveness of the proposed methodology and the AI prediction of building resilience in achieving these key objectives.

7.1.1 Simulations of BEM and SDPA models

Archetype Selection for the Study

For this study, it was imperative to choose an archetype that accurately reflects the vulnerability and resilience requirements for thermal and seismic hazards. Given the aim to create a pipeline workflow to achieve resilience scores for both thermal and seismic hazards in a multi-hazard approach, the location had to be selected meticulously.

New Delhi was chosen as the study location due to its classification under seismic zone 4 and its frequent experiences with extreme heat waves. These combined hazards often result in prolonged power outages, forcing residents to endure harsh conditions within their homes. Furthermore, New Delhi has a significant population of low-income groups who live in substandard housing conditions without adequate power backup systems. Many individuals within this demographic do not have homes at all.

In response to this housing crisis, the Government of India, under the Pradhan Mantri Awas Yojana (PMAY) scheme, has been developing approximately 10 million houses across the country, with New

Delhi included in this plan. However, these new houses could greatly benefit from the integration of passive design techniques to maintain comfortable indoor conditions during power outages.

The archetype chosen for this study was low-cost housing. The architectural details of these houses were extracted from government documents, ensuring that the study accurately represents the typical housing conditions faced by low-income groups in New Delhi.

Thermal Resilience Assessment

To assess the thermal resilience of facade systems, a Typical Meteorological Year (TMY) database for New Delhi was obtained from the EnergyPlus Weather (EPW) website. This data was crucial for conducting dynamic thermal simulations. To create a diverse range of facade combinations, house plans extracted from official documents were paired with various types of bricks used across the country, resulting in a wide array of scenarios.

EnergyPlus dynamic simulations were conducted on these different models, varying in house plans, building materials with different thermal properties, thermal absorption, thermal reflectance, indoor air speed, orientation, and window-to-wall ratio. A total of 2600 simulations were performed to measure indoor thermal conditions under New Delhi's TMY using the Standard Effective Temperature (SET) as the intensity measure. Functionality loss was quantified as the degree-hours when SET exceeded the threshold of 28 degrees, relative to the total number of hours in the analysis period. This metric was termed Spatial THERMAL Autonomy of the house, expressed as a percentage.

The study successfully evaluated the facades of different housing units with various permutations and combinations of features. However, certain assumptions made during the assessment of thermal resilience require further validation. For instance, indoor air speed was considered to range from 0.8 m/s to 1.2 m/s, based on the assumption that no forced ventilation would result in the minimum indoor air speed, and some ventilation (natural or using a small energy-efficient fan) would achieve 1.2 m/s. The impact of heatwaves was assessed using natural ventilation with a minimum Air Changes per Hour (A.C.H.), calculated based on the window-to-wall ratio and floor space. This needs further research validation.

Despite these assumptions, the impact of key features such as thermal absorption, wall properties, and indoor air speed proved significant, enabling the machine learning model to effectively learn and predict outcomes.

Seismic Resilience Assessment

For the seismic resilience assessment, historical seismic data from seven different events in India was gathered. Dynamic simulations were conducted on various housing units, using inter-storey drift angles as a demand parameter to indicate the impact of seismic hazards on the facades. A limitation of this analysis was the assumption that the housing structural systems were portal frames for all houses, and a linear static analysis was used to calculate deflection in one direction.

The seismic performance assessment followed the FEMA-58 methodology. Scripts were generated for probabilistic calculations and the accumulation of losses using the fragility database from the Performance Assessment Calculation Tool (PACT). Functionality loss was calculated as the fraction of the repair cost to the replacement cost of the facade, while economic loss was based on the total repair cost of the facade.

Although the repository contained sufficient data on curtain walls, information on masonry infill systems and concrete cladding systems was sourced from the literature. This comprehensive approach allowed for a detailed assessment of the seismic resilience of various facade systems, highlighting areas for further improvement and research.

7.1.2 Surrogate modelling

Why a Surrogate model?

In this study, a surrogate model was developed using machine learning techniques to streamline the process of resilience analysis for building facades. The model processes simulation data and provides tailored recommendations based on user inputs, significantly reducing computational demands and facilitating rapid assessments.

The process begins with data pre-processing to ensure suitability for machine learning models. For thermal resilience, features are normalized, and dimensionality reduction techniques are applied to simplify the data. Clustering methods are used to identify distinct patterns within the thermal data.

Various machine learning models, including Random Forest Regressor and others, are employed to predict thermal autonomy. User inputs such as wall thickness, shading parameters, window-to-wall ratio, indoor air speed, thermal properties, and building orientation are collected and fed into the model to predict the Spatial Thermal Autonomy. This metric indicates how well a building can maintain comfortable indoor temperatures without mechanical systems.

For seismic resilience, the model predicts the drift angle, a critical parameter for assessing building sway during an earthquake. User-provided structural and seismic parameters, including building dimensions and potential earthquake magnitude, are processed using the Random Forest Regressor. This helps engineers and architects evaluate the structural performance and stability of buildings under seismic loads.

The surrogate model serves several key functions:

- Approximation of Complex Simulations: It approximates the results of detailed thermal and seismic simulations, enabling quick predictions without the need for extensive computational resources.
- Reduction in Computational Cost: By providing fast predictions, the model reduces the computational cost and time associated with traditional simulation methods.
- Facilitating Rapid Assessments: The model allows for swift evaluations of building facades under various conditions, aiding architects and engineers in making informed decisions quickly.
- Handling Multi-Hazard Scenarios: The model integrates both thermal and seismic resilience assessments, providing a comprehensive tool for evaluating building facades against multiple hazards.
- Learning from Extensive Data: The model is built on a large dataset from simulations, capturing complex relationships between various input parameters and resilience outcomes.

This surrogate model, through efficient and accurate predictions, serves as a valuable tool for assessing and enhancing the thermal and seismic resilience of building facades, contributing to safer and more sustainable building designs.

7.1.3 Recommendations related to the results and Limitations

Understanding the results

The analysis of the correlation heatmap reveals important insights into the factors that influence thermal autonomy in buildings. The results show that materials with high thermal absorbance tend to increase heat gain, which reduces thermal efficiency. This suggests that selecting materials with lower thermal absorbance can significantly enhance a building's thermal performance.

Shading emerges as a crucial factor in improving thermal resilience. The presence of effective horizontal and vertical shading can mitigate heat gain and enhance the building's ability to maintain comfortable indoor temperatures. This indicates the importance of integrating shading strategies into building designs to improve thermal autonomy.

The relationship between wall thickness and the window-to-wall ratio highlights the balance needed between structural integrity and thermal performance. Thicker walls are generally beneficial for thermal autonomy as they reduce heat transfer. However, buildings with larger windows require thicker walls for structural support, which can affect thermal characteristics. This trade-off must be carefully managed to optimize both structural and thermal performance.

Ventilation and airflow management are also critical components of thermal resilience. Higher indoor air speeds and well-designed airflow management systems can significantly improve thermal autonomy. Features like optimal angles and shading lengths play a vital role in enhancing ventilation effectiveness and maintaining comfortable indoor temperatures.

Larger living areas typically feature more extensive windows, which can impact thermal performance. Therefore, careful consideration of the window-to-wall ratio in larger spaces is necessary to maintain thermal efficiency. Additionally, the orientation of buildings has a significant influence on thermal performance, underscoring the need for strategic orientation based on local climatic conditions.

By addressing these key factors—material selection, shading strategies, wall thickness, ventilation, window-to-wall ratios, and building orientation—housing designs can be optimized to achieve higher thermal resilience and comfort for occupants. These insights provide a foundation for making informed recommendations that enhance the thermal performance of low-cost housing units, contributing to safer and more sustainable living environments

Thermal Performance Improvement

To enhance the thermal performance of low-cost housing units, recommendations are made based on the top-performing features identified using unsupervised machine learning models. These recommendations are designed with budget considerations in mind, utilizing indigenous practices and local materials to ensure cost-effectiveness. Key recommendations include:

- Enhanced Wall Insulation: Using locally available materials to improve wall insulation can significantly reduce heat transfer, maintaining comfortable indoor temperatures.
- Shading Devices: Implementing external shading devices to minimize solar heat gain through windows.
- Improved Ventilation: Utilizing passive ventilation techniques, such as strategically placed vents and openings, to increase indoor air circulation and reduce indoor temperatures.

These measures aim to improve the Spatial Thermal Autonomy (STA) by reducing the degree-hours when indoor temperatures exceed comfort thresholds. While the recommendations are based on literature and assumptions, physical validation through field testing is necessary to quantify the actual improvements in STA.

Seismic Resilience Enhancement

For seismic resilience, the focus is on improving the drift angles, which directly impacts the fragility curves related to structural damage. Recommendations include:

- Horizontal Seismic Bands with Bamboo Reinforcement: Incorporating horizontal seismic bands made from bamboo, which provides flexibility and strength, helping to distribute seismic forces evenly across the structure.
- Vertical Seismic Bands with Steel Reinforcement: Adding vertical seismic bands with steel reinforcement to enhance the structural integrity and prevent collapse during seismic events.
- Ferro Cement Roofing: Using ferro cement roofing, which is 60% lighter, reduces the overall weight of the structure, thereby lowering the seismic forces acting on the building.
- 2 Brick Thick Rat Trap Bonded Wall with Corner Reinforcement: Constructing walls using a 2-brick thick rat trap bond method with corner reinforcements to improve the stability and load-bearing capacity of the walls.
- Minimum 10mm Reinforcing Bars Embedded in Brick Masonry: Embedding at least 10mm reinforcing bars within the brick masonry to increase the tensile strength and resistance to seismic forces.
- Hollow Interlocking CSEB Block Wall: Utilizing hollow interlocking Compressed Stabilized Earth Blocks (CSEB) for wall construction to provide better interlocking and stability while reducing weight.

These recommendations aim to shift the fragility function of the damage states for concrete towards the positive y-direction. This shift reduces the probability of failure for each damage state, thereby decreasing the functionality drop in the resilience curve. Consequently, this leads to reduced economic losses and shorter repair times.

However, the recommendations are currently based on simulations that considered only portal frames of concrete construction. Also, the percentage improvements are approximations derived from a combination of empirical data, case studies, and structural engineering principles. For precise quantifications, detailed numerical simulations and field validations specific to the context of low-cost housing in India would be required. Implementing these recommendations will significantly improve the seismic resilience of low-cost housing units, ensuring better safety and stability during earthquakes.

7.2 Conclusion

The resilience assessment conducted in this study provided a comprehensive set of performance indicators, including thermal autonomy and drift angle, which served as critical decision-making criteria. To visually represent these attributes for each facade system, a radar chart was utilized, allowing for clear comparison and informed decision-making.

During the early design phases, creating detailed models to evaluate multiple design options can be extremely time-consuming. However, with the implementation of the predictive model developed in this study, many design options can be explored in a very short time. By quickly changing the inputs and obtaining immediate results, architects and engineers can efficiently evaluate the multifunctionality of various facade systems and their ability to withstand multiple hazards. This rapid evaluation process ensures a holistic approach and minimizes unnecessary iterations across various facade-related domains in later stages. The ability to quickly identify the facade system with the highest combined attribute value enables informed decision-making, highlighting the option with the least combined loss and indicating superior resilience compared to other systems under consideration.

In situations where the system is already established, such as in retrofitting projects, improving performance based on the existing system is essential. To aid in this process, a Python script was created. This script gathers user inputs and provides customized recommendations accordingly. For example, if the current system comprises facade components with moderate seismic and thermal performance, the script can suggest upgrades or modifications to enhance these components. This method allows for configuring an overall improved system by replacing different facade components. Moreover, the script supports partial improvements based on the specific weights of importance defined by the project, ensuring targeted and efficient enhancements.

By understanding and applying these performance indicators and recommendations, this study provides a framework for making strategic decisions that enhance both the thermal and seismic resilience of building facades, ultimately contributing to safer and more sustainable built environments.

7.3 Future Research needs

Expanding the Geographical Reach

To enhance the applicability of this research, future studies should focus on expanding the geographical reach of the project. Conducting resilience assessments in different locations will provide a more comprehensive understanding of how various climatic and seismic conditions impact building facades. Additionally, incorporating more categorization in terms of comfort levels will allow for a tailored approach to different regions, ensuring that the recommendations are relevant and effective for diverse environmental conditions.

Predicting Future Scenarios

Currently, the model uses a Typical Meteorological Year (TMY) file from the EPW database to simulate thermal performance. However, to increase the model's robustness and relevance, it is essential to enable predictions for future scenarios. Integrating future climate data into the model will allow for a more accurate assessment of how buildings will perform under changing climatic conditions, thereby improving the resilience planning for future uncertainties.

Incorporating Diverse Archetypes

The current study focuses on low-cost housing in New Delhi, India. To broaden the scope and utility of the model, it is necessary to provide new data for the machine learning model to predict resilience for different building archetypes. By including a variety of housing types and architectural styles from different regions, the model can offer more comprehensive and versatile recommendations applicable to a wider range of buildings.

Validating Economic Loss Estimates

The economic loss calculations in this study are based on cost figures relevant to European standards. For the model to be truly effective in the Indian context, it is crucial to validate these costs using local data. Future research should focus on gathering and integrating cost information specific to India, ensuring that the economic loss predictions are accurate and relevant for local conditions.

Validating Downtime Figures

Similar to the economic loss estimates, the downtime figures used in this study are derived from the PACT database, which is based on European standards. To provide more accurate resilience assessments for Indian buildings, it is important to validate these figures with local data. Future efforts should aim at collecting downtime data specific to the Indian context to refine the model's predictions and recommendations.

Developing Local Fragility Functions

The fragility functions used in this study are not entirely accurate for local facade construction methods. To improve the precision of the resilience assessments, it is necessary to develop fragility functions that reflect the characteristics of local construction practices. This will involve collecting empirical data on the performance of local building materials and construction techniques under seismic stress, thereby enhancing the model's ability to predict damage and resilience accurately.

By addressing these future needs, the model can be significantly improved to provide more accurate, relevant, and comprehensive resilience assessments for a wider range of buildings and locations. This will ultimately contribute to the development of safer and more resilient built environments globally

08

Reflection

This section reflects on the methodology, challenges, and outcomes of integrating thermal and seismic resilience analyses into a cohesive script for low-cost housing in New Delhi. It highlights the comprehensive control over data and simulations, the invaluable guidance from mentors, and the practical and academic advancements achieved. The project underscores the importance of machine learning in resilience prediction, offering significant societal benefits and transferable methodologies for future applications.

08. Reflection

Personal Reflection:

The approach I took worked quite well. I had complete control over the dataset created from multiple thermal and seismic simulations on Grasshopper, ensuring consistency in the results. Once the results were generated, I could clearly identify the key features defining facade resilience. The graphs and plots effectively communicated how the analysis worked, enhancing my understanding of the process.

Through my simulations and data analysis, I gained a deep understanding of the critical factors that contribute to the thermal and seismic resilience of facades. The consistent platform for both types of simulations provided a cohesive framework, enabling me to comprehend the underlying mechanics and the significance of various features. Both of my mentors were instrumental in guiding me through the project stages. Initially, I struggled to define the scope of my project, but their support and guidance helped me refine my research questions and approach. Despite being in the United States for most of the third and fourth quarters, Alessandra provided valuable input through Zoom calls, focusing on thermal resilience. Simona, being on campus, offered more frequent in-person guidance, especially during a challenging period in March when I faced health issues and lagged in my work.

I translated the feedback from Alessandra and Simona into actionable steps, modifying my simulation models to achieve more accurate results. Their expertise in their respective fields helped me refine my approach and incorporate critical insights into my workflow. The feedback not only improved the accuracy of my models but also informed the recommendations I will present in my final presentations. This project has significantly accelerated my learning curve over the past four months. Combining visual coding in Grasshopper with textual coding in Python, I developed a model that predicts resilience with 99% accuracy. A year ago, I would have laughed at the idea of my thesis involving coding, but this experience has broadened my expertise in building physics, seismic analysis, and coding.

As an architect, coding was not part of my undergraduate curriculum, but the successful integration of these skills into my thesis was highly appreciated. This experience has opened new avenues in an industry increasingly reliant on architects and engineers who can code. I am grateful to the university for providing this opportunity to explore and expand my potential.

What is the relation between your graduation (project) topic, the studio topic (if applicable), your master track (A,U,BT,LA,MBE), and your master programme (MSc AUBS)?

My graduation topic is “Enhancing Building Facade Resilience Analysis through Machine Learning: Optimizing Workflow for Seismic and Heat Wave resilience measures” which is a subset of the Studio topic “Digital design tool for climate resilient structures”. This research primarily focuses on the improvement of the existing digital workflow that calculates façade resilience in a multi-hazard scenario.

This thesis is categorized under the Building Technology track, specifically under the chairs of Structural Design and Façade & Product Design. The project requires a multidisciplinary approach, necessitating the gathering of knowledge from structural design, façade design, building physics, and machine learning techniques. The project's anticipated result is to offer designers, architects, and decision-makers swift and invaluable insights into building envelope design. The current process involves substantial manual effort to explore new design possibilities by adjusting specific parameters and creating a detailed Building energy Simulation model as well as seismic model. The objective is to reduce the time required for modifying inputs, ultimately improving overall resilience against environmental challenges.

How did your research influence your design/recommendations and how did the design/recommendations influence your research?

Research Influence on Design/Recommendations:

My research aimed to address several key questions:

- What does resilience mean in terms of facade design?
- Where in India is there a need to conduct resilience analysis based on climatic conditions and earthquake data?
- Which part of society can benefit most from resilience research?
- Which archetype has readily available information for analysis?
- What machine learning techniques can be used to predict resilience scores?

Through understanding resilience in facade design, I concluded that it is crucial to develop design strategies that ensure buildings are resilient not only to current conditions but also to future scenarios. This urgency is driven by the rapid pace of climate change.

India was selected as the focus of my study for several reasons. Northern India, particularly New Delhi, experiences extreme weather conditions and falls within seismic zone 4, making it a prime candidate for resilience analysis.

Additionally, the Indian government's Pradhan Mantri Awas Yojana aims to build 10 million low-cost housing units by 2024. My detailed study of these housing units in terms of thermal and seismic resilience revealed critical insights. Poor residents are likely to be uncomfortable during heatwaves, especially during power outages, and they may not afford the repair costs following a seismic event.

Design/Recommendations Influence on Research:

The insights gained from my research significantly shaped the recommendations provided. By applying machine learning techniques to predict resilience scores, I was able to offer practical solutions. These solutions help architects and engineers understand the resilience of their designs and make informed recommendations for improvement.

For instance, the recommendations aimed at extending the comfort hours within these homes, thereby improving living conditions during extreme weather events and reducing the financial burden of repairs after earthquakes. This feedback loop between research and design ensures that the recommendations are grounded in rigorous analysis and are practically applicable, ultimately enhancing the resilience of low-cost housing units in India.

How do you assess the value of your way of working (your approach, your used methods, used methodology)?

The initial proposal for my work was ambitious, and I had high expectations for conducting detailed research on various facade archetypes, including glass, concrete, and composite facades. However, as I delved deeper into the research, I realized that time constraints necessitated a more focused approach. Consequently, I narrowed my research to a single archetype that would benefit those most in need.

Despite the initial lack of readily available data, I overcame this by synthesizing a substantial dataset from various sources. I acquired house plans that would be constructed, providing a close approximation to real-life construction typology. However, this was insufficient on its own, as I also needed information on the different building blocks used in construction. I researched the most common building materials in the Indian market and their respective properties, greatly aided by the research conducted by CEPT University. This allowed me to create numerous combinations of house plans with different materials, enhancing the realism and applicability of my research.

The real-life applicability of these scenarios adds significant value to my research and design recommendations. The methods used to calculate both thermal and seismic resilience have been verified, and I have created the best possible scenarios for analysis. Multiple simulations were conducted, and the results were consolidated into an Excel sheet, which serves as the basis for the machine learning model.

One impressive aspect of this approach is its scalability. There is no limit to the amount of data that can be incorporated into the Excel sheet. By providing more data on different building typologies, weather conditions, and materials, the reach of my prediction model can extend beyond low-cost housing in New Delhi to other parts of the world. This adaptability indicates that the methodology I have devised can be adopted for future studies in various contexts.

Thus, my approach, methods, and methodology have proven to be effective and valuable. The combination of real-life construction scenarios, extensive data synthesis, and scalable predictive modelling ensures that my research can provide practical and impactful recommendations, both now and in the future.

How do you assess the academic and societal value, scope, and implication of your graduation project, including ethical aspects?

Academic Value:

My graduation project contributes significantly to the academic field by advancing the understanding of resilience in building design, particularly within the context of thermal and seismic hazards. The innovative use of machine learning to predict resilience scores is a key academic contribution, offering a novel approach to evaluating building performance. The project also synthesizes extensive data on building materials and typologies, providing a valuable resource for future research. By narrowing the focus to a specific archetype and context, I demonstrated the feasibility and applicability of my methodology, setting a precedent for similar studies in different regions and under various conditions.

Societal Value:

The societal value of my project is substantial, particularly for vulnerable populations in regions prone to extreme weather and seismic activity. The project addresses the urgent need for resilient housing in North India, where climatic conditions and seismic risks are significant. By focusing on low-cost housing, the project directly benefits those most in need, providing practical solutions that can enhance their safety and comfort. The insights and recommendations generated by my research can inform architects, engineers, and policymakers, helping them design and implement more resilient housing strategies. This has the potential to improve living conditions, reduce repair costs, and increase the overall well-being of the affected communities.

Scope and Implication:

The scope of my project extends beyond New Delhi and North India. The methodology and predictive model developed can be adapted and applied to various regions and contexts globally. This scalability enhances the project's impact, as it can inform resilience strategies in diverse settings. The implications of this work are far-reaching, as it provides a framework for integrating resilience into building design, which is crucial in the face of climate change and increasing urbanization. By demonstrating the practical application of machine learning in resilience assessment, the project also encourages the adoption of advanced technologies in the construction industry.

Ethical Aspects:

Ethically, the project emphasizes the importance of equitable and inclusive design. By targeting low-cost housing, it addresses the needs of marginalized communities who are often disproportionately affected by environmental hazards. The research adheres to ethical standards in data collection and analysis, ensuring accuracy and reliability. Moreover, the project's recommendations aim to enhance the quality of life for vulnerable populations without imposing additional financial burdens. By promoting resilience in housing, the project contributes to social justice and equity, ensuring that all individuals have access to safe and comfortable living conditions.

How do you assess the value of the transferability of your project results?

The value of the transferability of my project results lies in its adaptable methodology, scalability, practical applicability, policy relevance, educational potential, and ethical considerations. These elements ensure that the project's findings can be effectively applied to various contexts, thereby enhancing building resilience and contributing to the broader field of sustainable and resilient architecture.

The methodological framework I developed for assessing thermal and seismic resilience is highly transferable. By using machine learning to predict resilience scores based on a comprehensive dataset of building materials, typologies, and climatic conditions, the approach can be adapted to different contexts and regions. This adaptability ensures that other researchers and practitioners can apply the same methodology to assess building resilience in various settings, making the results broadly applicable. One of the key strengths of my project is its scalability. By consolidating data into an Excel sheet, it accommodates extensive and varied datasets, allowing the predictive model to be used in different geographical locations and for various housing types. The model's utility is enhanced by its ability to incorporate diverse building typologies, weather files, and materials.

The practical recommendations generated are based on universally applicable principles, making them adaptable for architects, engineers, and policymakers to improve building resilience across different environments. The methodology offers a robust framework for integrating resilience considerations into building codes and construction practices, informing policy and urban planning on a broader scale.

By focusing on low-cost housing and vulnerable populations, the project highlights the importance of equitable and inclusive design. This ethical perspective is applicable to other regions facing similar socio-economic and environmental challenges, promoting a holistic approach to resilience that addresses both the physical aspects of buildings and the well-being of their inhabitants.

How can the integration of machine learning and building simulations be further optimized to enhance the accuracy and applicability of resilience predictions in diverse architectural contexts? (Self-reflection question)

To further optimize the integration of machine learning and building simulations, several steps can be taken. First, expanding the dataset to include a wider variety of building typologies, climatic conditions, and material properties will enhance the model's robustness and accuracy. Incorporating advanced machine learning techniques, such as deep learning and ensemble methods, can improve predictive performance. Additionally, refining the simulation parameters to better reflect real-world conditions will increase the applicability of the results. Collaboration with experts in various regions can help tailor the model to specific architectural contexts. Continuous validation and updating of the model with new data will ensure its relevance and accuracy over time. By focusing on these areas, the predictive model can become a powerful tool for architects and engineers globally, helping to design more resilient buildings.

What are the potential socio-economic impacts of implementing your resilience recommendations in low-cost housing developments, and how can these impacts be measured and evaluated over time? (Self-reflection question)

Implementing resilience recommendations in low-cost housing can significantly improve the safety and comfort of vulnerable populations, reducing their exposure to extreme weather and seismic events. The socio-economic impacts include decreased repair costs, improved health and well-being, and enhanced overall quality of life. These benefits can reduce economic strain on both individuals and communities. To measure and evaluate these impacts, longitudinal studies should be conducted, tracking metrics such as repair costs, health outcomes, and occupant satisfaction over time. Surveys, interviews, and data analysis can provide insights into the long-term benefits of the implemented recommendations. By systematically evaluating these factors, policymakers and stakeholders can ensure that resilience strategies are effectively enhancing the lives of low-income residents.

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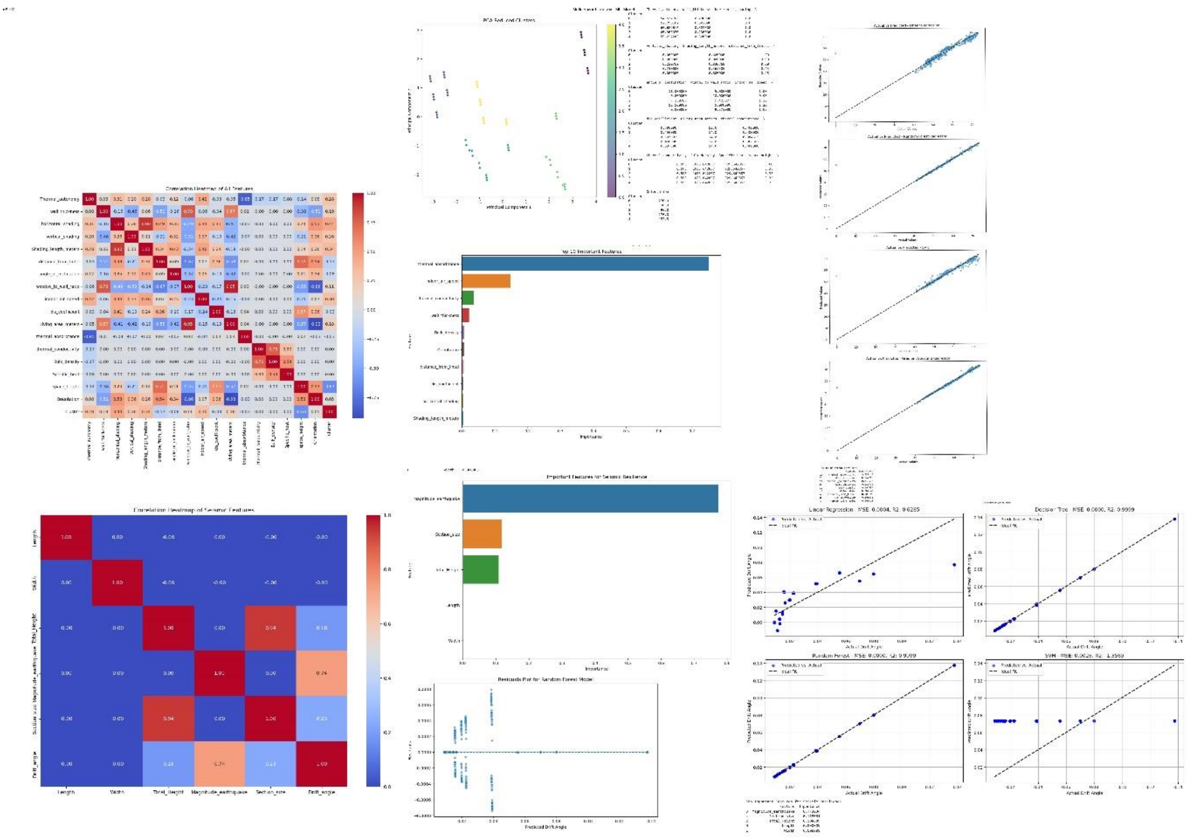
Appendix

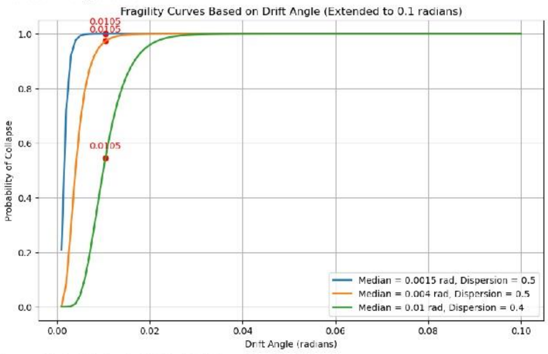
In [4]:
```python
import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingRegressor, RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error, r2_score
from scipy.stats import norm

# Load the data for thermal resilience
thermal_data = pd.read_csv('BEM_data_for_ML_2.csv')
seismic_data = pd.read_csv('Formatted Residence Dimensions.csv')
seismic_data_numerical = seismic_data[['Length', 'Width', 'Total_Height', 'Magnitude_earthquake', 'Section_size', 'Drift_angle']]

# Preprocessing for thermal resilience
thermal_scaler = StandardScaler()
thermal_features = thermal_data.drop('Thermal_autonomy', axis=1)
thermal_target = thermal_data['Thermal_autonomy']
thermal_features_scaled = thermal_scaler.fit_transform(thermal_features)

# Preprocessing for seismic resilience
seismic_X = seismic_data_numerical.drop('Drift_angle', axis=1)
seismic_y = seismic_data_numerical['Drift_angle']

# Split the data for training and testing
thermal_X_train, thermal_X_test, thermal_y_train, thermal_y_test = train_test_split(thermal_features_scaled, thermal_target, test_size=0.2, random_state=42)
seismic_X_train, seismic_X_test, seismic_y_train, seismic_y_test = train_test_split(seismic_X, seismic_y, test_size=0.2, random_state=42)

# PCA for dimensionality reduction
pca = PCA(n_components=2)
pca_features = pca.fit_transform(thermal_features_scaled)

# K-means clustering
kmeans = KMeans(n_clusters=5, random_state=42)
clusters = kmeans.fit_predict(pca_features)

# Visualization of PCA results with K-means clustering
plt.figure(figsize=(10, 8))
plt.scatter(pca_features[:, 0], pca_features[:, 1], c=clusters, cmap='viridis', edgecolor='k', alpha=0.6)
plt.title('PCA Reduced Clusters')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar()
plt.show()

# Compare cluster characteristics
thermal_data['Cluster'] = clusters
cluster_means = thermal_data.groupby('Cluster').mean()
print(cluster_means)

# Train models for thermal resilience
thermal_models = {
    'Linear Regression': LinearRegression(),
    'Random Forest Regressor': RandomForestRegressor(n_estimators=100, random_state=42),
    'SVR': SVR(),
    'Gradient Boosting Regressor': GradientBoostingRegressor(n_estimators=100, random_state=42)
}

thermal_model_performance = {}
for model_name, model_instance in thermal_models.items():
    model_instance.fit(thermal_X_train, thermal_y_train)
    predictions = model_instance.predict(thermal_X_test)
    mse = mean_squared_error(thermal_y_test, predictions)
    r2 = r2_score(thermal_y_test, predictions)
    thermal_model_performance[model_name] = {'MSE': mse, 'R2': r2}
    # Plot actual vs predicted values
    plt.figure(figsize=(10, 6))
    sns.scatterplot(x=thermal_y_test, y=predictions, alpha=0.6)
    plt.plot([thermal_y_test.min(), thermal_y_test.max()], [thermal_y_test.min(), thermal_y_test.max()], 'k--', lw=2)
    plt.title(f'Actual vs Predicted - {model_name}')
    plt.xlabel('Actual Values')
    plt.ylabel('Predicted Values')
    plt.show()

# Feature importance for Random Forest Regressor
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(thermal_features_scaled, thermal_target)
feature_importances = rf.feature_importances_
features_list = thermal_features.columns
importance_df = pd.DataFrame({'Feature': features_list, 'Importance': feature_importances})
top_10_features = importance_df.sort_values(by='Importance', ascending=False).head(10)
print("Top 10 Important Features:")
print(top_10_features)

plt.figure(figsize=(12, 8))
sns.barplot(x='Importance', y='Feature', data=top_10_features)
plt.title('Top 10 Important Features')
plt.show()

# Correlation heatmap
correlation_matrix = thermal_data.corr()
plt.figure(figsize=(14, 10))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm', cbar=True)
plt.title('Correlation Heatmap of All Features')
plt.show()

# Train models for seismic resilience
seismic_models = {
    'Linear Regression': LinearRegression(),
    'Decision Tree': DecisionTreeRegressor(random_state=42),
    'Random Forest': RandomForestRegressor(random_state=42),
    'SVM': SVR()
}

seismic_model_performance = {}
fig, axs = plt.subplots(2, 2, figsize=(15, 10))
axs = axs.flatten()
for i, (name, model) in enumerate(seismic_models.items()):
    model.fit(seismic_X_train, seismic_y_train)
    predictions = model.predict(seismic_X_test)
    mse = mean_squared_error(seismic_y_test, predictions)
    r2 = r2_score(seismic_y_test, predictions)
    seismic_model_performance[name] = {'MSE': mse, 'R2': r2}
    axs[i].scatter(seismic_y_test, predictions, alpha=0.6, color='blue', label='Predicted vs. Actual')
    axs[i].plot([seismic_y.min(), seismic_y.max()], [seismic_y.min(), seismic_y.max()], 'k--', lw=2, label='Ideal Fit')
    axs[i].set_title(f'{name} - MSE: {mse:.4f}, R2: {r2:.4f}')
    axs[i].set_xlabel('Actual Drift Angle')
    axs[i].set_ylabel('Predicted Drift Angle')
    axs[i].legend()
    axs[i].grid(True)

plt.tight_layout()
plt.show()

# Feature importance for Random Forest Regressor for seismic resilience
rf_seismic = RandomForestRegressor(n_estimators=100, random_state=42)
rf_seismic.fit(seismic_X_train, seismic_y_train)
seismic_feature_importances = rf_seismic.feature_importances_
seismic_features_list = seismic_X.columns
seismic_importance_df = pd.DataFrame({'Feature': seismic_features_list, 'Importance': seismic_feature_importances})
seismic_top_features = seismic_importance_df.sort_values(by='Importance', ascending=False).head(10)
print("Top Important Features for Seismic Resilience:")
print(seismic_top_features)

plt.figure(figsize=(12, 8))
sns.barplot(x='Importance', y='Feature', data=seismic_top_features)
plt.title('Important Features for Seismic Resilience')
plt.show()

# Residual plot for the best model (assuming Random Forest performed best)
best_seismic_model = seismic_models['Random Forest']
best_seismic_predictions = best_seismic_model.predict(seismic_X_test)
residuals = seismic_y_test - best_seismic_predictions

plt.figure(figsize=(10, 6))
sns.scatterplot(x=best_seismic_predictions, y=residuals, alpha=0.6)
plt.hlines(y=0, xmin=best_seismic_predictions.min(), xmax=best_seismic_predictions.max(), linestyles='dashed')
plt.title('Residuals Plot for Random Forest Model')
plt.xlabel('Predicted Drift Angle')
plt.ylabel('Residuals')
plt.show()
```

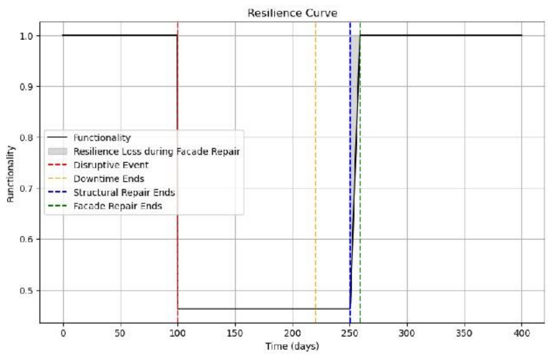
```python
# Correlation heatmap for seismic features
seismic_correlation_matrix = seismic_data_numerical.corr()
plt.figure(figsize=(14, 10))
sns.heatmap(seismic_correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm', cbar=True)
plt.title('Correlation Heatmap of Seismic Features')
plt.show()

# Predict functions
def predict_thermal_autonomy(user_input):
    user_input_array = np.array(user_input).reshape(1, -1)
    scaled_input = thermal_scaler.transform(user_input_array)
    predicted_autonomy = thermal_models['Gradient Boosting Regressor'].predict(scaled_input)
    return predicted_autonomy[0]

def predict_drift_angle(length, width, total_height, magnitude_earthquake, section_size):
    input_features = pd.DataFrame([[length, width, total_height, magnitude_earthquake, section_size]],
                                  columns=['Length', 'Width', 'Total_Height', 'Magnitude_earthquake', 'Section_size'])
    return seismic_models['Random Forest'].predict(input_features)[0]

# User input functions
def get_user_features():
    print("Please enter the following details for thermal autonomy prediction:")
    wall_thickness = float(input("Wall thickness (in meters): "))
    horizontal_shading = int(input("Horizontal shading (1 for present, 0 for absent): "))
    vertical_shading = int(input("Vertical shading (1 for present, 0 for absent): "))
    shading_length = float(input("Shading length (in meters): "))
    distance_from_shading = float(input("Distance from shading (in meters): "))
    angle_of_inclination = int(input("Angle of inclination (in degrees): "))
    window_to_wall_ratio = float(input("Window to wall ratio (as percentage): "))
    indoor_air_speed = float(input("Indoor air speed (in m/s): "))
    discharge_coefficient = float(input("Discharge coefficient: "))
    living_area = float(input("Living area (in square meters): "))
    thermal_absorbance = float(input("Thermal absorbance (0-1): "))
    specific_heat = float(input("Specific heat of the material: "))
    thermal_conductivity = float(input("Thermal conductivity of the material (in W/mK): "))
    bulk_density = float(input("Bulk density of the material (in kg/m3): "))
    space_height = float(input("Space height (in meters): "))
    orientation = int(input("Orientation (degrees relative to north): "))

    user_input = [wall_thickness, horizontal_shading, vertical_shading, shading_length, distance_from_shading,
                  angle_of_inclination, window_to_wall_ratio, indoor_air_speed, discharge_coefficient,
                  living_area, thermal_absorbance, specific_heat, thermal_conductivity, bulk_density,
                  space_height, orientation]
    return user_input

def get_seismic_features():
    print("Please enter the following parameters for drift angle prediction:")
    length = float(input("Enter Length: "))
    width = float(input("Enter Width: "))
    total_height = float(input("Enter Total Height: "))
    magnitude_earthquake = float(input("Enter Magnitude of Earthquake: "))
    section_size = float(input("Enter Section Size: "))
    return length, width, total_height, magnitude_earthquake, section_size

# Data for blocks with better thermal properties
blocks_data = {
    'thermal_conductivity': [0.48, 0.6, 0.57, 0.76, 0.53, 0.39, 0.42, 0.5, 0.42, 0.38, 0.55, 0.54, 0.74, 0.97, 1.12, 0.8, 0.58, 0.67, 0.59, 0.42, 0.41, 0.64, 0.51, 0.86, 0.8, 0.53, 0.39, 0.5, 0.36, 0.67, 0.52, 0.65, 0.5, 0.17, 0.19, 0.59
    'Bulk_density': [1599, 1777, 1654, 1887, 1738, 1604, 1512, 1447, 1503, 1264, 1780, 1716, 1819, 2119, 2028, 1975, 1895, 1958, 1807, 1657, 1648, 1798, 1737, 1878, 1844, 1475, 1299, 1807, 1543, 2048, 1682, 1989, 1722, 608, 623, 1630, 17
    'Specific_heat': [907, 921, 917, 927, 960, 909, 926, 936, 935, 927, 952, 923, 978, 916, 955, 928, 924, 947, 934, 940, 927, 918, 946, 938, 924, 962, 924, 961, 908, 976, 936, 929, 925, 875, 831, 908, 934, 912, 928, 928, 969, 932],
    'Block_name': ['RB01', 'RB02', 'RB04', 'RB06', 'RB07', 'RB09', 'RB10', 'RB11', 'RB14', 'RB15', 'RB20', 'RB21', 'RB23', 'RB03', 'RB05', 'RB12', 'RB18', 'RB19', 'RB13', 'RB16', 'RB17', 'RB22', 'RB08', 'FB01', 'FB02', 'FB03', 'FB04', 'F
}

blocks_df = pd.DataFrame(blocks_data)

# Function to provide recommendations
def provide_recommendations(spatial_thermal_autonomy):
    if 40 <= spatial_thermal_autonomy <= 60:
        suggestions = {
            'thermal_absorbtance': "Apply reflective coating to reduce thermal absorbtance, add a second layer of cladding, or provide a green facade. Reflective coating is the cheapest option.",
            'indoor_air_speed': "Use passive techniques like evaporative cooling, providing more jaali walls, and installing heat vents to improve indoor air speed and quality.",
            'thermal_conductivity': "Use blocks with better thermal properties.",
            'wall_thickness': "Increase wall thickness to enhance insulation and reduce energy loss."
        }
        print("\nSuggestions for Improvement (40-60% Thermal Autonomy):")
        for feature, desc in suggestions.items():
            if feature in top_10_features['Feature'].values:
                print(f"{feature}: {desc}")

        # Recommend better block based on thermal conductivity
        best_block = blocks_df.loc[blocks_df['thermal_conductivity'].idxmin()]
        print(f"\nRecommended Block for Better Thermal Properties:\n{best_block}")

    elif spatial_thermal_autonomy > 60:
        print("\nThe design is decent. Further improvements can be made by applying reflective coatings, adding a second layer of cladding, providing a green facade, using passive techniques for air speed improvement, and selecting block

# Main script
if __name__ == "__main__":
    user_input_thermal = get_user_features()
    thermal_result = predict_thermal_autonomy(user_input_thermal)
    print(f"Predicted thermal autonomy: {thermal_result:.2f}%")

    provide_recommendations(thermal_result)

    length, width, total_height, magnitude_earthquake, section_size = get_seismic_features()
    seismic_result = predict_drift_angle(length, width, total_height, magnitude_earthquake, section_size)
    print(f'Predicted Drift Angle: {seismic_result:.4f}')

    # Fragility curves for brick facade
    medians = [0.0015, 0.004, 0.01]
    dispersions = [0.5, 0.5, 0.4]

    def fragility_function(drift_angle, median_da, sigma_lnda):
        return norm.cdf(np.log(drift_angle) - np.log(median_da), scale=sigma_lnda)

    plot_drift_angles_extended = np.linspace(0.001, 0.1, 100)

    plt.figure(figsize=(10, 6))
    probability_values = []
    for median_da, sigma_lnda in zip(medians, dispersions):
        fragility_values = fragility_function(plot_drift_angles_extended, median_da, sigma_lnda)
        plt.plot(plot_drift_angles_extended, fragility_values, label=f'Median = {median_da} rad, Dispersion = {sigma_lnda}', linewidth=2)
        prob_value = fragility_function(seismic_result, median_da, sigma_lnda)
        plt.scatter([seismic_result], [prob_value], color='red')
        plt.annotate(f'{seismic_result:.4f}', (seismic_result, prob_value),
                     textcoords="offset points", xytext=(0,10), ha='center', color='red')
        probability_values.append(prob_value)

    plt.xlabel('Drift Angle (radians)')
    plt.ylabel('Probability of Collapse')
    plt.title('Fragility Curves Based on Drift Angle (Extended to 0.1 radians)')
    plt.legend()
    plt.grid(True)
    plt.show()
    print('Damage state 1 - Detachment of infill, light diagonal cracking')
    print('Damage state 2 - Extensive diagonal cracking')
    print('Damage state 3 - Corner crushing and sliding of mortar joints')

    Lr_ci = [682740, 747787.5 , 956450]
    V_t = 1

    if len(probability_values) == 3:
        probability_values.append(0)

    economic_loss = sum([(probability_values[i] - probability_values[i+1]) * Lr_ci[i] * V_t for i in range(3)])
    print(f'Estimated Economic Loss: {economic_loss:.2f}')
    # Define the total replacement cost
    replacement_cost = 1680000  # Updated value

    # Repair times in days
    structural_repair_time = 30  # Updated value
    facade_repair_time = 8.5  # Updated value
    hvac_repair_time = 0  # No HVAC system

    # Utility disruption times in days
    electrical_disruption = 4
    water_disruption = 21
    gas_disruption = 0  # No gas disruption

    # Delays in days due to impeding factors
    inspection_delay = 5
    financing_delay = 42
    mobilization_delay = 14
    permitting_delay = 21

    # Function to calculate total downtime
    def calculate_downtime():
        # Total delay due to impeding factors
        total_impeding_delay = inspection_delay + financing_delay + mobilization_delay + permitting_delay
```

```
        # Total repair time (assuming sequential repairs)
        total_repair_time = structural_repair_time + hvac_repair_time + facade_repair_time

        # Calculate total downtime
        total_downtime = max(total_impeding_delay + total_repair_time, total_impeding_delay + water_disruption)
        return total_downtime

    # Calculate total downtime
    downtime = calculate_downtime()

    # Initial functionality drop based on repair cost ratio
    initial_functionality_drop = economic_loss / replacement_cost

    # Functionality loss function
    def Q(t, initial_drop, downtime, structural_repair_time, facade_repair_time):
        if t < 100:
            return 1  # Full functionality before the earthquake event
        elif t < 100 + downtime:
            return 1 - initial_drop  # Functionality during downtime
        elif t < 100 + downtime + structural_repair_time:
            return 1 - initial_drop  # Functionality during structural repair
        elif t < 100 + downtime + structural_repair_time + facade_repair_time:
            repair_fraction = (t - 100 - downtime - structural_repair_time) / facade_repair_time
            return 1 - initial_drop * (1 - repair_fraction)  # Gradual recovery during facade repair
        else:
            return 1  # Full functionality restored after repairs

    # Generate time series for visualization
    total_days = 400
    time_points = np.linspace(0, total_days, 1000)
    functionality_values = [Q(t, initial_functionality_drop, downtime, structural_repair_time, facade_repair_time) for t in time_points]

    # Plot the resilience curve
    plt.figure(figsize=(10, 6))
    plt.plot(time_points, functionality_values, label='Functionality', color='black')
    plt.fill_between(time_points, functionality_values, 1, where=(time_points > 100 + downtime + structural_repair_time) & (time_points < 100 + downtime + structural_repair_time + facade_repair_time), alpha=0.3, color='gray', label='Resil
    plt.axvline(100, color='red', linestyle='--', label='Disruptive Event')
    plt.axvline(100 + downtime, color='orange', linestyle='--', label='Downtime Ends')
    plt.axvline(100 + downtime + structural_repair_time, color='blue', linestyle='--', label='Structural Repair Ends')
    plt.axvline(100 + downtime + structural_repair_time + facade_repair_time, color='green', linestyle='--', label='Facade Repair Ends')
    plt.xlabel('Time (days)')
    plt.ylabel('Functionality')
    plt.title('Resilience Curve')
    plt.legend()
    plt.grid(True)
    plt.show()

print(f"Total estimated downtime: {downtime} days")
print(f"Initial functionality drop: {initial_functionality_drop:.2f}")
```




```
Please enter the following details for thermal autonomy prediction:
Wall thickness (in meters): 0.35
Horizontal shading (1 for present, 0 for absent): 1
Vertical shading (1 for present, 0 for absent): 0
Shading length (in meters): 0.6
Distance from shading (in meters): 0.2
Angle of inclination (in degrees): 0
Window to wall ratio (as percentage): 10
Indoor air speed (in m/s): 0.8
Discharge coefficient: 0.6
Living area (in square meters): 14
Thermal absorbance (0-1): 0.8
Specific heat of the material: 950
Thermal conductivity of the material (in W/mK): 0.48
Bulk density of the material (in kg/m3): 1599
Space height (in meters): 3.35
Orientation (degrees relative to north): 180
C:\Users\hp\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but StandardScaler was fitted with feature names
  warnings.warn(
Predicted thermal autonomy: 47.27%

Suggestions for Improvement (40-60% Thermal Autonomy):
thermal_absorbtance: Apply reflective coating to reduce thermal absorbtance, add a second layer of cladding, or provide a green facade. Reflective coating is the cheapest option.
indoor_air_speed: Use passive techniques like evaporative cooling, providing more jaali walls, and installing heat vents to improve indoor air speed and quality.
thermal_conductivity: Use blocks with better thermal properties.
wall_thickness: Increase wall thickness to enhance insulation and reduce energy loss.

Recommended Block for Better Thermal Properties:
thermal_conductivity    0.17
Bulk_density             608
Specific_heat            875
Block_name              AB01
Name: 33, dtype: object
Please enter the following parameters for drift angle prediction:
Enter Length: 4
Enter Width: 4
Enter Total Height: 3.35
Enter Magnitude of Earthquake: 5.5
Enter Section Size: 0.35

 Predicted Drift Angle: 0.0105
```






```
Damage state 1 - Detachment of infill, Light diagonal cracking
Damage state 2 - Extensive diagonal cracking
Damage state 3 - Corner crushing and sliding of mortar joints
Estimated Economic Loss: 859751.05
```

```
Total estimated downtime: 120.5 days
```