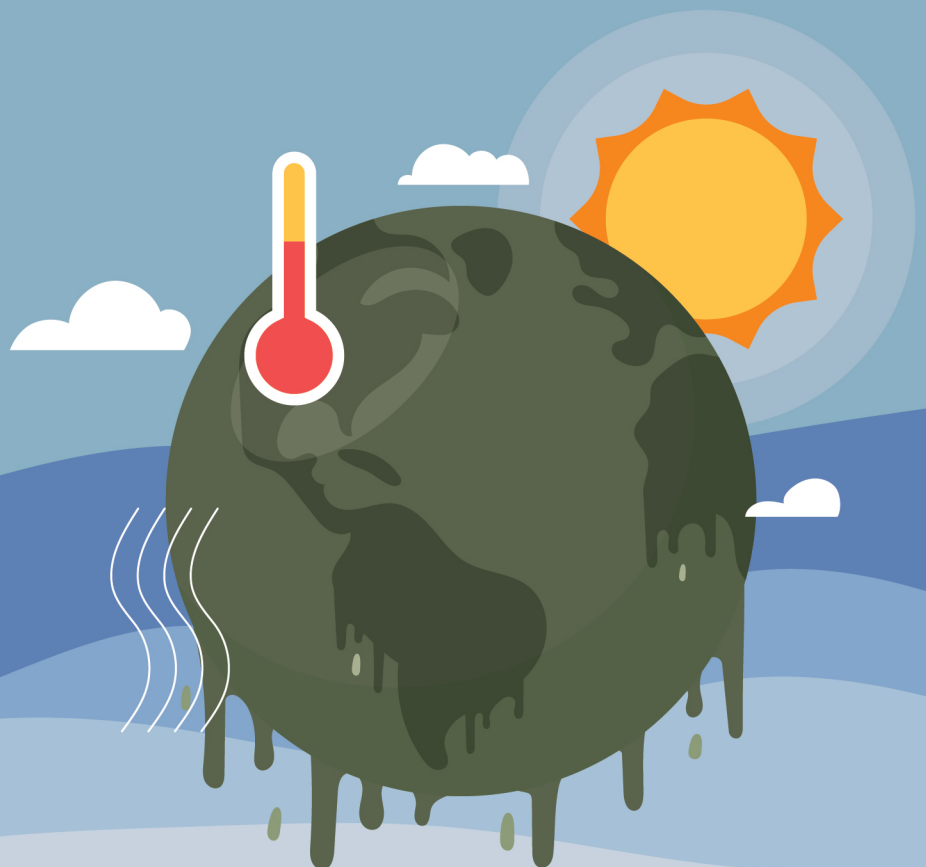


A Digital Design Tool for Floods and Heatwaves Resilient Facade System

Quantification of Facade Resilience

AR3B025: Building Technology Graduation Studio

Aashish Sadaphal



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Preface

During my master's studies in the Building Technology track at TU Delft, I had an exceptionally positive experience with the AE+T faculties. They provided essential guidance within an innovative and collaborative environment that fostered my growth. The emphasis on sustainable and forward-thinking solutions in building technology deeply influenced my approach to the field.

A project in my previous quarter on earthquake resilience sparked my interest in the resilience of the built environment. This, combined with my interest in building façade design, led me to research façade resilience for my graduation study. Working on this topic enhanced my knowledge of resilience and the impact of climate change on the built environment.

I would like to express my deepest gratitude to my mentors, Dr. Simona Bianchi and Dr. Alessandra Luna Navarro. Their invaluable guidance, expertise, and encouragement motivated me to work in the right direction. Their insightful feedback and unwavering support have been instrumental in shaping the direction and quality of this research. I am also grateful to PhD candidate Kyujin Kim for sharing her knowledge and providing assistance during the literature review. I also want to acknowledge the assistance of ChatGPT, which played a crucial role in code fixing, text modifying, and enhancing my understanding of the literature study in a better way.

Lastly, I am thankful to my mom, dad, brother, and sister, who always encouraged me throughout my master's studies. Their belief in my abilities and constant support has been a source of inspiration and strength. I also want to thank myself for the hard work and perseverance in seeking new solutions, even after facing many challenges during the research.

*[Aashish Sadaphal]
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Abstract

The escalating challenges caused by the climate change, notably floods and heatwaves, highlights the urgent need for robust resilience strategies in infrastructure and urban ecosystems. This research identifies critical gaps in existing methodologies and tools for assessing resilience, particularly during extreme events. Key issues include the absence of specialized tool for facade resilience quantification, limited multi-hazard assessment methodologies and a scarcity of quantitative methods in existing literature. In order to fill these gaps, this study formulates a research question: How can we identify the optimal facade system that is resilient against heatwaves and floods?

A quantitative approach is employed, integrating an interdisciplinary perspective that encompasses structural design, facade design, climate design and hazard engineering. The methodology involves an extensive literature review, computational simulations, machine learning models, sensitivity analysis and resilience matrix for quantification of flood and heatwaves resilient facade system.

This study fills crucial gaps by offering a framework to assess facade resilience against these hazards. It identifies influential facade parameters and primary hazard stressors, crucial for informed decision-making by designers and engineers. The study culminates in a resilience quantification for multi-hazard assessment, empowering stakeholders to design resilient facade systems tailored to specific environmental contexts. The research findings contribute to advancing knowledge in building facade resilience, offering practical guidance for enhancing resilience in the face of evolving environmental challenges.

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Nomenclature

Abbreviations

Abbreviation	Definition
ISA	International Standard Atmosphere
IMD	India Meteorological Department
IPCC	Intergovernmental Panel on Climate Change
WHO	World Health Organisation
WHO	World Health Organisation
ANN	Artificial Neural Network
SA	Sustainability Analysis
EPW	EnergyPlus Weather file
IAQ	Indoor Air Quality
KPI	Key Performance Indicator
PMV	Predicted Mean Vote
RMSE	Root Mean Square Error
CSV	Comma-Separated Values
RDI	Resilience Development Initiative
UHI	Urban Heat Island
AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
MIC	Microbiologically induced corrosion
SMCE	Spatial Multi-Criteria Evaluation
WUMTP	Weighted Unmet Thermal Performance
MCDM	Multi-Criteria Decision Making
SET	Standard Effective Temperature
PPD	Predicted Percentage of Dissatisfied
TMY	Typical Meteorological Year
PET	Physiological Equivalent Temperature
WWR	Wall-to- Window Ratio
COP	Coefficient of Performance
MSE	Mean Squared Error
GPR	Gaussian Process Regression
RBF	Radial Basis Function
SHGC	Solar Heat Gain Coefficient
FHRC	Flood Hazard Research Centre
NMF	Neutral Modelling Format
CFD	Computational fluid dynamics
ReLU	Rectified Linear Unit
MAE	Mean Absolute Error
HR	Heatwaves Resilience
FR	Flood Resilience
...	

Symbols

Symbol	Definition	Unit
V	Velocity	[m/s]
T	Temperature	[°C]
g	Gravity acceleration	[m/s ²]
F_{total}	Total hydraulic force	[N]
P_{total}	Stagnant pressure	[N/m ²]
P_{static}	Static pressure	[N/m ²]
P_{dynamic}	Dynamic pressure	[N/m ²]
W	Panel width	[m]
h	Flow depth	[m]
H	Facade height	[m]
q	Distributed load per unit	[N/m]
R_a, R_b	Reaction forces	[N]
M_{max}	Applied max. bending moment	[N·m]
ρ	Density	[kg/m ³]
σ	Bending stress	[N/m ²]
I	Moment of inertia	[m ⁴]
M_{allow}	Allowable bending moment	[N·m]

Research Framework

1.1. Background

In recent years, the escalating frequency and intensity of climate-related events, such as floods and heat-waves, have emphasized the urgent need for resilient infrastructure, particularly in the field of building design. The construction industry is grappling with the challenge of adapting to a changing climate, necessitating innovative solutions to fortify structures against extreme environmental conditions.

The Intergovernmental Panel on Climate Change (IPCC) warns of a concerning trajectory, projecting a significant temperature rise of at least 1.5°C within the next two decades (IPCC, 2023). This alarming trend underscores the increasing impacts of climate change, resulting in more frequent and intense environmental events. A recent report by the World Meteorological Organization further accentuates this reality, revealing that over the past 50 years, approximately 12,000 extreme events have occurred globally. These events have tragically claimed over 2 million lives and inflicted substantial economic losses surpassing 4.3 trillion dollars (WHO, 2022)

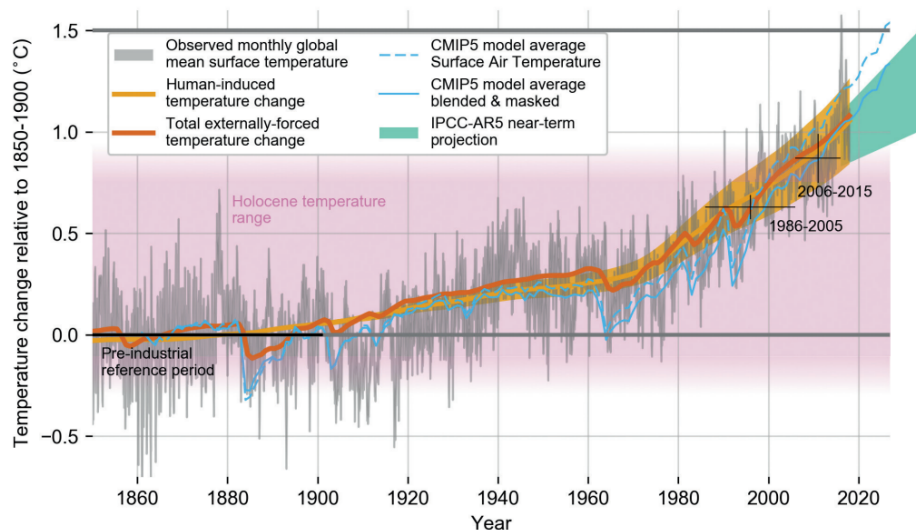


Figure 1.1: Graphical representation of Evolution of global mean surface temperature (GMST) over the period of instrumental observations (Allen et al., 2018)

Amidst these challenges, the imperative to bolster infrastructure against climate-related adversities becomes increasingly evident. Buildings stand as the front line defence against such threats, making the

integration of advanced digital design tools a crucial strategy to enhance the resilience of building facades in the face of floods and heatwaves. This research aims to explore the efficacy of a specific digital design tool within this urgent context, providing actionable insights for architects, engineers, and policy-makers engaged in the pursuit of climate-resilient infrastructure.

1.2. Problem statement

The current global scenario is marked by severe climate change, giving rise to a range of devastating hazards, with floods and heatwaves standing out as having profound impacts on infrastructure, human health, and ecosystems. In addressing these challenges, this research identifies key issues that demand immediate attention (Quesada-Ganuza et al., 2023).

One such concern is the limited focus on facade resilience. Although ongoing projects assess resilience on broader geographic scales such as cities, districts, and regions, there remains a critical need for a specialized tool or method designed to evaluate resilience and performance at the facade level, particularly during extreme events.

Another critical problem is the lack of a comprehensive multi-hazard assessment. The absence of tools that can assess the impact of both floods and heatwaves makes it challenging to fully comprehend the extent of risks and vulnerabilities. A holistic approach that considers multiple hazards is essential for a more accurate understanding of the potential impacts.

Moreover, the research highlights the significant impact of small-scale flooding on building facades. Even seemingly minor flood events can result in substantial economic losses, emphasizing the necessity for a comprehensive assessment that takes into account the impact of small-scale flooding on facade resilience.

Furthermore, the predominance of qualitative assessments in the existing literature underscores a notable gap. The absence of quantitative assessment tools hinders the ability to make informed decisions during the design process. Thus, there is a pressing need to develop a tool that provides designers with quantitative data, enabling them to make well-informed decisions and enhance resilience in the face of climate-induced challenges.

1.3. Research objective

1.3.1. Primary Objective

The aim of this research is to develop a digital tool that assesses the resilience of building facades in case of multi-hazard events, considering floods and heatwaves. The primary goal is to investigate the influence of façade parameters and hazard stressors on the resilience of the facade system. This research will allow the designers by providing insights to take informed decisions in the façade design process ultimately enhancing overall resilience. The outcome of this research will be a digital environment in which façade parameters and hazard intensity data will be input parameters. Within this tool, these inputs will undergo analysis with the help of computational simulation software, generating graphical representations illustrating the relationship between each stressor and performance indicators. The tool will differentiate and evaluate the varying impacts of distinct stressors. The ultimate output of this tool will be a resilience score for the facade, offering a quantitative measure of its ability to withstand and recover from the effects of floods and heatwaves.

1.3.2. Limitations

The scope of this study is limited to the development of a tool for assessing the resilience of building envelopes. This evaluation method employs a multi-criteria approach to identify the impact on both facade integrity and building occupants during flooding and heatwaves. Throughout the research, factors unrelated to the facade, such as building occupancy and equipment load, are held constant to isolate the influence of facade parameters on performance indicators.

1.3.3. Result

The study culminates in the creation of a digital tool for facade designers, facilitating the evaluation of facade resilience. This tool integrates a thorough workflow, gathering data and conducting simulations for floods and heatwaves, subsequently employing a supervised machine learning using Artificial Neural Network regression model for result prediction. Furthermore, the study incorporates sensitivity analysis to pinpoint crucial facade parameters. This user-centric tool offers a simplified, practical methodology for designers to follow during facade design, while also serving as a versatile tool for multi-hazard assessment at the facade level.

1.4. Research Question

1.4.1. Primary Research Question

During the literature review conducted for this thesis, several significant research gaps emerged. Firstly, a notable absence of a simplified, practical methodology for designers to adhere to during the facade design process was noted. Secondly, while numerous projects are presently underway to evaluate resilience at the district, city, and regional levels, a conspicuous absence persists regarding tools or methods capable of assessing facade resilience. Furthermore, a deficiency in available tools capable of addressing multi-hazard scenarios was observed, with most existing tools focusing solely on singular hazards.

The research question for this study is derived from the identified research gaps identified during the literature review. The thesis hence asks,

'How can we identify the optimal facade system that is resilient against heatwaves and floods?'

To advance the research further, several sub-questions have been formulated to systematically dissect the overarching research inquiry.

1.4.2. Research Sub-Questions

As mentioned above, the sub-questions aim to provide a structured approach to exploring the complexities of building facade resilience in the context of multi-hazard scenarios and to guide the research towards comprehensive and actionable conclusions. The sub-questions are mentioned below:

1. What are the most probable stressors associated with heatwaves and floods that should be considered in the research, and how do they impact building facades and indoor comfort?
2. What existing methodologies or frameworks are available for assessing the resilience of building envelopes/facades, and how do they address multiple hazards?
3. What input parameters (including facade parameters and hazard stressors) have the most significant impact on the output?
4. How can we quantify the flood and thermal resilience of building facades?
5. How can we define the total resilience loss, including heatwave and flood resilience loss, for a facade system using a multi-criteria decision-making process?

1.5. Research Methodology

The primary objective of this study is to develop a digital design tool for assessing the resilience of building facades in the face of multi-hazard events, specifically focusing on floods and heatwaves. To achieve this, a quantitative research approach is employed, integrating an interdisciplinary perspective that encompasses structural design, facade design, climate design, and hazard engineering. The study unfolds through several distinct phases.

The initial phase of this study entails an extensive review of pertinent literature to establish a robust theoretical framework for subsequent analyses. This comprehensive review addresses various inquiries, including the identification of existing methodologies within the domain and the delineation of current research gaps. Drawing insights from these gaps, the research questions for this investigation are formulated. Following this, all parameters impacting indoor comfort and building facade performance are meticulously identified. Maintaining constancy in all input variables, except for facade parameters and hazard intensity (e.g., occupancy, lighting load, equipment load), a configuration of facade parameters and hazard intensity (specifically, in the context of floods) is devised for computational simulation.

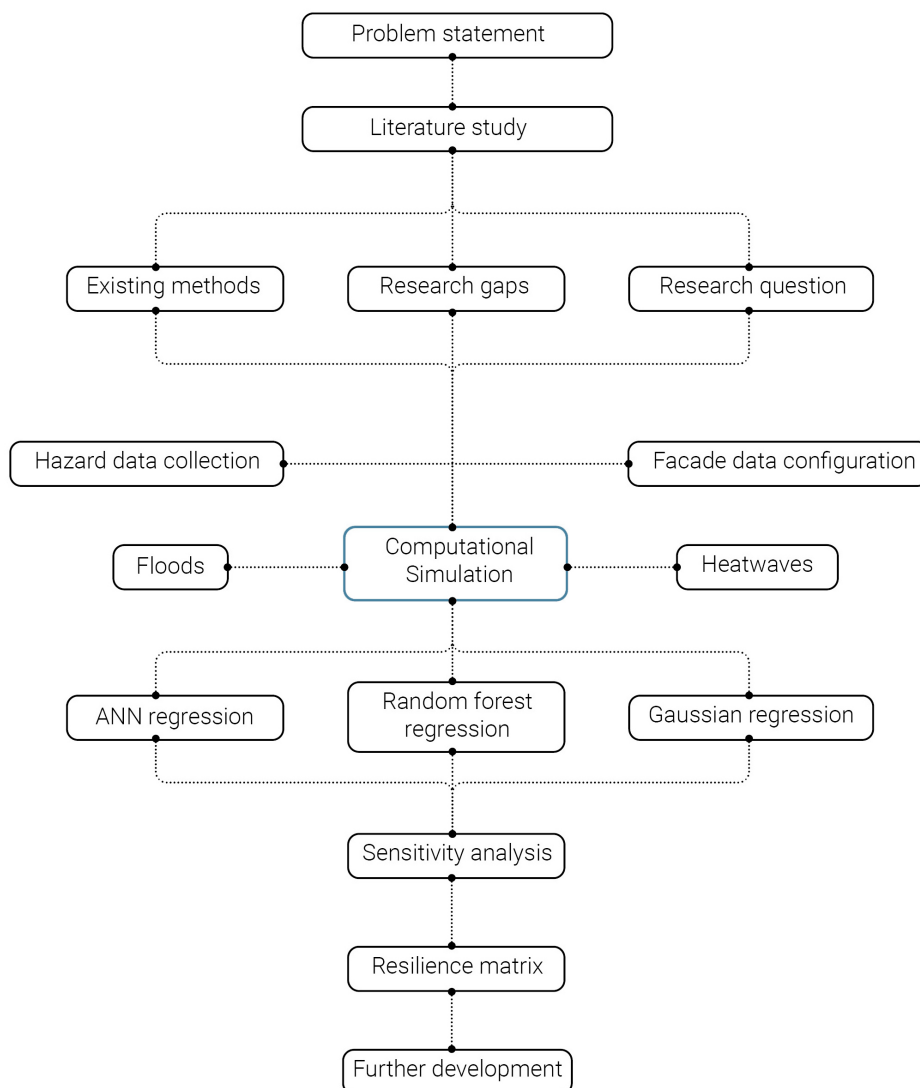


Figure 1.2: Graphical representation of overall workflow (Source: Author)

Post-computational simulation, all input and output variables are meticulously cataloged into a CSV file.

Utilizing these parameters, a correlation matrix is constructed to discern the influence of each variable on others, thereby facilitating the identification of the most impactful input variables. Subsequently, these significant variables undergo further configuration to enhance accuracy for sensitivity analysis. Additionally, this dataset is leveraged for sensitivity analysis utilizing Sabol's method, a variance-based approach, to ascertain both the individual influence of inputs on outputs and the collective effects of inputs on output values. Subsequently, a surrogate machine learning model is developed utilizing an Artificial Neural Regression model to predict output values based on input values. The study culminates in the development of resilience metrics, providing a quantitative measure for assessing the resilience loss of building facades.

Incorporating an interdisciplinary approach, the study integrates structural design, facade design, climate design, and hazard engineering to ensure a comprehensive understanding of facade resilience. A multi-criteria decision-making process is employed to identify and compare decision parameters relevant to facade resilience.

1.6. Research outline

This graduation report contains seven chapters as follows:

Chapter 1: Research framework

This chapter explains the research framework, starting with the problem statement due to devastating hazards, and follows up with the research objectives, research questions, and research methodology for this study.

Chapter 2: Literature Study

It defines resilience and facade resilience, explaining their importance. It states the impact of floods and heatwaves on the building envelope and human comfort. It also provides a comparative analysis of existing methodologies, highlighting key findings and research gaps.

Chapter 3: Quantification of thermal resilience

This chapter describes the methodology used for quantifying thermal resilience, including all the steps taken for calculating the thermal resilience of the facade.

Chapter 4: Quantification of flood resilience

This chapter describes the methodology used for quantifying flood resilience, including all the steps taken for calculating the flood resilience of the facade.

Chapter 5: Case study- Chennai, India

This chapter provides an example of using the tool for calculating facade resilience through a case study and explains the multi-hazard approach considered in the study.

Chapter 6: Conclusion and Discussion

This chapter concludes the research with a discussion on the results, which include the resilient score of the facade. It also suggests further research directions in this field.

Chapter 7: Reflection

This chapter describes the overall engagement with the graduation topic within the master track "Building Technology" and discusses the impact of this research on society, academics, and real-world scenarios.

2

Literature Study

2.1. Resilience

“Resilience is the capacity to adapt to changing conditions and to maintain or regain functionality and vitality in the face of stress or disturbance. It is the capacity to bounce back after a disturbance or interruption.”(RDI, 2015).

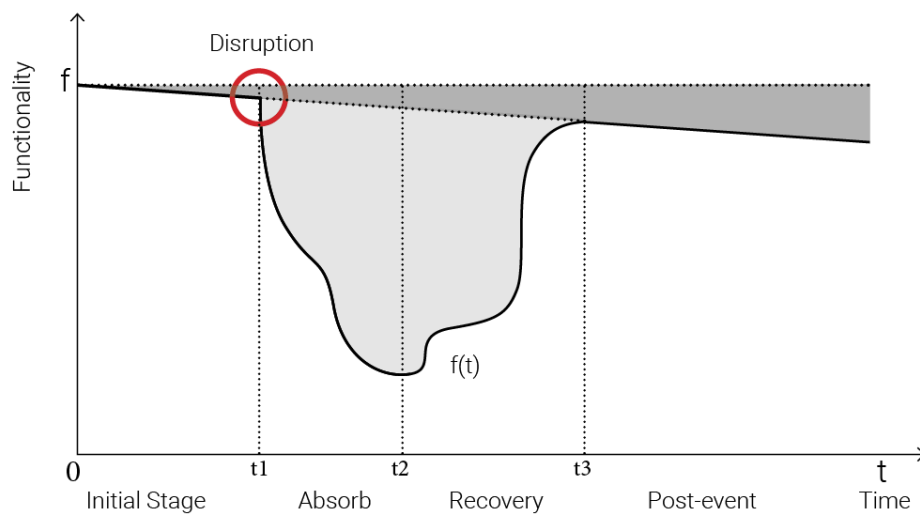


Figure 2.1: Graphical representation of Resilience curve (Source: Author)

2.1.1. Defining façade resilience

“Building facade resilience” refers to the ability of a building’s exterior structure, specifically its facade, to withstand and recover from various external challenges and stresses, including but not limited to environmental, architectural, and structural factors. The facade is the outer shell or face of a building, and its resilience is crucial for maintaining the overall integrity, safety, and functionality of the structure. Resilience in the context of building facades involves designing and constructing the exterior elements to endure adverse conditions such as extreme weather events, floods, seismic activity, extreme temperature, and other environmental factors. Additionally, it considers the ability of the facade to resist wear and deterioration over time due to factors like pollution, UV radiation, and other environmental stresses.

2.1.2. Significance of resilience in the context of floods and heatwaves

Facade resilience in the context of floods and heatwaves refers to the ability of building facades to withstand and adapt to the impacts of these extreme weather events. The significance of facade resilience lies in its contribution to the overall resilience of buildings and communities. In case of floods, resilient facades can help prevent water ingress during floods, protecting the building's interior, occupants, and valuable assets. Moreover, it can help maintain the structural integrity of a building, ensuring that the building remains functional and safe for occupants. Resilient building envelopes can also minimize water damage, reducing the need for extensive repairs and associated costs after a flood event. During heatwaves, resilient building exterior can maintain the comfortable indoor temperatures, reducing the risk of heat-related illnesses and enhancing the well-being of occupants. Effective façade designed to provide effective insulation and shading can contribute to reduce cooling energy demand and reduce the need for repairs or replacements of overheated façade components. With the increasing frequency and intensity of extreme weather events due to climate change, resilient facades become crucial for adapting buildings to these changing conditions. They contribute to long-term sustainability by helping structures withstand the challenges posed by floods and heatwaves.

2.2. Understanding floods and heatwaves: the impact on building skin.

2.2.1. Overview of floods and heatwaves

Floods have caused millions of fatalities, billions of economic losses in the last twenty years. As per a report by World Health Organization (WHO, 2022), more than 2 billion of people affected due to this disruptive event and around 656 billion US dollar of economic losses has recorded in the period of 1998-2017. Floods are the most frequent type of natural disasters characterized by an overflow of water onto normally dry land, often occur due to various factors and vary in scale and intensity. One primary reason is heavy rainfall, which can lead to rivers, lakes, and other water bodies overflowing their banks. Storm surges from tropical storms and hurricanes, snowmelt during warmer seasons, and sudden, intense rainfall causing flash floods are also common contributors. Additionally, failures in dams or levees can release large amount of water, leading to downstream flooding. There are different types of floods (Gentile et al., 2022), each with its unique characteristics (as shown in the Table 2.1).

Heatwaves, characterized by prolonged periods of excessively high temperatures, have become increasingly prevalent in recent years, a trend attributed to the changing climate and global warming. These extreme heat events pose substantial risks to human health, agriculture, and ecosystems. The combination of soaring temperatures and elevated humidity levels during heatwaves can lead to severe heat-related illnesses and stress, particularly affecting vulnerable populations. A recent example highlights the severity of this issue, with a heatwave in the Pacific Northwest of the United States and Canada in late June 2021 (White et al., 2023) shattering temperature records. The town of Lytton in British Columbia, Canada, experienced a new record temperature of 49.6 degrees Celsius (121.3 degrees Fahrenheit), highlighting the unprecedented intensity of the heatwave. Heatwaves are categorized into different types, including meteorological heatwaves driven by atmospheric conditions, urban heatwaves exacerbated by urbanization, and marine heatwaves that affect oceanic regions (refer Table 2.1 for more details).

Table 2.1: Table presenting the types of Hazards and Causes

Type of Hazard	Cause of Hazard
Flood	
Flash flood	<ul style="list-style-type: none"> • Sudden and intense floods • occurring within a short period • often triggered by heavy rainfall or dam breaks.
River flood	<ul style="list-style-type: none"> • Overflow of river, stream • Due to heavy rainfall and melting snow
Coastal flood	<ul style="list-style-type: none"> • Occur along the coastal areas. • Due to storm surges, high tides, and Tsunamis.
Heatwaves	
Meteorological Heatwaves	<ul style="list-style-type: none"> • Driven by prolonged periods of extreme heat due to atmospheric conditions.
Urban Heatwaves	<ul style="list-style-type: none"> • Exacerbated by urbanization, with heat retention in urban areas leading to elevated temperatures

2.2.2. Specific challenges posed to the building façade

Floods pose numerous challenges to building envelope, ranging from structural concerns to the functionality of the building. One of the primary challenges is structural damage, as floodwater can exert immense pressure on building exterior, affecting the stability and safety of the entire building. Additionally, prolonged exposure to water can deteriorate the building materials, leading to long-term structural issues. Another significant challenge is erosion, especially in the case of flash floods and river floods. The erosive force of the water can strip away soil around the building's foundation, potentially undermining its stability. Floodwater often carry sediments and debris that can leave stubborn stains and discoloration on the building envelop, and prolonged presence of moisture can introduce contaminants and pollutants that may lead to Mold growth, affecting both aesthetics and air quality (Ettinger et al., 2016).

Heatwaves marked by prolonged period of extreme temperatures, also present distinctive challenges to the building envelope (Hong et al., 2023). One major concern is thermal discomfort to the occupants, resulting the increase in cooling demand, which can affect energy efficiency of the building. Another concern is thermal expansion of building materials that can lead to cracking, warping, and bending. In urban areas, where the phenomenon of Urban Heat Island effect is exacerbated during heatwaves, buildings may experience increased thermal stress. Leading to deterioration of facade materials and impacting their durability and performance. In this paper, stressors are defined based on the impacts of floods and heatwaves on building facades. These stressors serve to quantify the scale and intensity of hazards and understand their impact on each performance indicator. Performance indicators act to measure the reduction in functionality of the facade. For further information, refer to Table 2.2.

Table 2.2: Table presenting the Evaluation framework

Stressors	Impact	Performance Indicators
Flood		
Inundation depth (water height)	<ul style="list-style-type: none"> • Structural damage: <ul style="list-style-type: none"> – Physical damage or cracks – Shift – Potential collapse – Erosion in foundation • Material deterioration: <ul style="list-style-type: none"> – Erosion and corrosion – Contamination on facade – Mold growth 	<ul style="list-style-type: none"> • Structural assessment: <ul style="list-style-type: none"> – Applied load calculations by water and debris. – Bending moment of the surface – Structure load simulation for the joinery failure • Material assessment: <ul style="list-style-type: none"> – Water resistivity of the material. – Water flow simulation. – Water-material contact.
Duration	<ul style="list-style-type: none"> – Moisture penetration 	
Flow velocity	<ul style="list-style-type: none"> – Saltwater Intrusion 	
Debris content	<ul style="list-style-type: none"> – Discoloration & Stain 	
Heatwaves		
Outdoor temperature	<ul style="list-style-type: none"> • Increase in discomfort: <ul style="list-style-type: none"> – Thermal discomfort – Visual discomfort • Structural damage: <ul style="list-style-type: none"> – Thermal expansion: warping, bending, cracking. • Material deterioration: <ul style="list-style-type: none"> – Damage to the sealants and adhesives – Moisture loss 	<ul style="list-style-type: none"> • Thermal comfort: <ul style="list-style-type: none"> – SET (indoor air temperature) – Humidity • Visual comfort: <ul style="list-style-type: none"> – Daylighting • Energy consumption: <ul style="list-style-type: none"> – Heating load – Cooling load – Lighting load
Duration	<ul style="list-style-type: none"> – Facade discoloration 	
Urban heat island effect	<ul style="list-style-type: none"> • Energy consumption: <ul style="list-style-type: none"> – Cooling load increase 	

2.2.3. Importance of Resilience in mitigating impacts

The significance of facade resilience in mitigating the impacts of floods and heatwaves is crucial. Facades, as the outermost protective layer of structures, assume a critical role in safeguarding occupants, preserving structural integrity, and minimizing damage during extreme weather events (Patterson et al., 2017). A resilient facade serves as a primary defence mechanism, preventing water ingress and potential structural harm during floods, while concurrently maintaining occupant safety and well-being. Similarly, in the context of heatwaves, a well-designed facade with effective insulation and shading elements contributes to the creation of comfortable indoor environments, safeguarding occupants from the adverse effects of extreme temperatures. The structural integrity preserved by resilient facades not only ensures the longevity of buildings but also protects valuable assets within, reducing economic losses associated with repairs and replacements. Furthermore, energy-efficient facades, capable of regulating indoor temperatures during heatwaves, contribute to sustainability goals by reducing reliance on mechanical cooling systems. The adaptability of resilient facades to changing climate conditions positions them as essential components for climate change mitigation and underscores their pivotal role in fortifying

urban resilience. This research emphasizes the multidimensional importance of facade resilience, offering valuable insights into its implications for occupant safety, structural durability, energy efficiency, and broader community resilience in the face of escalating climate-related challenges.

2.3. Previous Studies on Facade Resilience

2.3.1. Existing methods for assessment of resilience

The assessment of resilience has become a crucial subject, particularly in light of the escalating frequency and intensity of extreme disruptive events linked to climate change. Numerous studies have been undertaken to evaluate the resilience of buildings, regions, and cities. The following Table 2.3 presents an overview of existing research and outlines the methods employed to assess resilience in each study. Additionally, it outlines the decision parameters (criteria) considered in these assessments and the corresponding performance indicators used to demonstrate the study results.

Table 2.3: Table presenting the existing methods for resilience evaluation.

References	Scale	Hazard	Method used	Criteria for evaluation	Results
(Klijn et al., 2015)	Building	Flood	<ul style="list-style-type: none"> Quantitative assessment AHP- Multi criteria evaluation method Weighting all the criteria in terms of importance Assessed on brickwork 	<ul style="list-style-type: none"> Compressive strength Transverse tensile strength shear strength Adhesive tensile strength adhesive shear strength Water absorption characteristic Water permeability Dimensional stability Thermal conductivity Drying characteristics Accessibility disassembly capability Microbial infestation and microbially induced corrosion (MIC) - Electrolytic (metal) corrosion 	Selecting best type of brickwork based on the important criteria.
(Favoio et al., 2022)	Facade	Multi-hazard (Floods, Wind-storms, Heat-waves)	<ul style="list-style-type: none"> Qualitative assessment Based on likelihood and severity of the hazard on a specific location 	Based on the location and hazard <ul style="list-style-type: none"> For floods: <ul style="list-style-type: none"> Increase in the average annual rainfall Sea level rise For Heatwaves: <ul style="list-style-type: none"> Increase in the average temperature 	Calculating the risk rating based on likelihood and severity of the hazard. Risk rating = Likelihood X Severity

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Table 2.3 – Continued from previous page

References	Scale	Hazard	Method used	Criteria for evaluation	Results
(Mazzorana et al., 2014)	Building	Flood	<ul style="list-style-type: none"> Quantitative assessment Computational simulation for analysing the fluid flow impact for structural integrity of the building. 	<ul style="list-style-type: none"> Flow velocity. Flow dept Elevation change 	Generated waterflow force on building surface to see the vulnerable points (i.e. windows, doors, and joints)
(Shahri et al., 2020)	Urban	Flood	<ul style="list-style-type: none"> Used GIS and PTVA-3 for flood mapping. AHP method for finding the importance of the criteria. 	<ul style="list-style-type: none"> Topographic elevation. Topographic slope Topographic relation to tsunami direction Coastal proximity Coastal shape 	Classifying vulnerability through the map (High , Medium and Low)
(Afifah, Sani & Hizbaron, Dyah Rahmawati, 2020)	Urban	Flood	<ul style="list-style-type: none"> AHP & Spatial Multi-criteria evaluation (SMCE) Data from Survey + Literature study. 	<ul style="list-style-type: none"> Hazard: <ul style="list-style-type: none"> Depth Frequency Duration Physical Parameter: <ul style="list-style-type: none"> Design Flood Elevation Building maintenance or existing damage Type of Materials Environmental: <ul style="list-style-type: none"> Source of tidal flood and their preventive measures Distance to water bodies Accessibility 	Classification of vulnerability (High , Moderate and Low)

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Table 2.3 – Continued from previous page

References	Scale	Hazard	Method used	Criteria for evaluation	Results
(Flores-Larsen et al., 2023)	Building	Heatwaves	<p>Ouzeau's method- three parameters are established:</p> <ul style="list-style-type: none"> • Spic: Temperature threshold signalling the detection of a heat event • Sdeb: Threshold determining the start and end of a heatwave. • Sint: Interruption threshold, indicating the conclusion of a heatwave. <p>Severity = $\sum (T_m - Sdeb) / (Spic - Sdeb)$</p>	<ul style="list-style-type: none"> • duration (number of days). • Intensity (the maximum mean daily temperature reached during the heatwave event) • Severity (the aggregated mean daily temperatures above Sdeb) 	Finding the heatwave events
(Homaei & Hamdy, 2021)	Building	Heatwaves	<ul style="list-style-type: none"> • Quantitative assessment • Simulation IDA Indoor Climate and Energy software (IDA ICE), which applies equation-based modelling in Neutral Modelling Format (NMF) 	<ul style="list-style-type: none"> • Outdoor temperature. • Duration 	Weighted unmet thermal performance (WUMTP) is a metrics for identifying the thermal resilience class using multi-phase resilience curve

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Table 2.3 – Continued from previous page

References	Scale	Hazard	Method used	Criteria for evaluation	Results
(Lassandro & Di Turi, 2019)	Facade	Heatwaves	<ul style="list-style-type: none"> Quantitative assessment Multi-criteria progressive decision method Sensitivity analysis 	<ul style="list-style-type: none"> Operative temperature. Sensible Cooling (absolute value) External Surface Temperature at pedestrian level Mean Radiant Temperature at pedestrian level. External Air Temperature at pedestrian level. Relative Humidity at pedestrian level. Wind Speed at pedestrian level 	Categorising the best design based on the important criteria
(Quesada-Ganuzá et al., 2023)	Urban	Heatwaves	<ul style="list-style-type: none"> MIVES methodology via GIS Model Combine with MCDM AHP for assigning weightage to the decision parameters 	<ul style="list-style-type: none"> Albedo of the space Normalized difference vegetation index Sky view factor Shadow fraction Air pollution GF Commercial activities on building Space linked to historical events Accessibility for ambulances or firefighters 	Categorizing from 1-9 classes and generating vulnerability assessment maps

2.3.2. Key findings from the past research

The existing studies offer a wealth of information on resilience, encompassing methods for assessment and the allocation of weightage factors for various parameters in multi-criteria decision-making processes. One of the most commonly employed methods in these studies (Attia et al., 2021), (Bianchi et al., 2024), (Quesada-Ganuzá et al., 2023), (Klijn et al., 2015) is the Analytic Hierarchy Process (AHP). AHP is a structured technique designed to address complex decisions by breaking them down into a hierarchical structure of criteria and alternatives. Subsequently, it involves evaluating and comparing these criteria and alternatives through pairwise comparisons.

The literature reviews provide insights into stressors associated with extreme events such as floods and heatwaves and their impact on resilience at the building, regional, or city level (refer Table 2.3). The research also delves into the repercussions on building or urban resilience and suggests mitigation strategies that could be implemented to alleviate the impact of these hazards.

2.3.3. Gaps and limitations in Existing Studies

As Shown in the Table 2.3, Despite the ongoing efforts to evaluate resilience at broader geographic scales such as city, district, and region, existing studies exhibit significant gaps and limitations, particularly in assessing resilience and performance at the facade level during extreme events. The lack of a dedicated tool or method tailored to this specific scale poses a substantial challenge. Additionally, the absence of comprehensive tools for multi-hazard impact assessment, integrating both floods and heatwaves, hinders a holistic understanding of risks and vulnerabilities. This limitation is particularly concerning as even minor flood events can disproportionately impact building facades,

leading to economic losses. Consequently, there is a pressing need for a tool that conducts a thorough assessment considering the nuanced effects of small-scale flooding on facade resilience. Moreover, the prevalent reliance on qualitative assessments in the literature underscores a significant gap in quantitative evaluation tools. The dearth of such tools highlights the necessity to develop instruments that provide designers with quantitative data, empowering them to make informed decisions during the design process. Addressing these gaps is crucial for enhancing the efficacy of resilience assessments and fostering more robust design practices.

3

Quantification of thermal resilience

3.1. Assessing Heatwave Impacts on Facades and Human Comfort

The quantification of thermal resilience of the building envelope involves a detailed and systematic workflow. Initially, the study targets heatwave stressors, including outdoor air temperature, relative humidity, wind speed, and the duration of heatwaves.

Subsequently, the study examines the impact of these heatwave stressors on the building facade and human comfort. This includes evaluating thermal and visual discomfort, cooling and lighting energy usage, and facade material deterioration due to moisture loss. Additionally, it considers facade discoloration and structural damage, which encompasses thermal expansion of facade components, as well as warping, cracking, and bending under extreme heat conditions.

To quantify these impacts, this study focuses on assessing human comfort by calculating values for Standard Effective Temperature (SET), Predicted Mean Vote (PMV), and Predicted Percentage of Dissatisfied (PPD), as well as the cooling energy demand during extreme heat events.

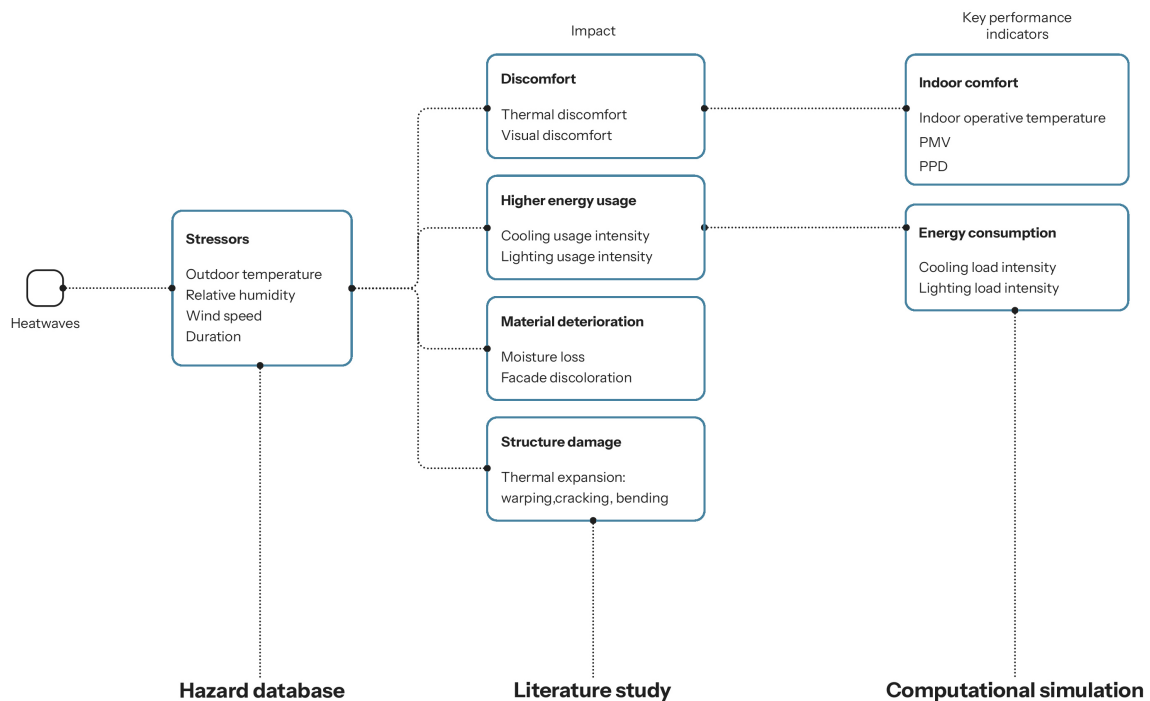


Figure 3.1: Graphical representation of heatwaves stressors, impacts and KPIs(Source: Author)

3.2. Computational Simulation for heatwaves

3.2.1. Heatwaves weather data generation

This study focuses on Chennai, India, which experiences both heatwaves and floods due to its geographical location. Weather data for Chennai were collected using the Ladybug tool, in the form of an EPW file in Typical Meteorological Year (TMY) format. However, this EPW file only provides typical weather data and does not account for extreme conditions. To simulate a heatwave scenario, a recent heatwave event (April-June 2021) in Chennai, during which temperatures exceeded 45 degrees Celsius, was identified. Data from this heatwave period were obtained from the nearest weather station in Chennai.

To replace the typical values with extreme scenario values in the EPW file, various tools were explored, including the CCWorldWeatherGen tool and the EnergyPlus Weather Converter tool. However, the EPW files generated by these tools were not compatible with the computational simulation software. Consequently, the Dragonfly plugin was utilized to convert the stressors (dry bulb temperature, relative humidity, wind speed, etc.) to reflect the extreme heatwave conditions from April to June 2021.

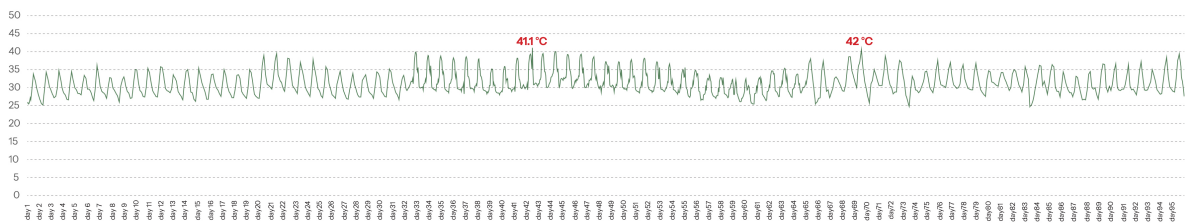


Figure 3.2: Graphical representation of outdoor temperature in typical weather condition (Source: Author)

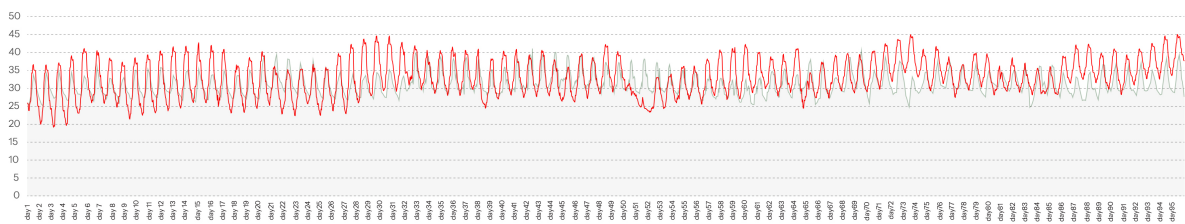


Figure 3.3: Graphical representation of heatwaves outdoor temperature 2021- Chennai,India (Source: Author)

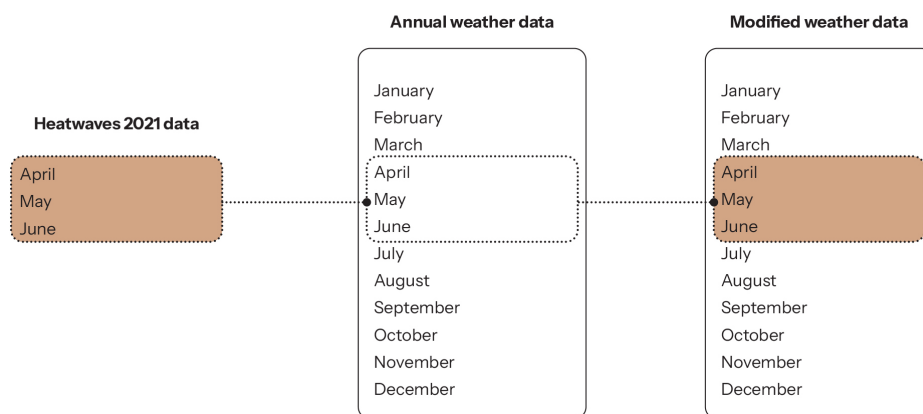


Figure 3.4: Graphical representation of weather data replacement (Source: Author)

3.2.2. Defining heatwaves scenario

According to the Indian Meteorological Department (IMD, 2022), a heatwave is defined as a condition when the temperature exceeds 40 degrees Celsius in plain regions and 30 degrees Celsius in hilly regions. Thermal sensation thresholds based on the Physiological Equivalent Temperature (PET) are identified and divided into two categories: cool-cold temperatures and warm-hot temperatures. As indicated in Table, an outdoor temperature of 35 degrees Celsius is considered strong heat stress (Cheung & Jim, 2019). This threshold is used to define warm, hot, and extremely hot temperatures during the summer period.

Thermal sensation and thermal stress classification scale of PET.

Thermal sensation	Physiological stress	Range (°C PET)
Very cold	Extreme cold stress	< 4
Cold	Strong cold stress	4 to 8
Cool	Moderate cold stress	8 to 13
Slightly cool	Slight cold stress	13 to 18
Neutral (comfortable)	No thermal stress	18 to 23
Slightly warm	Slight heat stress	23 to 29
Warm	Moderate heat stress	29 to 35
Hot	Strong heat stress	35 to 41
Very hot	Extreme heat stress	> 41

Table 3.1: Table presenting thermal sensation and thermal stress classification scale of PET

An assumption regarding the duration of heat stresses is also made, based on the statement that, for calculating thermal resilience in buildings, simulations should not be conducted using instantaneous temperature values that exceed a certain threshold. Instead, they should be performed over a specific time frame during which the heatwave occurs. This approach ensures a comprehensive assessment of the thermal resilience of buildings over the duration of the heatwave.

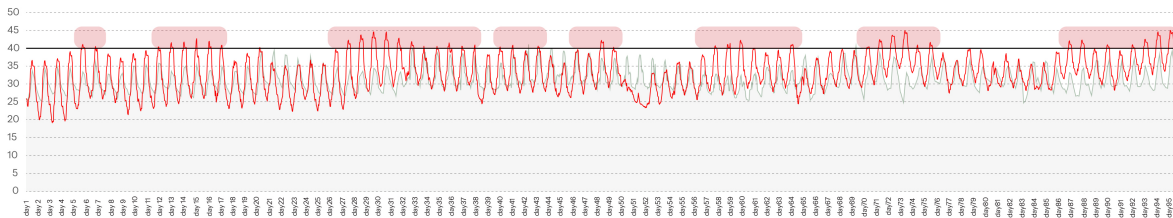


Figure 3.5: Graphical representation of heatwaves incidents (Source: Author)

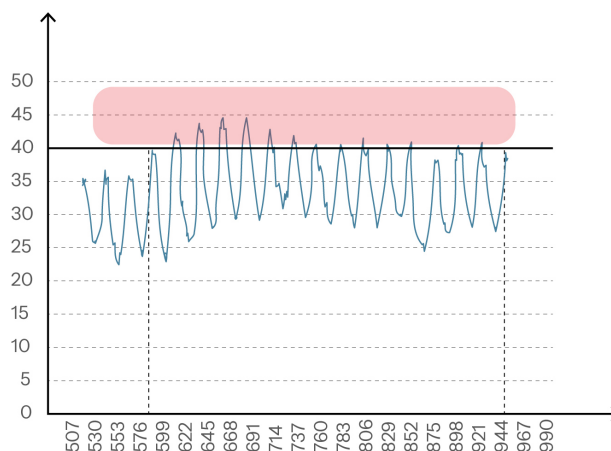


Figure 3.6: Graphical representation of heatwaves incident between 26th April to 8th May 2021 (Source: Author)

3.2.3. Defining input parameters for heatwaves

The computational simulation of heatwaves, designed to evaluate thermal comfort and cooling energy demands, necessitates detailed input of various material and building parameters. These parameters include building location, dimensions, orientation, materials, facade characteristics, and operational parameters such as occupancy, equipment load, and lighting load. To isolate the impact of facade parameters on thermal comfort and cooling energy usage, all other parameters are maintained at their default values (as illustrated in Figure X). This controlled approach ensures that any changes in the output parameters can be directly attributed to variations in the facade, thereby providing a precise understanding of the facade’s influence on building performance during extreme heat events.

Building parameters		Building Operational parameters		Facade parameters	
Project location	Chennai, India	Occupancy schdule	refer fig x	WWR	Variable
Building dimensions	60 X 40 m	lighting schedule	refer fig x	Aperature width	Variable
No. of floors	12	Cooling setpoints and setback	24 °C and 19 °C	Aperature height	Variable
F/F height	3.5 m	ventilation	0.0007 m3/s	Apertures	Variable
Analysis floor	6th	Infiltration	0.00025 m3/s	U-value	Variable
		Person density	0.07 Ppl/m2	SHGC	Variable
		lighting load	10 W/m2	Visible transmittance	Variable
		equipment load	14 W/m2	Opaque materials	Variable
		Efficiency of heating and cooling system	COP = 6	Thickness	Variable
		Non-operable windows		Conductivity	Variable
		Minimum clothing when Temp.>26 °C	0.46 (as per Schiavon clothing function)	Density	Variable
		Indoor air speed	0.1 m/s (by HVAC system)	Spec. heat	Variable
				Thermal absorption	Variable
				Solar absorption	Variable
				Visible absorption	Variable
				Surface reflectance	Variable

Table 3.2: Table presenting all input parameters for computational simulation

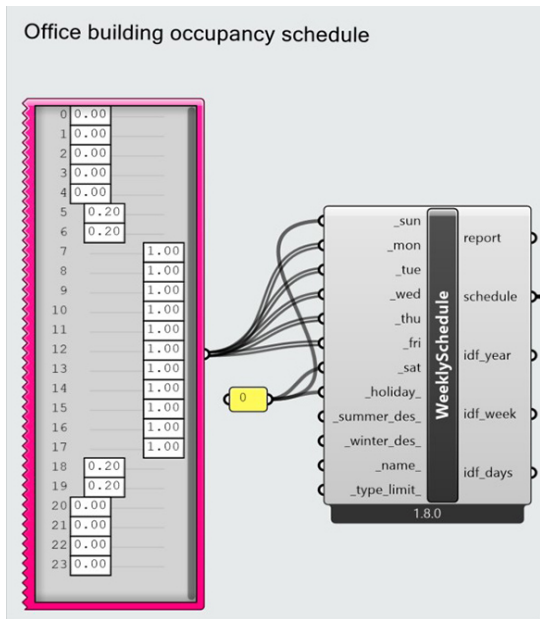


Figure 3.7: Graphical representation of office occupancy schedule

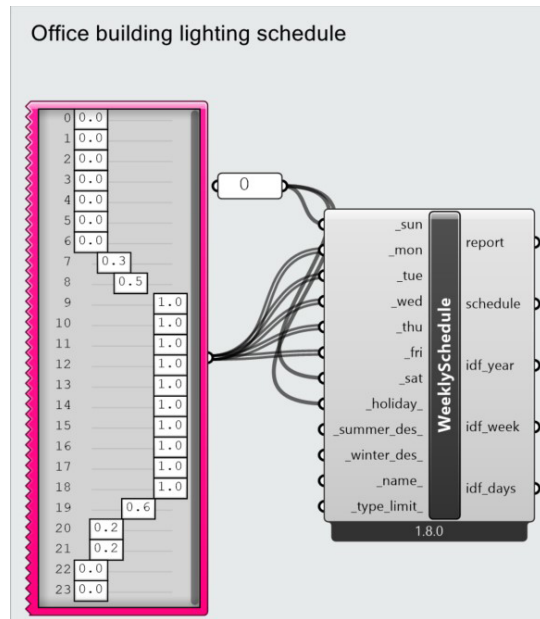


Figure 3.8: Graphical representation of office lighting schedule

3.2.4. Facade parameter configuration

The configuration of all facade parameters is based on their minimum and maximum values (as shown in Figure 3.3). Configuring facade parameters for simulating different scenarios involves setting up various elements that impact the energy efficiency, aesthetics, and functionality of a building's exterior. These elements include:

Material Properties

Thermal Properties

Configure the thermal conductivity, specific heat, and density of facade materials. High thermal resistance materials (low U-values) are preferred for better insulation.

Optical Properties

Set parameters for reflectance, transmittance, and absorptance. These affect how much solar radiation is absorbed or reflected by the facade.

Geometry and wall-window ratio

Surface Area and Shape

Vary the surface area and shape of the facade to study their impact on heat gain/loss and daylight penetration. Complex geometries can enhance or reduce solar exposure.

Window-to-Wall Ratio (WWR)

Adjust the proportion of windows to solid wall. Higher ratios increase natural light but can also increase heat gain/loss.

Facade parameters	
WWR	[0.1, 0.2, 0.4, 0.6, 0.75, 0.9]
Aperture width	
Aperture height	
Apertures	
U-value	[0.25, 0.5, 0.75, 1.0, 1.5, 1.75, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.8]
SHGC	[0.1, 0.2, 0.4, 0.6, 0.8, 0.9]
Visible transmittance	[0.2, 0.4, 0.6, 0.8, 0.9]
Opaque materials	
Thickness brick (meter)	[0.1, 0.2]
Conductivity brick (W/m.K)	[0.5, 0.84, 1.0]
Density brick (kg/m ³)	[500, 1000, 2000]
Spec. heat brick (J/kg. K)	[840]
Thermal absorption brick	[0.9]
Solar absorption brick	[0.7]
Visible absorption brick	[0.7]
Surface reflectance brick	[0.5]
Thickness Insulation (meter)	[0.05, 0.1, 0.15, 0.2]
Conductivity Insulation (W/m.K)	[0.025, 0.050]
Density Insulation (kg/m ³)	[25, 30, 35]
Spec. heat brick (J/kg. K)	[1400]
Thermal absorption Insulation	[0.9]
Solar absorption Insulation	[0.7]
Visible absorption Insulation	[0.7]
R-value opaque wall (m ² .K/W)	[1, 3, 4, 5, 6]

Table 3.3: Table presenting facade parameters configuration (Source: Author)

By systematically altering these facade parameters while keeping other building parameters constant, the simulation provides a clear understanding of how each element influences thermal comfort, cooling energy demands, and overall building performance under extreme weather conditions. This methodical approach ensures precise and reliable results that can inform the design of resilient and energy-efficient building facades.

3.2.5. Computational simulation

As mentioned in the previous section, all input parameters (both constant and variable) are meticulously defined to facilitate the simulation process. The simulations are conducted within the Rhino and Grasshopper environments using an array of plugins, including Ladybug Toolkit, Colibri, EnergyPlus, and OpenStudio. The simulation setup begins by defining critical building parameters: project location, orientation, building dimensions, number of floors, floor-to-floor height, and the analysis floor. Using the Honeybee (HB) tool, a detailed HB geometry is created for each floor individually. Honeybee divides each analysis floor into nine zones, with the central zone designated as a service core, characterized by unique energy requirements. Upon completing the zoning, the simulation separates all building elements, including interior walls, exterior walls, floors, and ceilings, to assign specific material properties to each component. Additionally, window parameters, such as dimensions and the window-to-wall ratio (WWR), are specified and integrated with the exterior walls once the HB geometry is finalized.

A comprehensive construction set, including all relevant material properties (U-value of glass and opaque walls, G-value, T-vis, thermal conductivity, and thermal absorption), is applied to the HB geometry. Furthermore, building operational parameters—encompassing occupancy schedules, lighting schedules, heating and cooling setpoints, cooling system efficiencies, person density, lighting load, and equipment load—are defined to create distinct program types for different zones (open office, closed office, and service areas). These program types are subsequently applied to the HB geometry, ensuring that all parameters are correctly configured for computational simulations. With the HB geometry configured, the simulation proceeds using EnergyPlus through the OpenStudio interface. The simulation incorporates a modified EPW file, reflecting extreme heatwave conditions. EnergyPlus processes this input and generates an SQL file that details all energy demands based on temperature setpoints and setbacks. The SQL file also provides Standard Effective Temperature (SET) values for all zones. The cooling energy demand is calculated by applying the Coefficient of Performance (COP) and the efficiency of the cooling system. For high-efficiency cooling systems, the COP is set at 6, while for low-efficiency systems, it is set at 3. An overall cooling energy efficiency factor of 0.85 is also applied to the final output.

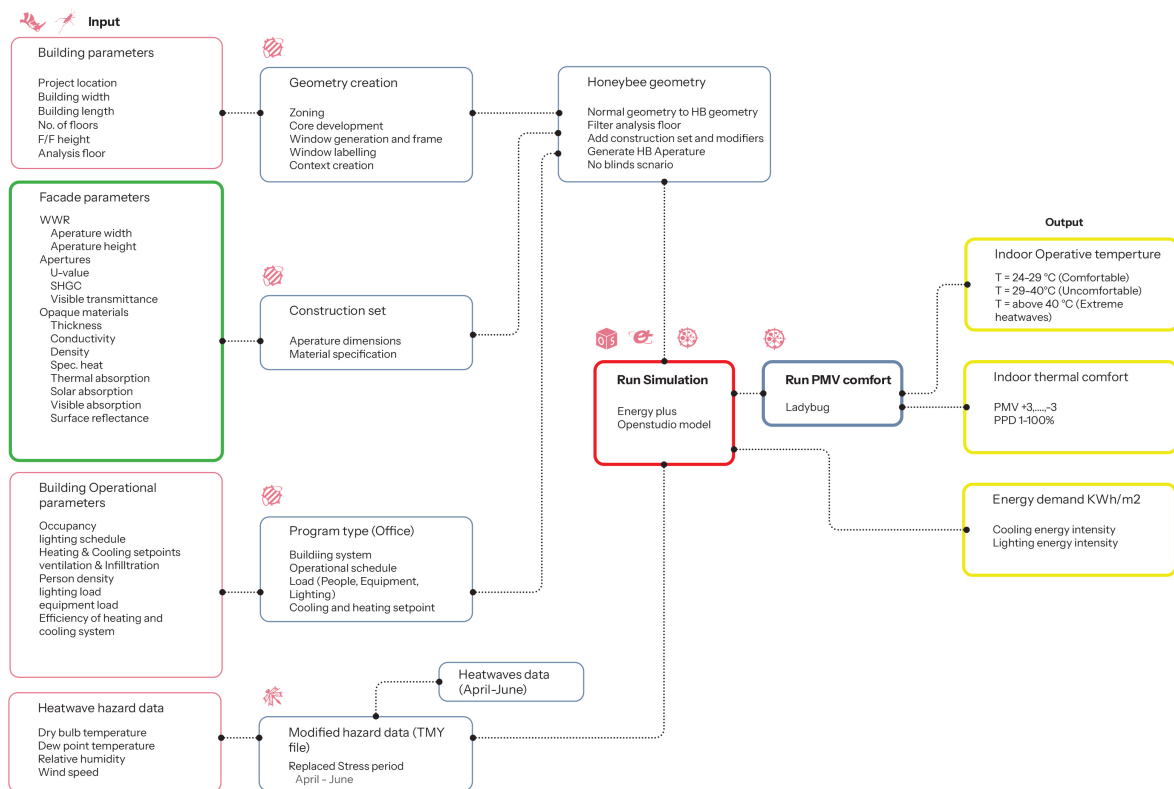


Figure 3.9: Graphical representation of heatwaves computational simulation (Source: Author)

To evaluate thermal comfort, a PMV (Predicted Mean Vote) comfort analysis is conducted, calculating PMV and PPD (Predicted Percentage of Dissatisfied) values. Given that the building is equipped with a cooling system, other

output variables, such as SET and indoor operative temperature, remain constant across different simulations. To comprehensively analyze the impact of varying facade configurations, the Colibri Iterator is employed to simulate thousands of scenarios. This approach allows for the systematic examination of how different facade parameters influence the building's thermal performance and energy consumption. Upon completion of the simulations, all input and output variables are saved in CSV format using the Colibri plugin. This CSV file, which includes columns for both input and output variables, serves as a vital dataset for subsequent sensitivity analysis and machine learning model training. The detailed data facilitates an in-depth understanding of the relationships between facade configurations and the building's thermal and energy performance, providing valuable insights for optimizing facade designs under extreme weather conditions.

3.3. Machine learning model for heatwaves

This research explores various machine learning models for data prediction, with a focus on regression models. The report outlines the process of preparing prediction data, training multiple regression models, and evaluating their performance using key metrics. The models discussed include Artificial Neural Networks (ANN), Random Forest, and Gaussian Process Regression.

Data preparation

The dataset utilized in this study consists of multiple input features and corresponding output variables. The data preparation steps include splitting the dataset into training and testing sets and standardizing the features.

Input and Output Variable Separation

```
X = data.iloc[:, :6].values
y = data.iloc[:, 6:].values
```

Here, X represents the input variables, while y denotes the output variable(s).

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
model = MLPRegressor(hidden_layer_sizes=(300, 150), activation='relu',
solver='adam', random_state=100)
model.fit(X_train_scaled, y_train)
```

Training and Testing Data Split

To evaluate the model's performance, we split the data into training and testing sets with an 80-20 split.

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=100)
```

3.3.1. Artificial Neural Network (ANN) Regression Model

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of biological brains. They consist of interconnected nodes organized in layers: an input layer receives data, hidden layers process it through weighted connections, and an output layer produces the final result. Through a training process called backpropagation, ANNs adjust the weights of these connections to minimize the difference between predicted and actual outputs, thus learning to recognize patterns and make predictions from input data. ANNs are powerful tools for tasks like image recognition, natural language processing, and predictive analytics due to their ability to learn complex relationships from large datasets.

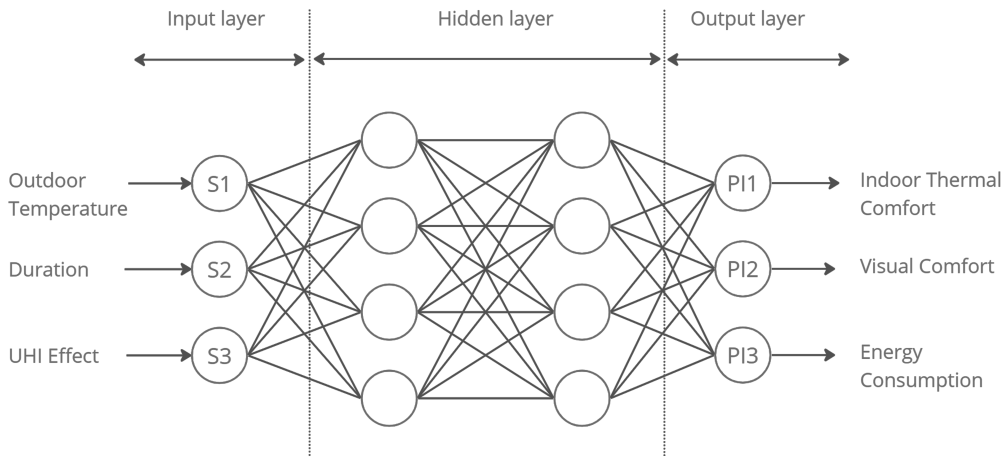


Figure 3.10: Graphical representation of Artificial Neural Network model in heatwaves workflow (Source: Author)

To enhance the efficiency and accuracy of the sensitivity analysis and reduce the computational burden associated with a large number of simulations, an Artificial Neural Network (ANN) regression model is integrated into the research workflow (Liu et al., 2019). We utilized the MLPRegressor from scikit-learn to create an ANN regression model with a specific architecture.

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
model = MLPRegressor(hidden_layer_sizes=(300, 150), activation='relu',
                    solver='adam', random_state=100)
model.fit(X_train_scaled, y_train)
```

Following the completion of the computational simulation phase, the extensive dataset generated from the simulations, including various stressors and their impacts on façade resilience, will be utilized to train the ANN model. The ANN will learn the complex relationships between input parameters (such as flood characteristics, heatwave conditions, and façade properties) and output performance indicators obtained from the simulations.

The trained ANN regression model will then serve as a surrogate for the computational simulations, allowing for rapid predictions of façade resilience under different multi-hazard scenarios. This integration aims to significantly reduce the computational time required for sensitivity analysis while maintaining a high level of accuracy. The ANN model's ability to capture intricate non-linear relationships within the dataset makes it a valuable tool for predicting façade performance under diverse conditions.

Moreover, the ANN regression model will contribute to the design phase by providing a streamlined approach for assessing various design solutions. Design scenarios can be rapidly evaluated using the trained model, facilitating the identification of optimal design solutions that enhance façade resilience against floods and heatwaves. The benefits of incorporating the ANN regression model include accelerated decision-making processes, resource efficiency, and the ability to explore a broader design space with reduced reliance on computationally intensive simulations. Overall, the integration of the ANN regression model represents a pivotal step in advancing the efficiency and effectiveness of the façade resilience assessment tool, offering a powerful means to navigate the complexities of multi-hazard scenarios.

The model's performance was evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) metrics.

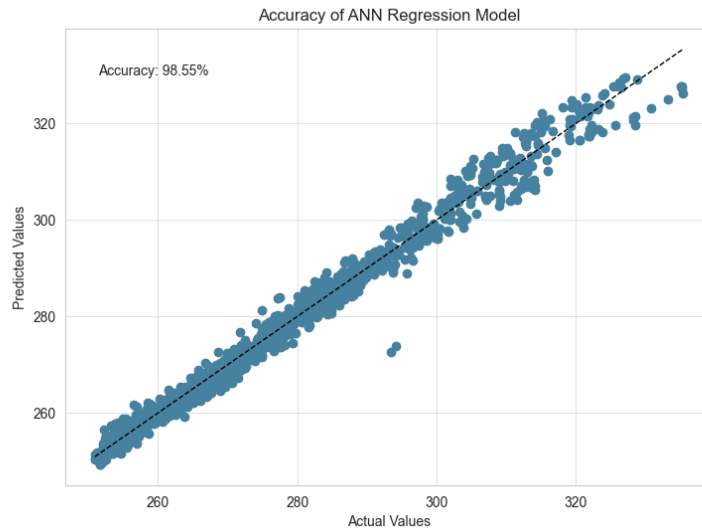


Figure 3.11: Graphical representation of ANN model accuracy (Source: Author)

3.3.2. Random Forest Regression Model

A Random Forest Regressor was employed on the dataset, offering an alternative approach to regression analysis. This model, belonging to the ensemble learning category, is particularly useful for regression tasks, aiming to forecast a continuous output variable from a set of input features. Comprising multiple decision trees, a Random Forest constructs each tree using a random subset of the training data and input features, thereby reducing overfitting and enhancing the model's resilience. During predictions, each tree independently forecasts the output value based on the input features. In regression scenarios, the final prediction typically entails averaging (or occasionally taking the median of) the predictions from all the trees.

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
regressor_dataset = RandomForestRegressor()
regressor_dataset.fit(X_train, y_train)
```

Similar to the ANN model, the Random Forest model's predictions were evaluated.

```
y_pred = regressor_dataset.predict(X_test)
mae_dataset = mean_absolute_error(y_test, y_pred)
prediction_model_accuracy = round((1 - mae_dataset) * 100, 1)
```

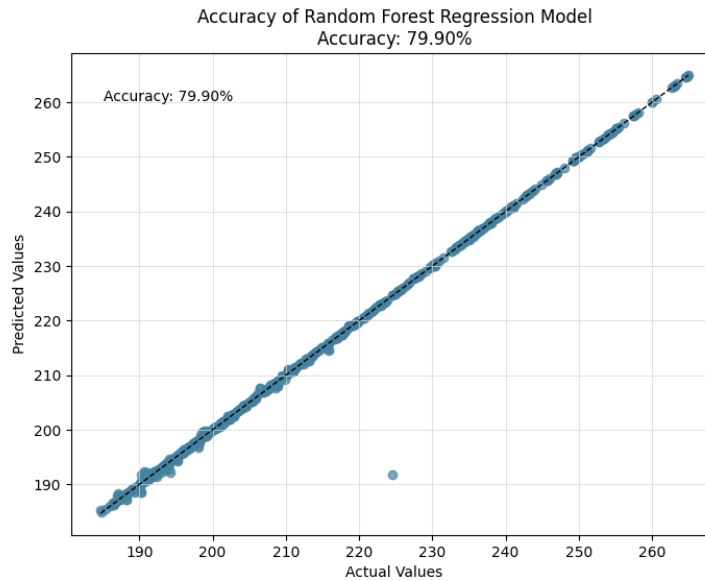


Figure 3.12: Graphical representation of RFB model accuracy (Source: Author)

3.3.3. Gaussian Regression model

This study also explored Gaussian Process Regression (GPR) with a Radial Basis Function (RBF) kernel due to its flexibility and accuracy in capturing the underlying patterns in the data. GPR is a non-parametric, probabilistic model used for regression tasks, based on the principles of Bayesian statistics. It uses Gaussian processes to predict continuous outputs.

```
kernel = RBF(length_scale=1.0)
model = GaussianProcessRegressor(kernel=kernel)
model.fit(X, y)
```

The core of GPR is the kernel function (also known as the covariance function), which measures the similarity between different data points. Common kernels include the RBF kernel, also known as the Gaussian kernel, which assumes that points closer together are more similar.

During training, GPR uses the data to learn the mean and covariance functions. Typically, the mean function starts as zero, and the covariance function is defined by the chosen kernel. The model then updates these functions based on the training data. For making predictions, GPR computes the mean and variance of the output at any given input point. This results in not only a prediction but also an uncertainty estimate (confidence interval) for each prediction. This feature is particularly useful for understanding the reliability of the model's predictions.

```
y_pred = model.predict(X)
mse = mean_squared_error(y, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y, y_pred)
```

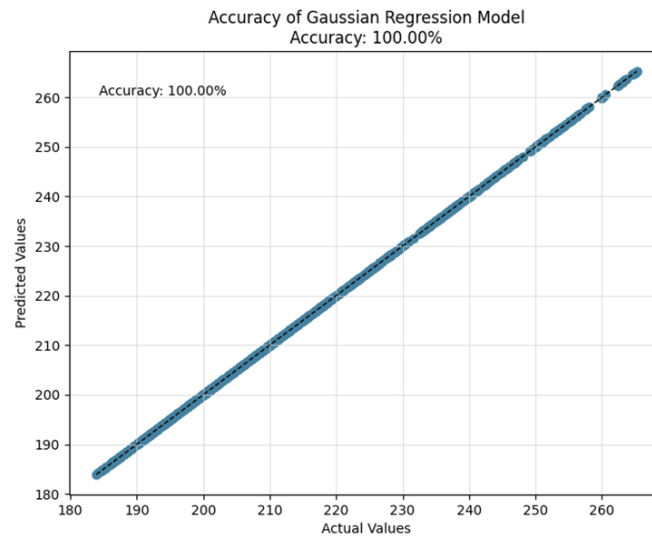


Figure 3.13: Graphical representation of Gaussian regression model accuracy (Source: Author)

3.3.4. Comparison of all machine learning models

Table 3.4: Table presenting all regression model performance comparison (Source: Author)

Metric	Model	Value
Mean Squared Error (MSE)	ANN	39.84
	Random Forest	1.55
	Gaussian	0.056 (best)
Root Mean Squared Error (RMSE)	ANN	6.312
	Random Forest	1.24
	Gaussian	0.236 (best)
R-squared (R^2)	ANN	0.878
	Random Forest	0.9926
	Gaussian	0.999 (best)
Accuracy Percentage	ANN	88.93%
	Random Forest	79.90%
	Gaussian	100% (best)

Based on the provided metrics, the Gaussian Process Regression Model performs the best across all available performance indicators:

- It has the lowest MSE and RMSE.
- It has the highest R^2 value, indicating the best fit to the data.
- It has the highest accuracy percentage.

Thus, the Gaussian Process Regression Model is the best model among the three for predicting the output in your dataset.

3.4. Sensitivity analysis for heatwaves

The process of estimating how target variables (performance indicators) change in relation to changes in input variables (stressors) and determining which input variables have the strongest impact on target variables is crucial. Sensitivity analysis plays a pivotal role in enhancing the robustness of the proposed methodology for assessing façade resilience in the context of multi-hazard events, specifically heatwaves. Following the computational simulations and

training of the machine learning model aimed at simulating the impact of stressors on the façade, sensitivity analysis becomes a critical step in discerning the relative importance and influence of each stressor on the performance indicators. By systematically varying input parameters and observing the corresponding changes in performance metrics, sensitivity analysis provides valuable insights into the sensitivity of the façade resilience model. This analysis not only highlights the most influential factors affecting façade performance but also aids in optimizing design solutions by prioritizing interventions that address the most critical stressors. The benefit of sensitivity analysis in this research lies in its ability to inform targeted and efficient design decisions, ensuring that the proposed digital tool accurately captures the nuances of multi-hazard resilience. Through this systematic examination, the research aims to enhance the precision and applicability of the tool, ultimately contributing to the development of more resilient building facades capable of withstanding the complex challenges posed by heatwaves.

3.4.1. Correlation matrix analysis

Following the completion of the simulations, a comprehensive dataset is generated, containing both input parameters and resulting output variables. This dataset is essential for constructing a correlation matrix, which is instrumental in understanding the relationships between different facade configurations and the building's thermal performance and energy consumption. The correlation matrix serves to quantify the strength and direction of relationships between various input parameters (such as material properties, geometry) and output parameters (such as cooling energy demand, PMV, PPD, SET). By analyzing these relationships, the correlation matrix helps identify which facade parameters have the most significant impact on the building's performance during heatwave conditions. Using programming language Python, the Pearson correlation coefficient is calculated for each pair of input and output variables. The Pearson correlation coefficient measures the linear relationship between two variables, ranging from -1 (perfect negative correlation) to 1 (perfect positive correlation), with 0 indicating no linear correlation.

The correlation matrix provides valuable insights into the sensitivity of the building's performance to various facade parameters. High positive or negative correlation coefficients indicate that changes in specific facade parameters significantly affect output variables. The findings from the correlation matrix analysis are crucial for optimizing facade designs. The matrix reveals that the window-to-wall ratio (WWR), the U-value of glass, and the SHGC value of glass have a significant positive influence on output variables. However, the R-value and the thickness of the opaque wall show a negative influence on output parameters. Additionally, the correlation matrix informs the sensitivity analysis and machine learning model training. By only focusing on the most influential parameters identified in the correlation matrix, the sensitivity analysis can provide deeper insights into how these parameters interact under various scenarios, leading to more robust and resilient building designs.

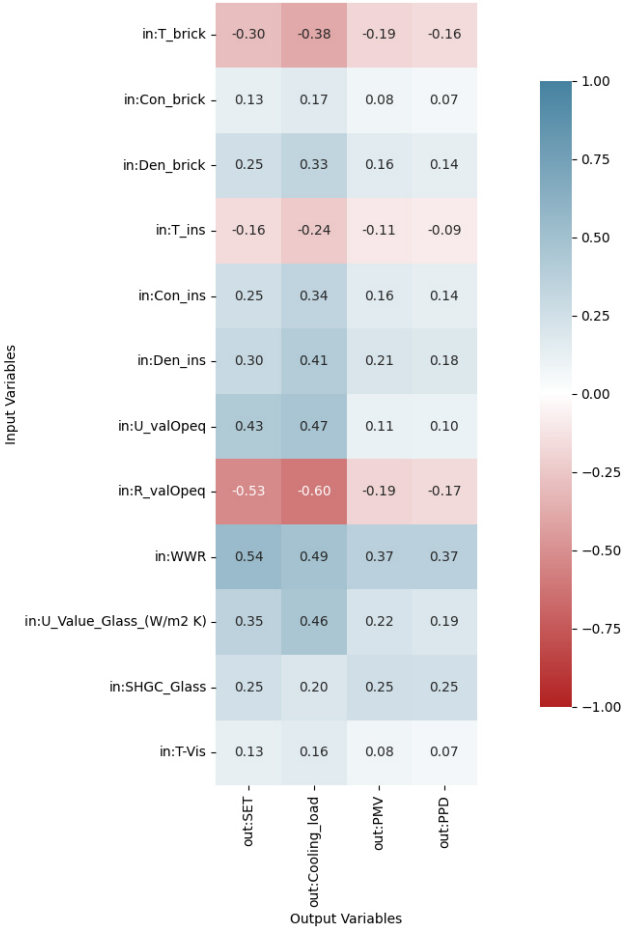


Figure 3.14: Graphical representation of correlation matrix with 12 input variables (Source: Author)

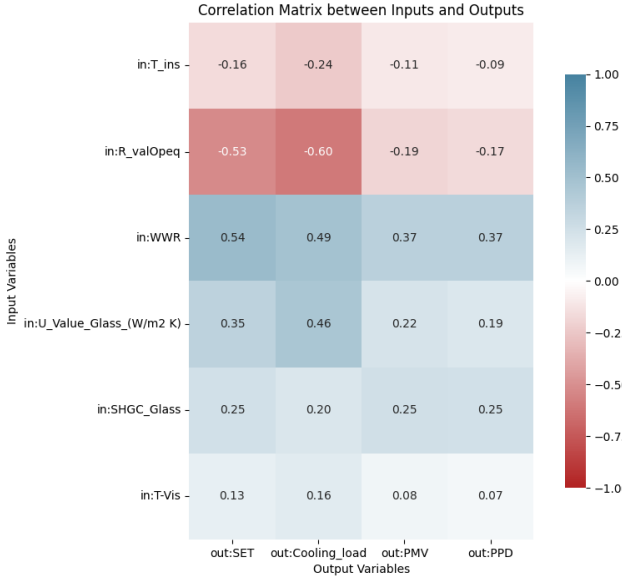


Figure 3.15: Graphical representation of correlation matrix with 6 input variables (Source: Author)

3.4.2. Variance based method- Sobol method

The Sobol method is a widely used technique for sensitivity analysis in the context of complex computational models. Developed by Ilya M. Sobol, this method falls under the category of variance-based sensitivity analysis, which aims to quantify the contribution of input variables to the output variance. It is particularly valuable in understanding the influence of each input variable, as well as their interactions, on the variability of the model output.

The Sobol method decomposes the output variance into contributions from individual input variables as well as their interactions. It uses a global sensitivity analysis approach, which means it considers the entire input space rather than focusing on local variations.

The main idea behind the Sobol method is to express the model output Y as a function of input variables $\mathbf{X} = (X_1, X_2, \dots, X_k)$:

$$Y = f(X_1, X_2, \dots, X_k)$$

Then, the total variance $V(Y)$ of the model output can be decomposed into contributions from each input variable and their interactions:

$$V(Y) = \sum_{i=1}^k V_i + \sum_{i<j} V_{ij} + \sum_{i<j<l} V_{ijl} + \dots + V_{1,2,\dots,k}$$

where V_i is the variance contribution of input X_i , V_{ij} is the variance contribution due to the interaction between X_i and X_j , and so on.

First Order Indices

The first-order Sobol index S_i measures the main effect of an input variable X_i on the output. It represents the proportion of the total variance $V(Y)$ that is attributable to X_i alone, ignoring interactions with other variables. Mathematically, it is defined as:

$$S_i = \frac{V_i}{V(Y)}$$

where $V_i = \text{Var}_{X_i}[E(Y | X_i)]$.

This index helps in understanding the direct impact of a single input variable on the output.

Total Order Indices

The total-order Sobol index S_{T_i} measures the overall effect of an input variable X_i on the output, including all interactions with other variables. It captures the total contribution to the output variance from X_i , both directly and through its interactions. It is defined as:

$$S_{T_i} = 1 - \frac{V_{\sim i}}{V(Y)}$$

where $V_{\sim i}$ is the variance of the output when X_i is fixed, thus representing the contribution of all other variables excluding X_i .

The total-order index is useful to understand the complete influence of each input variable on the output, including interactions.

Importance Using the Sobol Method

It is crucial to identify which input parameter and which combinations of input parameters have the most influence on output variables. That is why the Sobol method is implemented for sensitivity analysis. The first-order indices show the individual influence of each input parameter on the results (refer to Figure 3.16). The total order indices, on the other hand, show the combined interactive effect of input variables (refer to Figure 3.17).

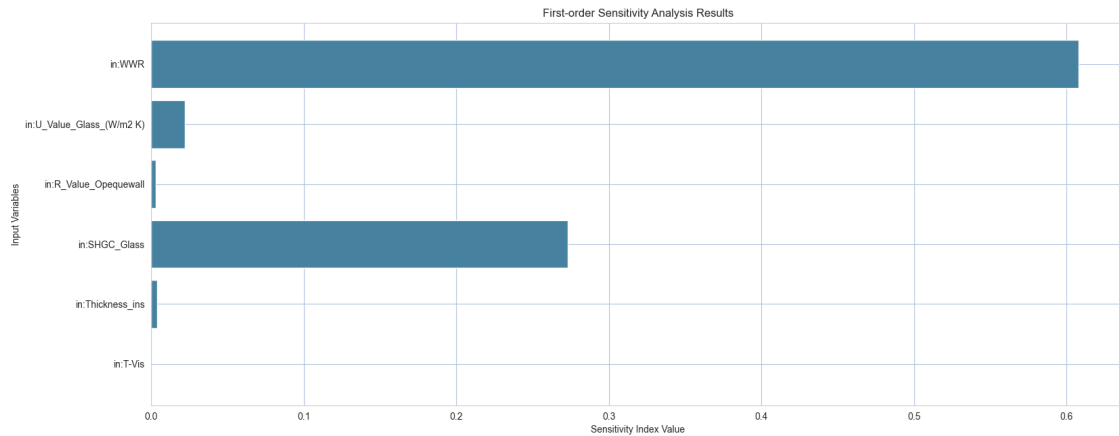


Figure 3.16: Graphical representation of first-order indices (Source: Author)

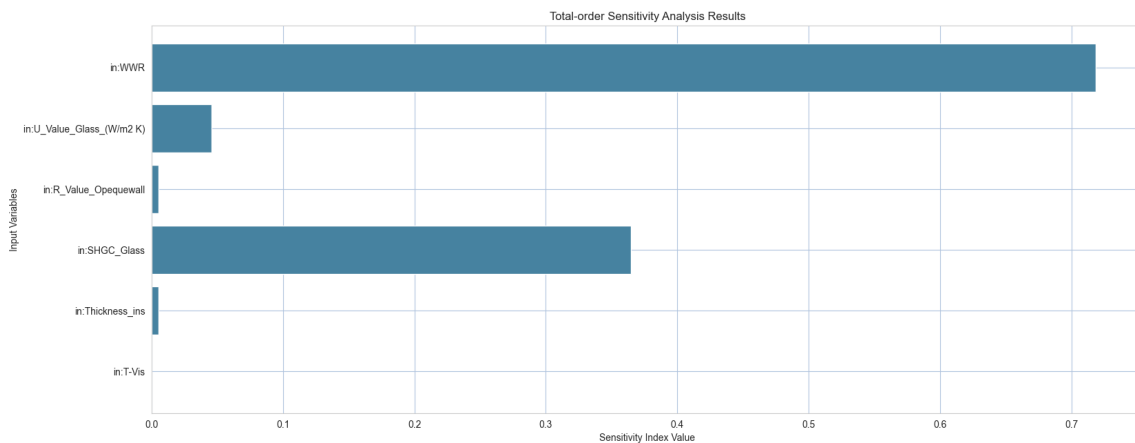


Figure 3.17: Graphical representation of total-order indices (Source: Author)

How the Sobol Method is Used for Sensitivity Analysis

Python programming language is used for sensitivity analysis. Below is an explanation of the code used for performing sensitivity analysis using the Sobol method:

Defining the Problem for Sensitivity Analysis

```
problem = {
    'num_vars': X.shape[1],
    'names': ['in:T-Vis', 'in:R_Value_Opequewall', 'in:Thickness_insulation (in mt)',
             'in:SHGC_Glass', 'in:U_Value_Glass_(W/m2 K)', 'in:WWR'],
    'bounds': [(inputs.iloc[:, i].min(), inputs.iloc[:, i].max()) for i in
               range(inputs.shape[1])],
    'dists': ['unif', 'unif', 'unif', 'unif', 'unif', 'unif']
}
```

num_vars: Specifies the number of variables, taken from the number of columns in the dataset **X**.

names: Lists the names of the input variables.

bounds: Defines the range of each variable, using the minimum and maximum values from the inputs **DataFrame**.

dists: Specifies the distribution of each variable; here, all variables are uniformly distributed.

Sampling Parameter Values Using Saltelli's Method

```
param_values = saltelli.sample(problem, 512)
```

saltelli.sample: The Saltelli sampling method is used to generate samples for the input variables. The Saltelli sampler generates $N \times (2D + 2)$ samples, where N is 512 (the argument we supplied) and D is 6 (the number of model inputs), resulting in 7168 samples.

Evaluating the output from the machine learning Model

```
Y = model.predict(param_values)
```

model.predict: Uses the machine learning model to predict the output Y for the generated sample input values `param_values`.

Performing Sensitivity Analysis Using Sobol Indices

```
Si = sobol.analyze(problem, Y)
```

Sobol analysis: This function calculates Sobol sensitivity indices based on the problem definition and the model predictions (Y). These indices measure the effect of each input variable on the output variance.

3.5. Resilience matrix for heatwaves

As mentioned in Section 2.1, resilience is the capability of a system to prepare for, absorb, adapt to, and recover from disruptive events. In the context of extreme heat stress, thermal resilience refers to the ability of a structure to maintain comfortable indoor temperatures and continue functioning effectively. This encompasses the capacity to withstand, adapt to, and recover from high heat conditions without significant loss of functionality.

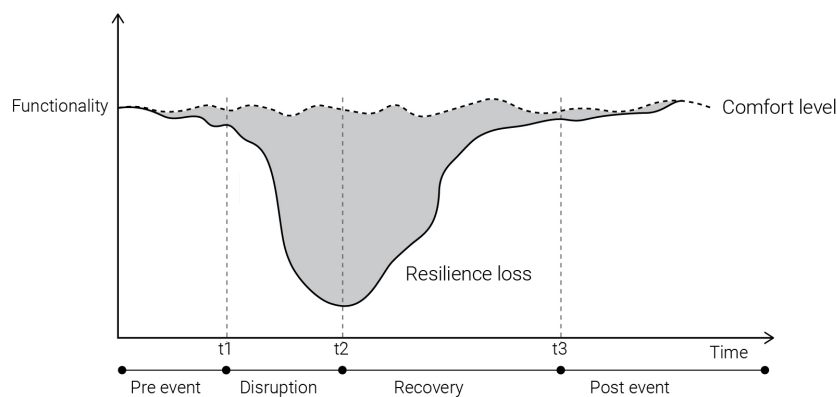


Figure 3.18: Graphical representation of resilience graph (Source: Author)

To quantify the thermal resilience of the building envelope, it is essential to define clear thermal resilience indicators and metrics. In this study, the cooling energy demand of the building is used as an indicator of thermal resilience. As outdoor temperatures rise, the cooling energy demand increases, requiring more energy to maintain a comfortable indoor temperature. Figure 3.19 illustrates the relationship between outdoor temperature and cooling energy demand over time. The left Y-axis represents outdoor temperature, while the right Y-axis represents cooling energy demand, with time plotted on the X-axis.

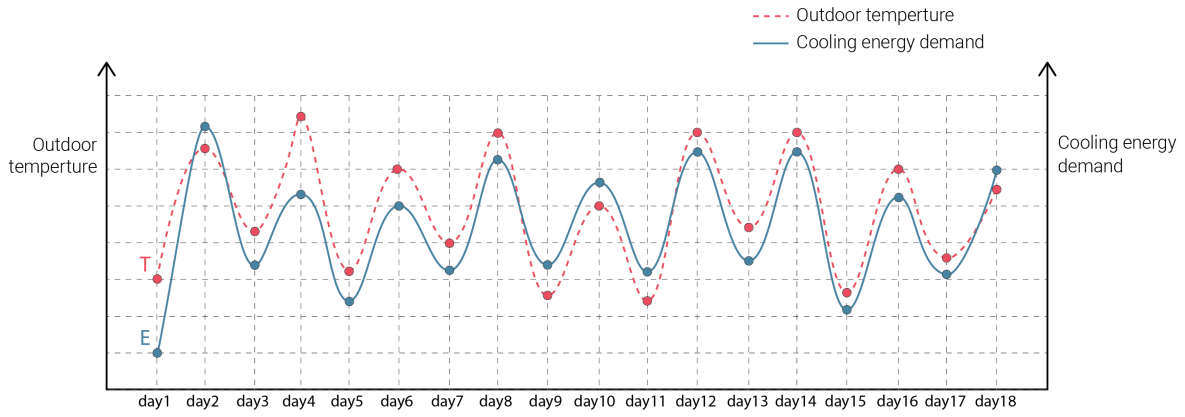


Figure 3.19: Graphical representation of temperature and cooling demand (Source: Author)

To assess resilience, a facade with consistent specifications was simulated under two scenarios (refer Figure 3.23). The first scenario represents conditions before a hazard, with outdoor temperatures in the typical range of 30–35 °C as per EPW weather file. The second scenario simulates extreme heat stress, where temperatures exceed 40 °C. In the first scenario, the facade system operates normally, with a typical cooling demand. However, under heatwave conditions, the facade system experiences increased stress, leading to a higher cooling demand to maintain indoor comfort levels.

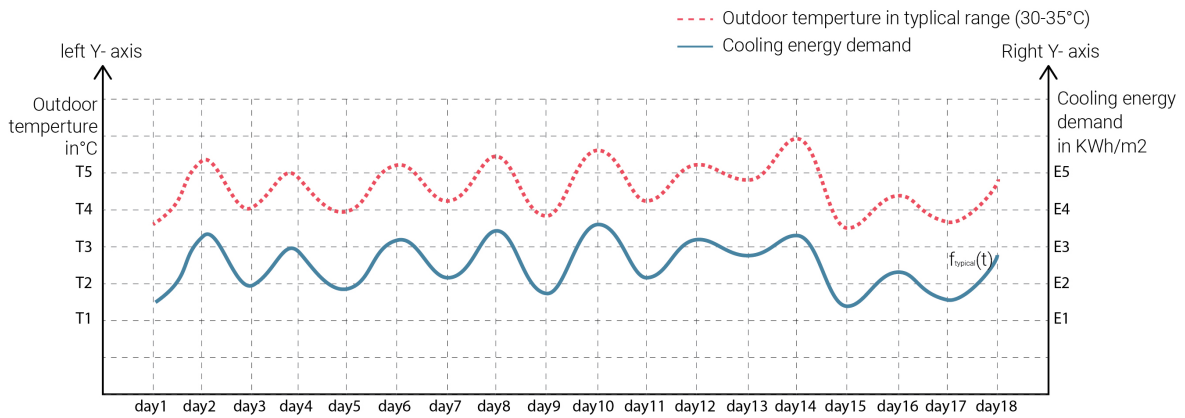


Figure 3.20: Graphical representation of temperature-cooling demand in typical conditions (Source: Author)

In the first scenario, outdoor temperature and cooling energy demand are plotted before the hazard (see Figure 3.20).

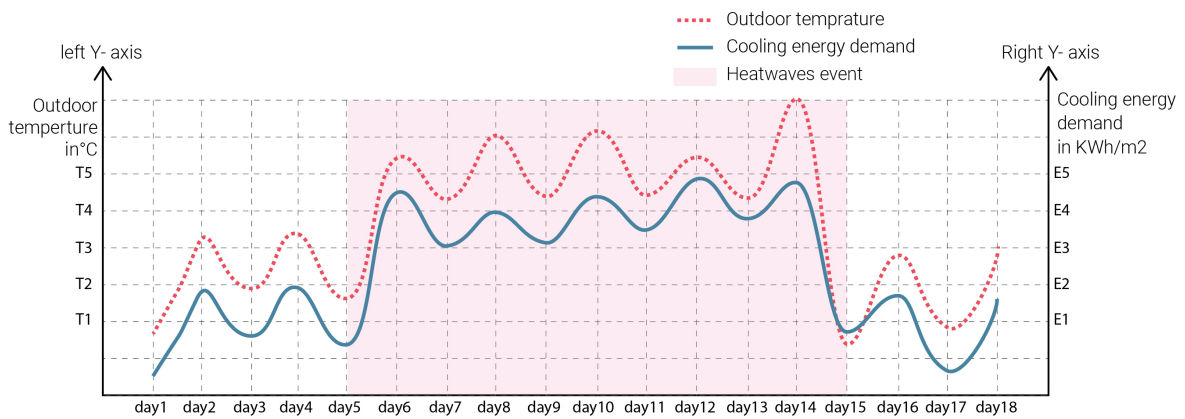


Figure 3.21: Graphical representation of temperature-cooling demand in heatwaves conditions (Source: Author)

In the second scenario, outdoor temperature and cooling energy demand are plotted during the heat stress event, which begins on day 5 and ends on day 15 (depicted in Figure 3.21). On day 5, when the heatwave starts, the temperature increases significantly, necessitating a corresponding increase in cooling energy demand to maintain indoor comfort.

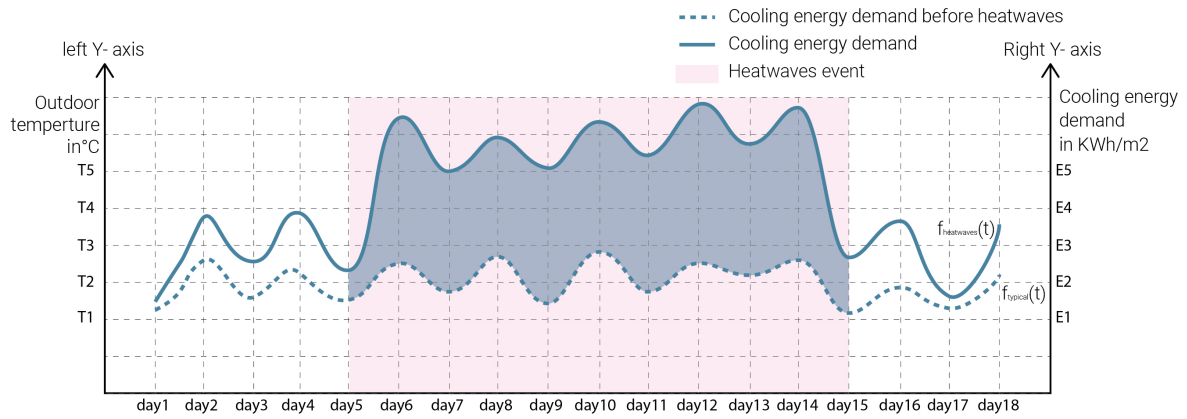


Figure 3.22: Graphical representation of resilience calculation by cooling demand

The graph in Figure 3.22 compares the cooling demand in both scenarios (before $f_{\text{typical}}(t)$ and during heatwaves $f_{\text{heatwaves}}(t)$) and quantifies the difference in terms of the additional cooling energy required during the extreme heat stress period. This difference can be referred to as the resilience loss of the facade system.

The resilience loss can be expressed as:

$$\text{Resilience loss} = \int_{t_1}^{t_2} (f_{\text{heatwaves}}(t) - f_{\text{typical}}(t)) dt$$

Overall thermal resilience matrix workflow

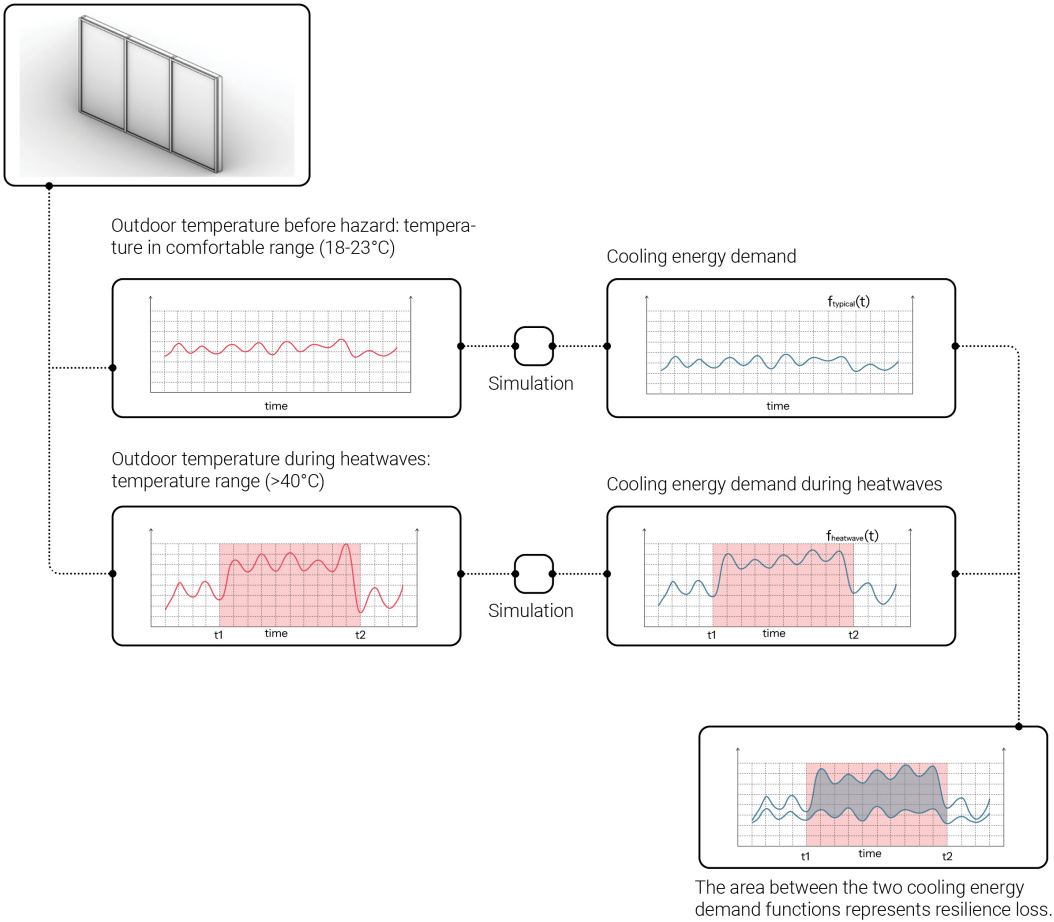


Figure 3.23: Graphical representation of thermal resilience quantification workflow

4

Quantification of flood resilience

4.1. Assessing Flood Impacts on Facades system

The quantification of flood resilience for the building envelope follows a methodology similar to that used for assessing heatwave resilience. Initially, the study identifies key flood stressors, including flood depth, flow velocity, debris content, and flood duration.

Subsequently, the study examines the repercussions of these flood stressors on the building facade and its structural integrity. This involves evaluating physical damage, such as cracks, shifts in the facade, and potential collapses. Additionally, the study considers material degradation resulting from prolonged water exposure and debris accumulation, which can further compromise the structure.

To quantify these impacts, the research focuses on calculating critical structural parameters, including hydraulic pressure, maximum bending, and deflection of the facade during flood events. These assessments are crucial for understanding the building envelope's resilience to flooding and for developing strategies to enhance its flood resistance.

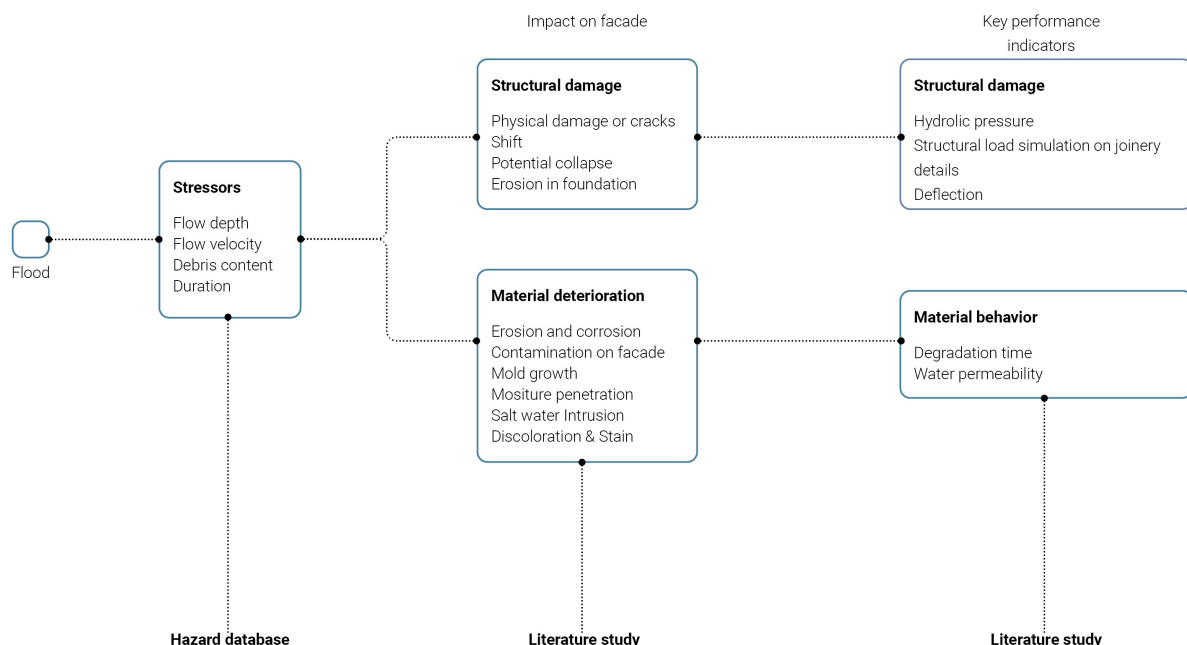


Figure 4.1: Graphical representation of floods stressors, impacts and KPIs(Source: Author)

4.2. Computational Simulation and Mathematical model for Floods

4.2.1. Defining input parameters for floods

Numerous studies have been conducted to identify the factors contributing to flood damage. The Flood Hazard Research Centre (FHRC) at Middlesex University in London has extensively researched flood damage in the UK (Kelman & Spence, 2004). They have developed manuals that illustrate how damage increases with water depth across different types of land use. These manuals also differentiate between two flood durations: less than 12 hours (short) and more than 12 hours (long). Another research by (Clausen, 1989), discusses how the speed of floodwater affects the damage. Clausen's findings, primarily based on the Dale Dyke dam failure in Sheffield in 1864, classify damage levels based on water velocity and a combined factor of flow rate and velocity ($f \cdot v$):

- When velocity (v) is less than 2 meters per second (m/s) or when the combined factor ($f \cdot v$) is less than 3 square meters per second (m^2/s), the damage is termed as "inundation damage" (minor damage from water coverage).
- When velocity exceeds 2 m/s and the combined factor is between 3 and 7 m^2/s , it results in "partial damage" (moderate damage).
- When velocity is over 2 m/s and the combined factor exceeds 7 m^2/s , it leads to "total destruction" (severe damage).

Clausen also identifies key factors for estimating flood damage: water depth, flow velocity, bed shear stress, dynamic forces (like flow momentum and stream power), rate of flood rise, and debris potential of the landscape. He considers flood duration important but does not list it as a separate parameter.

Debris content plays a pivotal role in exacerbating the severity of flood damage, primarily due to its propensity to induce both static and dynamic actions. During flood occurrences, the presence of debris can amplify the adverse impact on buildings and infrastructure through various mechanisms. Firstly, static debris actions manifest when sediment accumulates either externally or internally within a structure. Sediment deposited by the flood, such as soil backfill, exerts considerable forces on walls and foundations, potentially leading to structural compromise. The magnitude of these forces hinges upon a myriad of factors, encompassing the characteristics of sediment particles, soil compaction levels, and the geometric attributes of the soil mass. Secondly, dynamic debris actions represent another critical facet influenced by debris content. Debris carried by floodwaters can pose threats to buildings from both exterior and interior vantage points. External impacts may encompass objects such as cars or trees colliding with buildings, while internal impacts can ensue from furniture or other items buoyantly navigating within structures. The repercussions of dynamic debris actions can range from localized impacts, such as a log striking a building, to diffused pressures, exemplified by waves propelling stones and pebbles during storm surges. The presence of debris markedly amplifies the susceptibility of structures to damage during flood events. The table provides data to demonstrate how changes in debris content flow density affect flood impacts.

Flow	Sediment concentration in entire flow		Bulk density (kg/m^3)	Major sediment-support mechanism
	By weight	By volume		
Water flood	1–40%	0.4–20%	1010–1330	Electrostatic forces, turbulence
Hyperconcentrated	40–70%	20–47%	1330–1800	Buoyancy, dispersive stress, turbulence
Debris flow	70–90%	47–77%	1800–2300	Cohesion, buoyancy, dispersive stress, structural support

Table 4.1: Table presenting of flow density with debris content (Kelman & Spence, 2004)

To accurately assess the structural impact on building envelopes during flood events, it is essential to define appropriate input parameters to ensure the reliability and validity of simulation outcomes. This research specifically focuses on the impact of floods on building facades. Consequently, all relevant facade parameters, including dimensions and material properties, are utilized as input variables (refer to Figure 4.2). Additionally, critical flood stressors such as flood depth, flow velocity, flood duration and debris content are incorporated to simulate various hazard scenarios.

Facade parameters	
Facade span b/w panels (L)	Variable
Facade type	variable
Facade height	variable
Facade thickness	variable
Bending strength	variable
Max. bending moment capacity	variable
Allowable deflection limit (ASTME1300-20)	L/175

Table 4.2: Table presenting facade parameters for flood simulation (Source: Author)

Flood intensity	
Flood velocity	variable
Flood height	variable
Turbulent intensity	variable
Flood water density	variable

Table 4.3: Table presenting flood intensity parameters for simulation

4.2.2. Facade and Flood parameter configuration

To simulate various scenarios, the configuration of all input variables is defined based on their minimum and maximum values (refer to Table 4.4). In each scenario, all input parameters are used to calculate the output value. This approach allows for a comprehensive analysis of the resilience of various facade types under diverse flood conditions, providing valuable insights into the optimization of facade designs for enhanced flood resilience.

Facade parameters	
Facade span b/w panels (in_mt)	[0.5,0.7,1.0,1.5,2.0,2.4,2.7,3.0]
Facade type	Glass facade
Facade_Thickness_glass(in_mm)	[5,8,10,12,15,18,20,24]
Facade_height(in_mt)	[3.5,4.5]
Bending_strength(in_Mpa)	[32,35,40,45]
Flood intensity	
Flow_velocity(in_mt/s)	[0.1,0.2,0.5,0.8,1.1,1.2,1.5,1.8,2,2.5]
Flow_depth(in_mt)	[0.5,0.8,1.0,1.2,1.5,1.8,2.0,2.4]
Debris_content(in_kg/m3)	[1010,1500,1800,2300]

Table 4.4: Table presenting facade and flood parameter configuration (Source: Author)

4.2.3. Computational simulation

Once the configuration of all input variables, facade parameters, and hazard stressors are defined, these values are assigned to calculate the impact on the facade due to flooding. Computational simulation is conducted using the ANSYS Fluent tool with multiphase settings. To simulate a specific type of facade, the facade geometry needs to be created in Rhino 3D and converted into an STP file, which can then be imported into ANSYS Fluent for further analysis. After importing the 3D facade geometry into ANSYS Fluent, the simulation process comprises six stages:

ANSYS Geometry Creation:

The 3D geometry of the facade/building must be converted into ANSYS geometry. This conversion takes place in the Design Modeler tool within ANSYS Workbench. In Design Modeler, an enclosure around the facade geometry needs to be created to provide a volume for flood flow (refer to Figure 4.2).

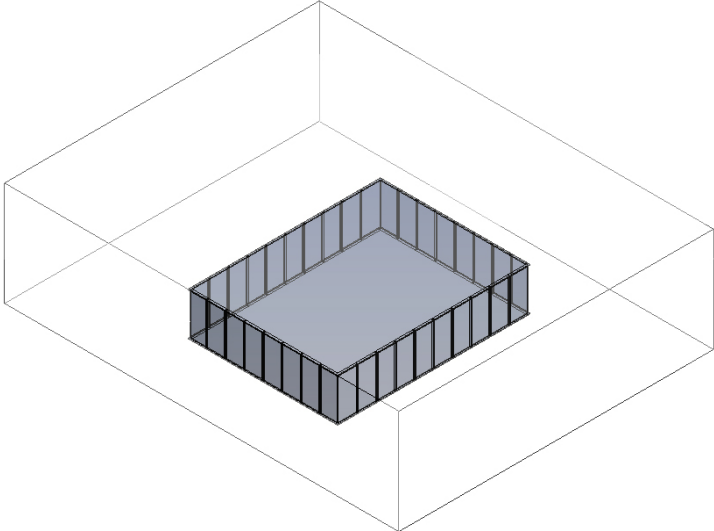


Figure 4.2: Graphical representation of ANSYS geometry creation (Source: Author)

Mesh Creation:

Once the ANSYS facade geometry and its enclosure are created, they need to be converted into mesh surfaces. The mesh size defines the accuracy of the model: smaller mesh sizes yield more accurate results but require more time to simulate. Once all surfaces are converted into a mesh, they are assigned different functions, such as the inlet of flood water, the outlet of flow, open surface, and ground. The facade geometry is assigned as an obstruction to calculate the impact of water flow (refer to Figure 4.3).

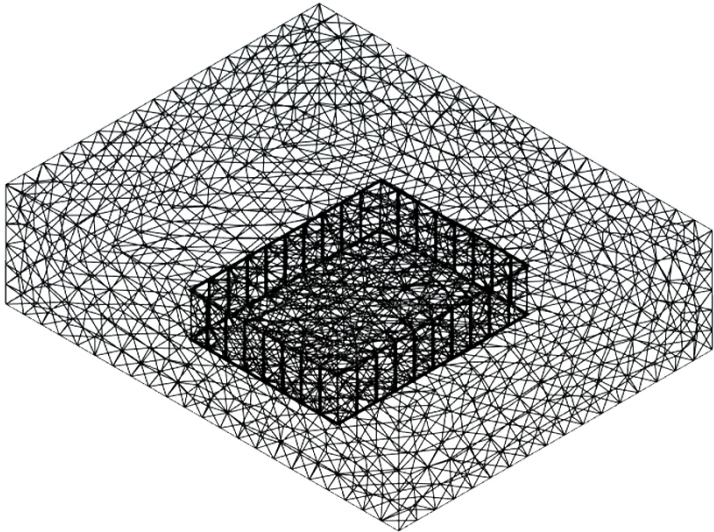


Figure 4.3: Graphical representation of ANSYS mesh creation (Source: Author)

Model Setup in ANSYS Fluent:

The generated mesh with assigned surfaces is transferred to ANSYS Fluent, where general properties such as gravitational acceleration ($g = 9.81 \text{ m/s}^2$) and multiphase settings (water and air) are defined. In this phase, flood stressors such as flood depth, flow velocity, and turbulence intensity are set for Computational Fluid Dynamics (CFD) analysis (refer to Figure 4.4).

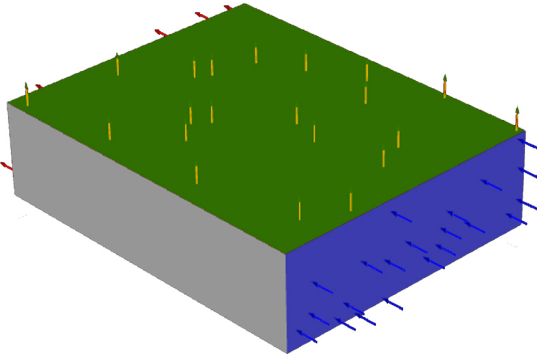


Figure 4.4: Graphical representation of ANSYS model setup (Source: Author)

Solution Initialization:

Once all the required parameters are set, the calculations are initialized, and the simulation is run.

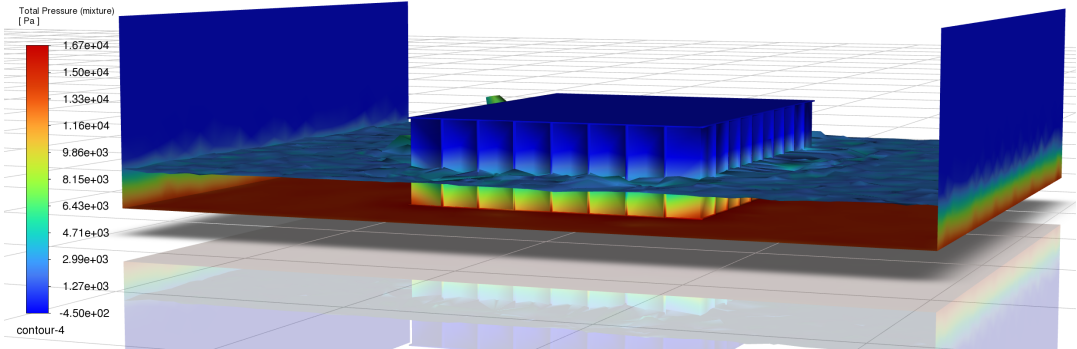


Figure 4.5: Graphical representation of flood simulation on facade (Source: Author)

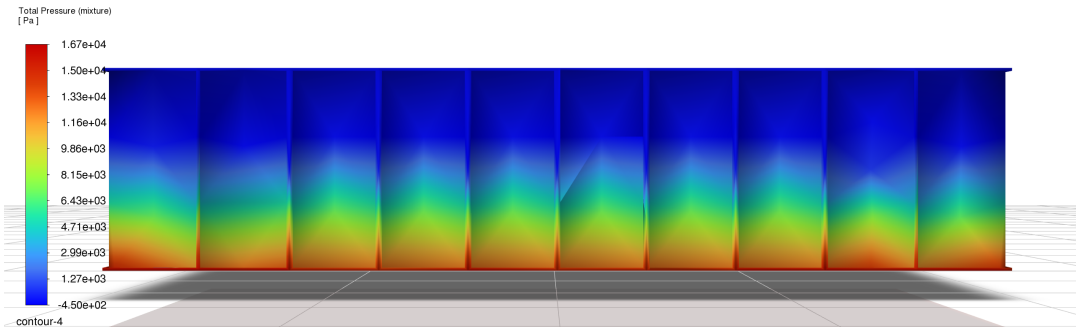


Figure 4.6: Graphical representation of total pressure on building facade (Source: Author)

Results Analysis:

The results include various types of hydraulic pressure on the facade (e.g., static pressure, dynamic pressure, total pressure), presented with heatmaps. These heatmaps show the pressure distribution on the facade and identify the vulnerable points (refer to Figure 4.6).

Overall computational workflow:

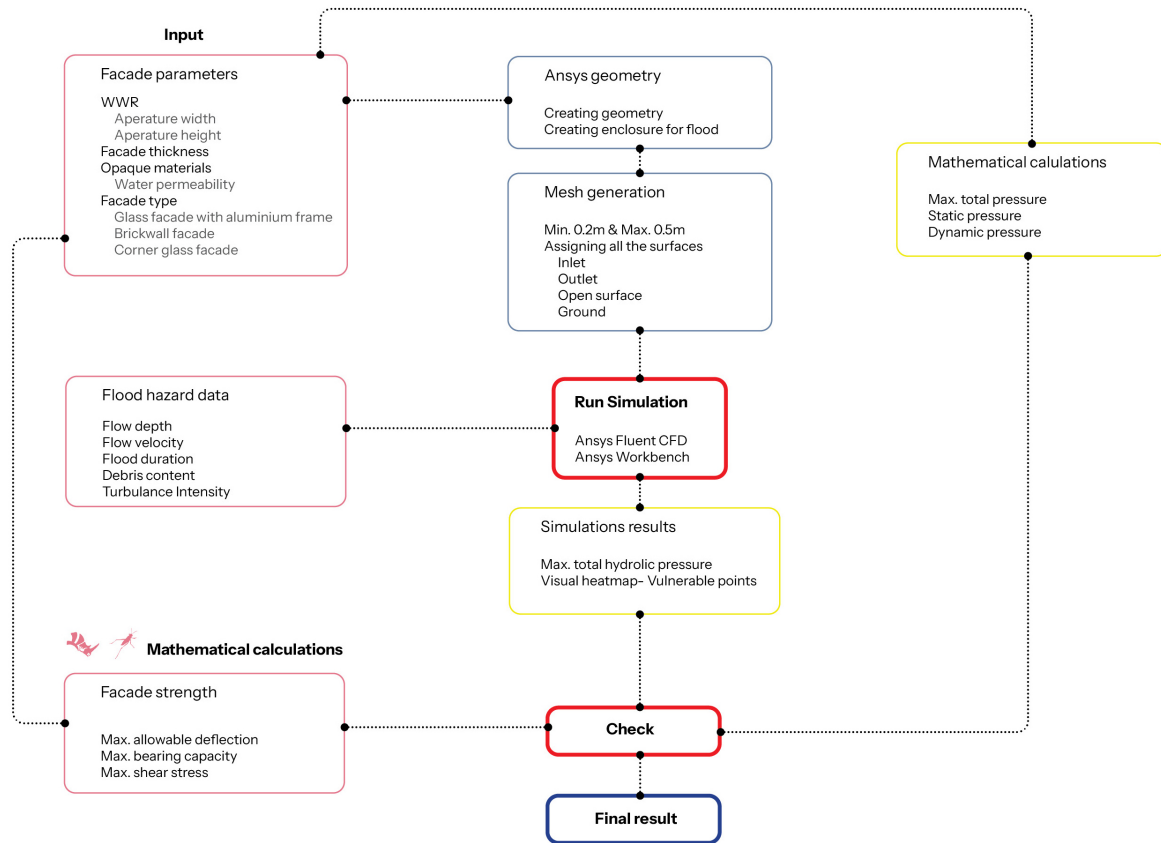


Figure 4.7: Graphical representation of floods computational simulation (Source: Author)

4.2.4. Mathematical calculations for flood impact

The primary objective of calculating the hydraulic pressure distribution using mathematical formulas is to verify the results obtained from CFD (Computational Fluid Dynamics) simulations. Additionally, this approach facilitates the calculation of outputs for 163,840 scenarios, which is infeasible through computational simulations alone. This research focuses on determining the static and dynamic hydraulic pressure distributions, the total force on the building envelope, and the maximum bending moment induced by hydraulic pressure.

The hydraulic static pressure at a depth h below the surface of a fluid is given by the equation:

$$P_{\text{static}} = \rho gh$$

Dynamic pressure is given by:

$$P_{\text{dynamic}} = \frac{1}{2} \rho v^2$$

Where:

- P_{static} is the pressure at depth h .
- ρ is the density of the fluid.
- g is the acceleration due to gravity.
- h is the depth of the fluid.
- P_{dynamic} is the dynamic pressure.
- v is the fluid velocity.

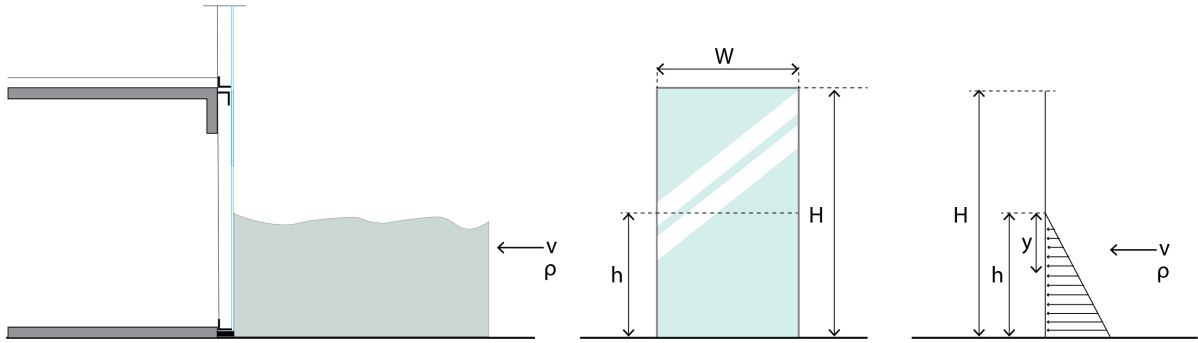


Figure 4.8: Graphical representation of hydraulic pressure on facade (Source: Author)

The total pressure in a fluid flow, combining static pressure and dynamic pressure, is given by:

$$P_{\text{total}} = P_{\text{static}} + P_{\text{dynamic}}$$

Therefore, the equation can also be written as:

$$P_{\text{total}} = \rho gh + \frac{1}{2} \rho v^2$$

Consider a horizontal strip of the facade at depth y with thickness dy . The force dF on this strip is:

$$dF = P(y) \cdot dy = \left(\rho gy + \frac{1}{2} \rho v^2 \right) \cdot dy \quad (4.1)$$

Total force:

To find the total force, integrate this expression from $y = 0$ (the base) to $y = h$ (the top of the water level) and W is the span of the facade:

$$F = \int_0^h \left(\rho gy + \frac{1}{2} \rho v^2 \right) W dy \quad (4.2)$$

Evaluating this integral:

$$F = \int_0^h (\rho gy) W dy + \int_0^h \left(\frac{1}{2} \rho v^2 \right) W dy \quad (4.3)$$

$$F = \rho g W \int_0^h y dy + \frac{1}{2} \rho v^2 W \int_0^h 1 dy \quad (4.4)$$

Now, combining the results:

$$F = \rho g W \left(\frac{h^2}{2} \right) + \frac{1}{2} \rho v^2 W (h) \quad (4.5)$$

Simplifying the expression:

$$F = \rho g W \frac{h^2}{2} + \frac{1}{2} \rho v^2 W h \quad (4.6)$$

$$F = \frac{1}{2} \rho g W h^2 + \frac{1}{2} \rho v^2 W h \quad (4.7)$$

So, the total force including both the hydrostatic and dynamic pressures is:

$$F_{\text{total}} = \frac{1}{2} \rho W h (gh + v^2) \quad (4.8)$$

This expression accounts for both the hydrostatic pressure due to the fluid's weight and the dynamic pressure due to its velocity.

So, the hydrostatic force is:

$$F_{\text{static}} = \frac{1}{2} \rho W g h^2 \quad (4.9)$$

and dynamic force is: W

$$F_{\text{dynamic}} = \frac{1}{2} \rho W v^2 h \quad (4.10)$$

Maximum Applied Bending Moment:

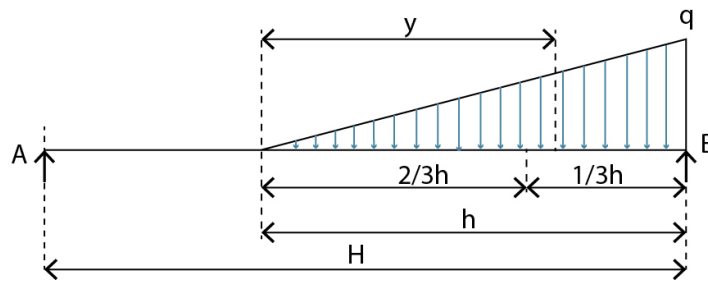


Figure 4.9: Graphical representation of non-uniformly distributed load on facade (Source: Author)

Where:

- q is the distributed load per unit length.
- H is the facade length.
- h is the flow depth.
- R_a is the reaction force at point A.
- R_b is the reaction force at point B.
- y is the length to max. bending moment point.

Dividing F_{total} by the span W of the glass facade will give us the distributed load q .

$$q = \frac{F_{\text{total}}}{W} \quad (4.11)$$

Total load:

$$R_a + R_b = \frac{1}{2} q h \quad (4.12)$$

At A moment is zero

$$\sum M_a = 0 \quad (4.13)$$

$$-\frac{1}{2}qh \left(H - \frac{h}{3} \right) + R_b L = 0 \quad (4.14)$$

Reaction force:

$$R_b = \frac{qh}{2H} \left(L - \frac{h}{3} \right) \quad (4.15)$$

$$R_a = \frac{qh^2}{6H} \quad (4.16)$$

Moment at y

$$-\frac{qh^2}{6H} (y + H - h) + \frac{1}{2} \left(\frac{qy^3}{3h} \right) + M = 0 \quad (4.17)$$

$$M = \frac{qy^3}{6h} - \frac{qh^2}{6H} (y + H - h) \quad (4.18)$$

Max. bending moment at $y = \frac{h}{\sqrt{3}}$:

$$M_{\max} = \frac{qh^2}{6} \left(0.42 \frac{h}{H} - 0.808 \right) \quad (4.19)$$

Allowable bending moment of the facade

$$\sigma = \frac{M_{\text{allowable}} \times y}{I} \quad (4.20)$$

Where:

σ is the bending stress.

M is the allowable bending moment to the member.

I is the moment of inertia of the member's cross-sectional area.

y is the distance from the neutral axis to the outermost fiber (often called the "extreme fiber" or "farthest fiber").

In order to calculate the resilience, both M_{\max} and $M_{\text{allowable}}$ were compared.

After taking into account the presence of debris within the water flow, it becomes evident that the floodwater, containing debris, flows in multiple layers, with a significant concentration of debris in the upper layers. As a result, the density of this upper layer exceeds that of layers devoid of debris. Additionally, the upper layer of water exhibits a higher velocity compared to the lower layer. Furthermore, variations in density across different layers are observed due to the accumulation of debris and sediment within the water column. This phenomenon is depicted in Figure 4.10.

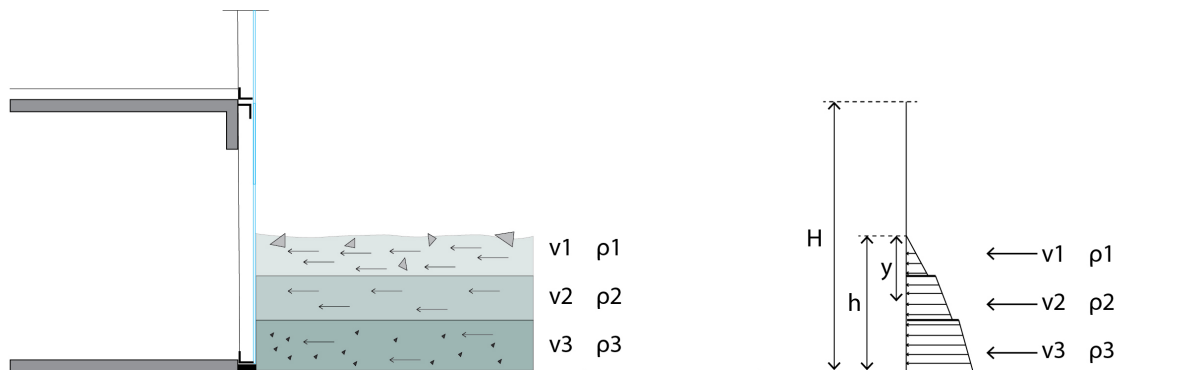


Figure 4.10: Graphical representation of different density and velocity flood (Source: Author)

The total force F exerted on the facade is the sum of the forces over these intervals:

$$\begin{aligned}
 F = & \rho_1 g W \int_0^{h_1} y \, dy + \frac{1}{2} \rho_1 v_1^2 W \int_0^{h_1} dy \\
 & + \rho_2 g W \int_{h_1}^{h_2} y \, dy + \frac{1}{2} \rho_2 v_2^2 W \int_{h_1}^{h_2} dy \\
 & + \rho_3 g W \int_{h_2}^{h_3} y \, dy + \frac{1}{2} \rho_3 v_3^2 W \int_{h_2}^{h_3} dy
 \end{aligned} \tag{4.21}$$

Where:

- ρ_1, ρ_2, ρ_3 are the densities for 1st, 2nd and 3rd layer respectively.
- v_1, v_2, v_3 are the velocities for 1st, 2nd and 3rd layer respectively.
- W is the width of the facade.
- h_1, h_2, h_3 are the depths for 1st, 2nd and 3rd layer respectively (refer Figure 4.10).

Integrating each term separately:

$$\begin{aligned}
 F = & \rho_1 g W \left(\frac{1}{2} h_1^2 + \frac{1}{2} v_1^2 h_1 \right) \\
 & + \rho_2 g W \left(\frac{1}{2} (h_2^2 - h_1^2) + \frac{1}{2} v_2^2 (h_2 - h_1) \right) \\
 & + \rho_3 g W \left(\frac{1}{2} (h_3^2 - h_2^2) + \frac{1}{2} v_3^2 (h_3 - h_2) \right)
 \end{aligned} \tag{4.22}$$

Finally, simplifying each integral:

$$\begin{aligned}
 F = & \rho_1 g W \left(\frac{1}{2} h_1^2 + \frac{1}{2} v_1^2 h_1 \right) \\
 & + \rho_2 g W \left(\frac{1}{2} (h_2^2 - h_1^2) + \frac{1}{2} v_2^2 (h_2 - h_1) \right) \\
 & + \rho_3 g W \left(\frac{1}{2} (h_3^2 - h_2^2) + \frac{1}{2} v_3^2 (h_3 - h_2) \right)
 \end{aligned} \tag{4.23}$$

Utilizing this mathematical approach, the output parameters comprising the total hydraulic pressure and the applied bending moment are delineated across 163,840 scenarios. These outputs serve as foundational data for the development and analysis of machine learning models, as well as for conducting sensitivity analyses.

4.3. Machine learning model for Floods

The primary objective of this study is to develop a machine learning model capable of predicting output values from input variables, thereby generating a large dataset. This extensive dataset will facilitate sensitivity analysis, enhancing the accuracy of the results. In the context of flood resilience quantification, this thesis investigates the efficacy of two prominent regression models: an Artificial Neural Network (ANN) and a Random Forest Regressor. The purpose of this investigation is to compare these regression models and assess their performance using a specified dataset.

4.3.1. Artificial Neural Network (ANN) Regression Model

As explained in Section 3.3.1 Artificial Neural Networks (ANNs) are a subset of machine learning algorithms modeled after the human brain. They consist of layers of interconnected nodes (neurons) that can learn complex patterns in data. An Artificial Neural Network (ANN) typically comprises three main layers: the input layer, one or more hidden layers, and the output layer (see Figure 4.11). The input layer is comprised of neurons, each representing an input feature. For instance, if there are 4 input features, the input layer will consist of 4 neurons, each corresponding to one feature. The hidden layers perform the majority of computations within the network. Neurons in these layers compute a weighted sum of inputs, add a bias term, and then pass the result through an activation function, such as ReLU (Rectified Linear Unit). The ReLU function introduces non-linearity into the model, enabling it to learn complex

patterns from the data. Finally, in regression tasks, the output layer typically contains one neuron that outputs a continuous value. Here, the activation function is often linear since the objective is to predict a range of values rather than discrete categories.

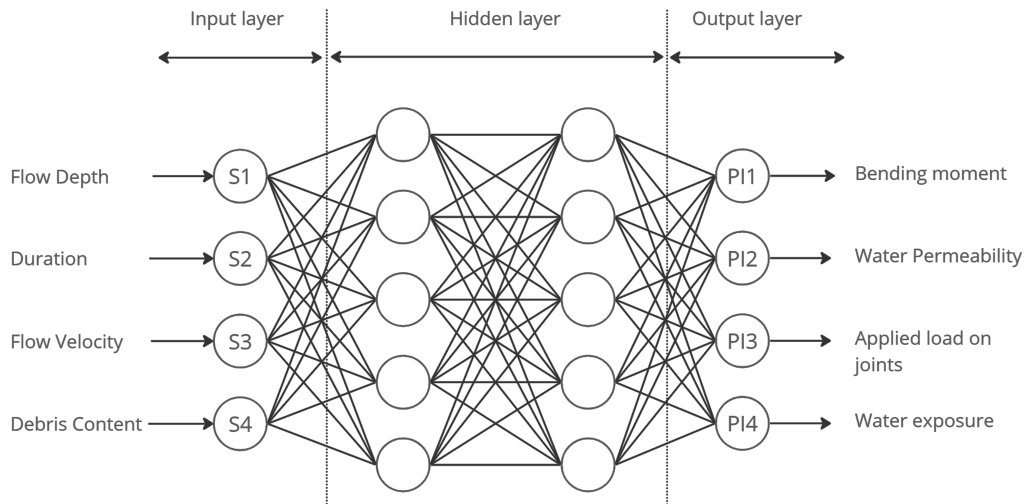


Figure 4.11: Graphical representation of Artificial Neural Network model in flood simulation workflow (Source: Author)

Data Preparation

Separating Input and Output Values

```
X = data.iloc[:, :7].values
y = data.iloc[:, 7:8].values
```

Splitting the Data

```
train_test_split(X, y, test_size=0.2, random_state=42)
```

Standardizing the Data

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Model Building

Model Architecture

```
model = Sequential()
model.add(Dense(64, input_dim=7, activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(1, activation='linear'))
```

Compiling the Model

```
model.compile(optimizer='adam', loss='mean_squared_error')
```

Model Training and Evaluation

Training

```
history = model.fit(X_train_scaled, y_train, epochs=10, batch_size=10,
                    validation_split=0.2)
```

Prediction and Inverse Transformation

```
y_pred = model.predict(X_test_scaled)
y_pred_inverse = scaler_y.inverse_transform(y_pred)
```

Performance Metrics

```
r2 = r2_score(y_test, y_pred)
accuracy_percentage = r2 * 100
plt.scatter(y_test, y_pred)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()])
```

The Figure 4.12 compares the predicted values with the actual values. It includes an ideal line where predictions would perfectly match the actual values. Most of the values lie close to this line, indicating a prediction accuracy of almost 100%.

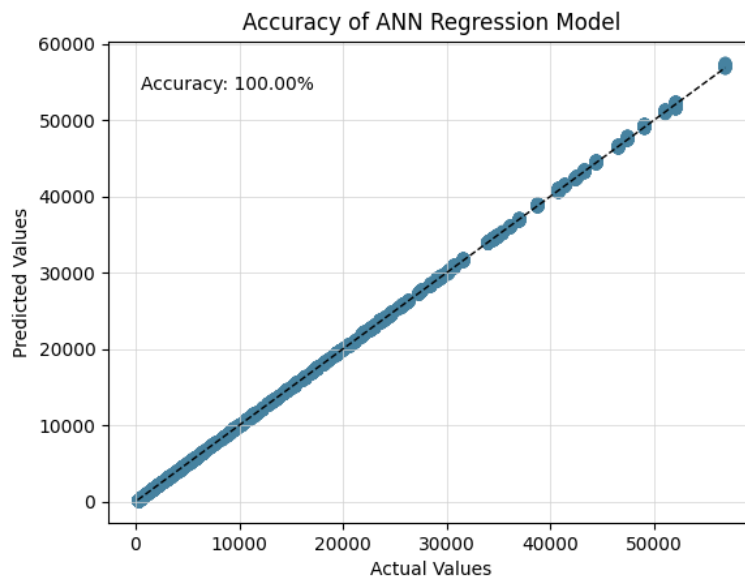


Figure 4.12: Graphical representation of accuracy of ANN model (Source: Author)

Loss Visualization

```
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
```

Loss visualization is an essential aspect of training machine learning models, providing insights into their performance and convergence. In the context of neural network training, loss refers to the discrepancy between the predicted output and the actual target values. By monitoring the loss over epochs, we can assess how well the model is learning from the data and whether it is overfitting or underfitting. A Figure 4.13 depicting the decrease in both

training and validation loss as epochs progress serves as a visual confirmation of the model's improving accuracy and generalization.

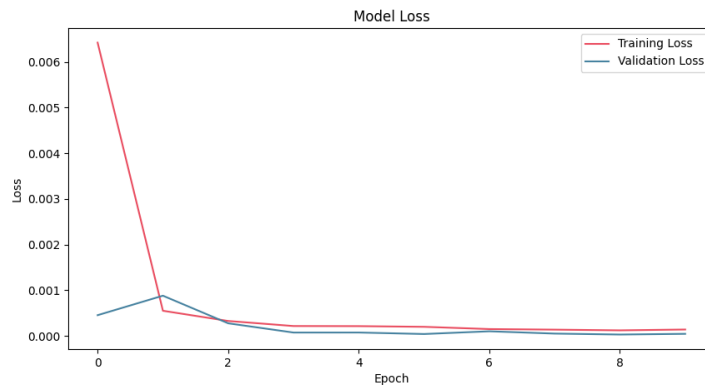


Figure 4.13: Graphical representation of loss visualization in ANN model (Source: Author)

4.3.2. Random forest regression model

As mentioned in Section 3.3.2 Random Forest is an ensemble learning method that combines multiple decision trees to improve the accuracy and robustness of predictions. It is particularly useful for both classification and regression tasks. In the context of regression, the model predicts a continuous value by averaging the outputs of individual decision trees.

Data Preparation

Separating Input and Output Values

```
X = data.iloc[:, :7]
y = data.iloc[:, 7:]
```

Splitting the Data

```
train_test_split(X, y, test_size=0.2, random_state=42)
```

Model Training and Evaluation

Initialize the Random Forest regressor and train the model on the training data.

```
regressor = RandomForestRegressor()
regressor.fit(X_train, y_train)
```

Predicts target values for the test set.

```
y_pred = regressor.predict(X_test)
```

Calculate mean absolute error (MAE), prediction accuracy, mean squared error (MSE), root mean squared error (RMSE), and compute the R-squared score.

```
mae = mean_absolute_error(y_test, y_pred)
accuracy = round((1 - mae) * 100, 1)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)
```

Create a scatter plot of actual versus predicted values, with an ideal line indicating perfect predictions.

```
plt.scatter(y_test, y_pred)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()])
```

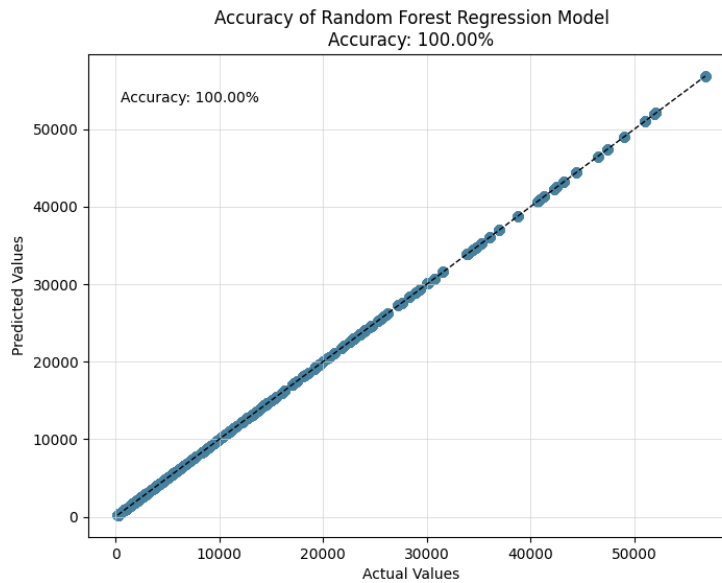


Figure 4.14: Graphical representation of accuracy of Random Forest regression model (Source: Author)

4.3.3. Comparison of all machine learning models

Table 4.5: Table presenting performance Comparison of Machine Learning Models (Source: Author)

Metric	ANN	Random Forest
Mean Squared Error (MSE)	17.56	0.86
Root Mean Squared Error (RMSE)	41.91	2.39
R-squared (R^2)	0.99	1.0
Accuracy Percentage	99.99%	100%

Based on the Table 4.5, both models provide 100% accuracy in predicting the output. However, the Random Forest Regression Model outperforms the other models across all available performance indicators:

- It has the lowest MSE and RMSE.
- It has the highest R^2 value, indicating the best fit to the data.
- It has the highest accuracy percentage.

4.4. Sensitivity analysis for floods

As discussed in Section 3.4, sensitivity analysis provides information on how changes in input variables impact the output. In the context of quantifying facade resilience against floods, the input variables include facade parameters and hazard stressors. Conducting this analysis helps identify which input parameter has a greater impact on the output. This assists facade designers in prioritizing influential variables when designing the building envelope. This research explores correlation matrix and Sobol's method for sensitivity analysis.

4.4.1. Correlation matrix analysis

To identify the relationship between each input parameter and the output value, a correlation matrix was employed. The results of this analysis indicate that flood stressors exert a more substantial impact on the output values than

facade parameters. As illustrated in Figure 4.15, facade parameters significantly influence the allowable bending moment of the facade, which is a logical outcome. However, when compared to flood stressors, all facade parameters exhibit a lesser degree of influence on the bending moment resulting from hydraulic pressure. Consequently, based on these influential parameters, facade designers can prioritize specific facade metrics to enhance the allowable bending capacity of the facade.

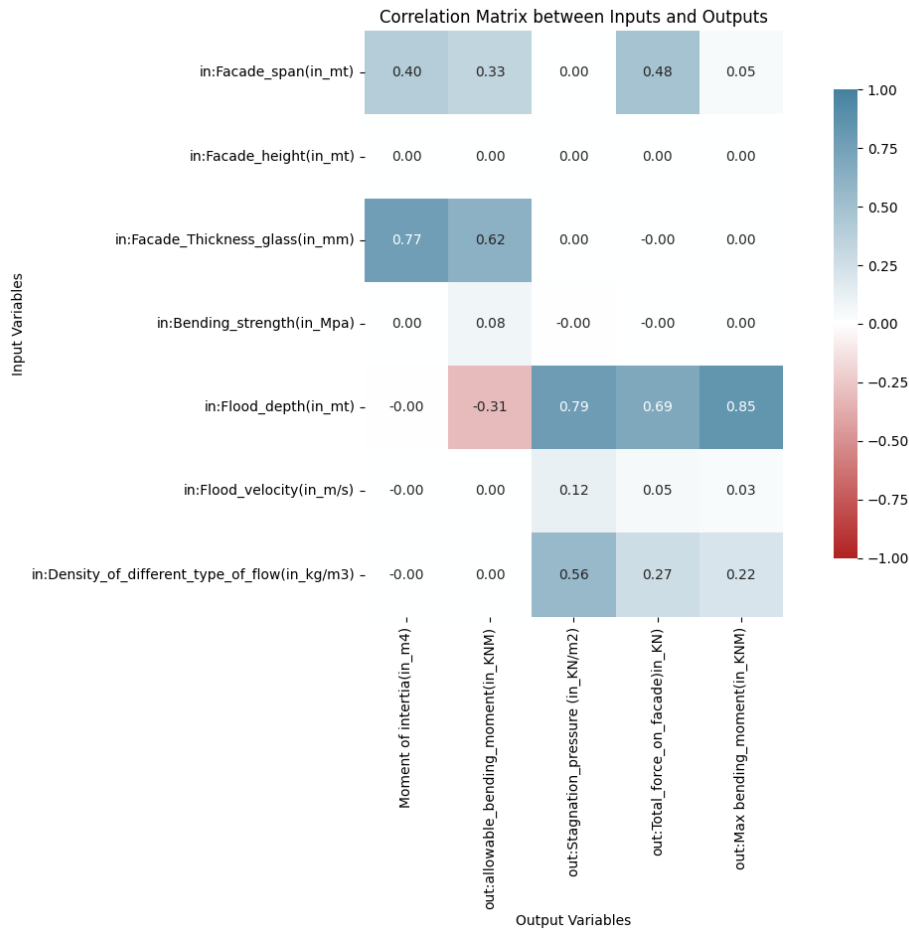


Figure 4.15: Graphical representation of correlation matrix with 7 input variables (Source: Author)

4.4.2. Variance based method- Sobol method

In this section, the Sobol method is employed to rank the input variables based on their influence on the outputs and to determine the interaction effects on output values. For flood resilience quantification, the same approach used for thermal resilience quantification in sensitivity analysis is applied. However, in this case, there are three output values defined through a mathematical model (refer to Section 4.2.4). Due to the mathematical approach, a large number of scenarios are possible for sensitivity analysis. Given that the dataset for flood resilience quantification has three outputs, three separate sensitivity analyses were conducted with all input variables.

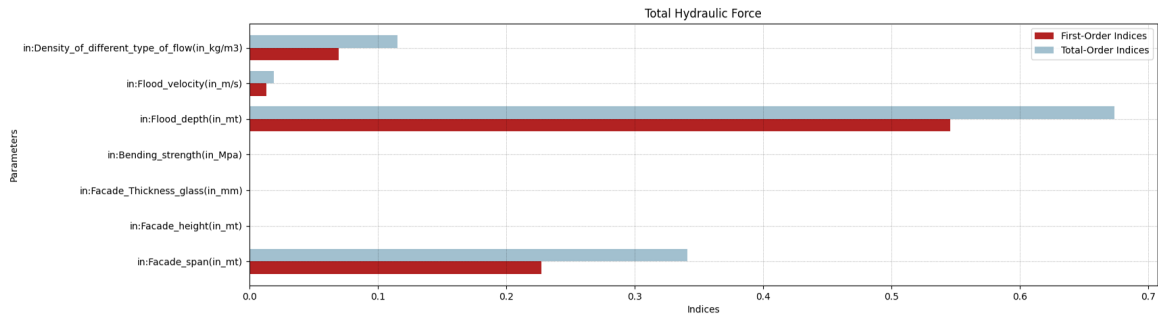


Figure 4.16: Graphical representation of sensitivity analysis on total hydraulic pressure (Source: Author)

The Figure 4.16 illustrates that the impact of flood depth emerges as paramount, followed sequentially by facade span, flow density, and flood velocity, on the overall hydraulic force acting upon the facade.

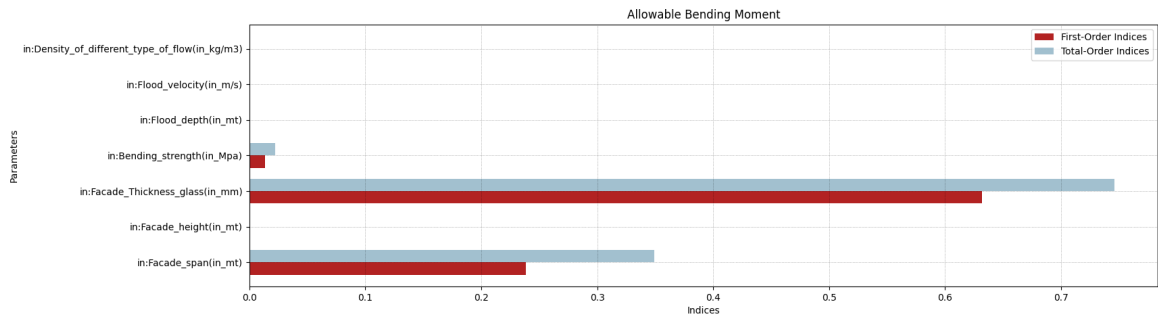


Figure 4.17: Graphical representation of sensitivity analysis on allowable bending moment (Source: Author)

The Figure 4.17 highlights that the thickness of the facade stands out as the primary influencer on the allowable bending moment capacity, with facade span ranking second, and the bending strength of the facade occupying the third position in terms of impact.

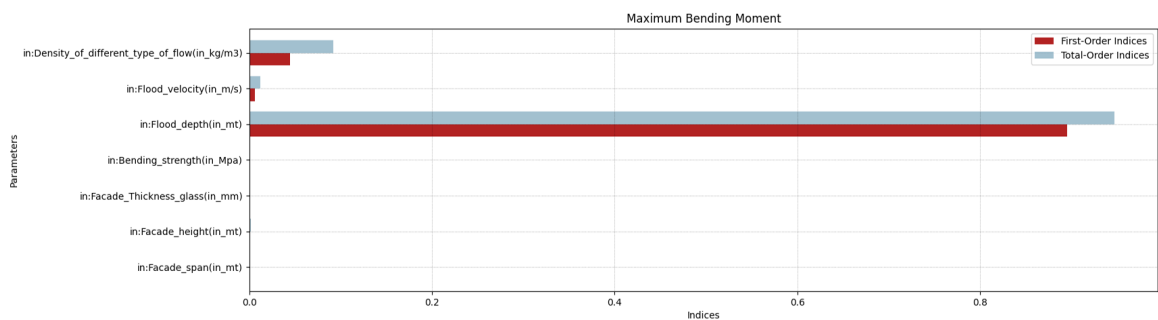


Figure 4.18: Graphical representation of sensitivity analysis on maximum applied bending moment (Source: Author)

The Figure 4.18 depicts that flood depth exerts the most notable influence on the maximum bending moment experienced, with density of the flow following closely behind, and flood velocity trailing as the third most influential factor.

How the Sobol Method is Used for Sensitivity Analysis

Python programming language is used for sensitivity analysis. Below is an explanation of the code used for performing sensitivity analysis using the Sobol method:

Defining function to calculate all three output values

```
def calculate_outputs(rho, sigma, W, h, v, H, t):
    # Constants
    g = 9.81 # acceleration due to gravity (m/s2)
    # Calculate Total Pressure (F)
    F = 0.5 * rho * W * g * h**2 + 0.5 * rho * W * v**2 * h
    # Calculate q (load per unit width)
    q = F / W
    # Calculate y (distance from neutral axis to extreme fiber)
    y = t / 2
    # Calculate moment of inertia (I)
    I = (W * t**3) / 12
    # Calculate allowable Bending Moment (BM)
    allowable_BM = sigma * I / y
    # Calculate Maximum Bending Moment (Max BM)
    max_BM = (q * h**2 / 6) * ((0.42 * h / H) - 0.808)
    return F, allowable_BM, max_BM
```

Mathematical formula for all output values

$g = 9.81 \text{ m/s}^2$ (acceleration due to gravity)

Total Pressure (F):

$$F_{\text{total}} = \frac{1}{2} \rho W h (gh + v^2) \quad (4.24)$$

Load per unit width (q):

$$q = \frac{F_{\text{total}}}{W} \quad (4.25)$$

Distance from neutral axis to extreme fiber (y):

$$y = \frac{t}{2} \quad (4.26)$$

Moment of inertia (I):

$$I = \frac{W \cdot t^3}{12} \quad (4.27)$$

Allowable Bending Moment (allowable_BM):

$$M_{\text{allowable}} = \frac{\sigma \cdot I}{y} \quad (4.28)$$

Maximum Bending Moment (max_BM):

$$M_{\text{max}} = \frac{qh^2}{6} \left(0.42 \frac{h}{H} - 0.808 \right) \quad (4.29)$$

Defining the Problem for Sensitivity Analysis

```
problem = {
    'num_vars': X.shape[1],
    'names': ['in:Facade_span(in_mt)', 'in:Facade_height(in_mt)',
              'in:Facade_Thickness_glass(in_mm)', 'in:Bending_strength(in_Mpa)',
              'in:Flood_depth(in_mt)', 'in:Flood_velocity(in_m/s)',
              'in:Density_of_different_type_of_flow(in_kg/m3)'],
    'bounds': [(inputs.iloc[:, i].min(), inputs.iloc[:, i].max()) for i in
                range(inputs.shape[1])],
    'dists': ['unif', 'unif', 'unif', 'unif', 'unif', 'unif', 'unif']
}
```

num_vars: Specifies the number of variables, taken from the number of columns in the dataset.

names: Lists the names of the input variables.

bounds: Defines the range of each variable, using the minimum and maximum values from the inputs DataFrame.

dists: Specifies the distribution of each variable; here, all variables are uniformly distributed.

Sampling Parameter Values Using Saltelli's Method

```
param_values = saltelli.sample(problem, 8192)
```

saltelli.sample: The Saltelli sampling method generates samples for the input variables. It produces $N \times (2D+2)$ samples, where N is 8192 and D is 7 (the number of model inputs), resulting in 131072 samples.

Evaluate the model with the adjusted sample size

```
Y = np.array([calculate_outputs(params[6], params[3], params[0], params[4],
                               params[5], params[1], params[2]) for params in param_values])
```

function: This function uses the mathematical model for the generated sample input values `param_values`.

Perform sensitivity analysis for each output separately using Sobol indices

```
output_titles = ["Total Hydraulic Force", "Allowable Bending Moment",
                 "Maximum Bending Moment"]
for i in range(Y.shape[1]):
    Si = sobol.analyze(problem, Y[:, i], print_to_console=False)
    first_order_indices = Si['S1']
    total_order_indices = Si['ST']
    print(output_titles[i])
    print("First-Order Indices:", first_order_indices)
    print("Total-Order Indices:", total_order_indices)
```

Sobol analysis: This function calculates Sobol sensitivity indices based on the problem definition and the model predictions (\mathbf{Y}). These indices measure the effect of each input variable on the output variance.

4.5. Resilience matrix for floods

Defining a resilience matrix for assessing facade resilience against floods involves a systematic approach aimed at evaluating and enhancing the ability of facade elements to withstand flood events. This process begins by establishing objectives, which include minimizing flood damage, ensuring structural integrity, and maintaining functionality during and after floods. A comprehensive risk assessment is then conducted, simulating different intensities of flood events on various facade types using Ansys Fluent and mathematical models (refer to Section 4.2.4).

The key outputs are defined from this assessment. The first output is the maximum applied bending moment, indicating the maximum bending moment that a particular flood event can exert on the building envelope. The second output is the allowable bending moment capacity of the facade, determined through mathematical analysis. Using these two outputs, the flood resilience matrix is constructed.

In Figure 4.19, both output values (applied bending moment and allowable bending moment) are plotted on a graph. The x-axis represents time, the left y-axis represents the bending moment, and the right y-axis represents the flood height. The allowable bending capacity is depicted as a straight line, indicating the bending moment limit. As the flood height increases, the applied bending moment also rises and can reach this allowable limit, at which point the facade is no longer considered resilient. The area difference between these two functions (outputs) represents the resilience loss of the facade, with a larger area indicating low resilience.

This resilience matrix enables an analysis to identify areas of strength and weakness, informing the prioritization of mitigation measures and improvements. Overall, the resilience matrix provides a structured framework for enhancing facade resilience against floods, thereby contributing to the overall resilience of buildings and communities to natural hazards.

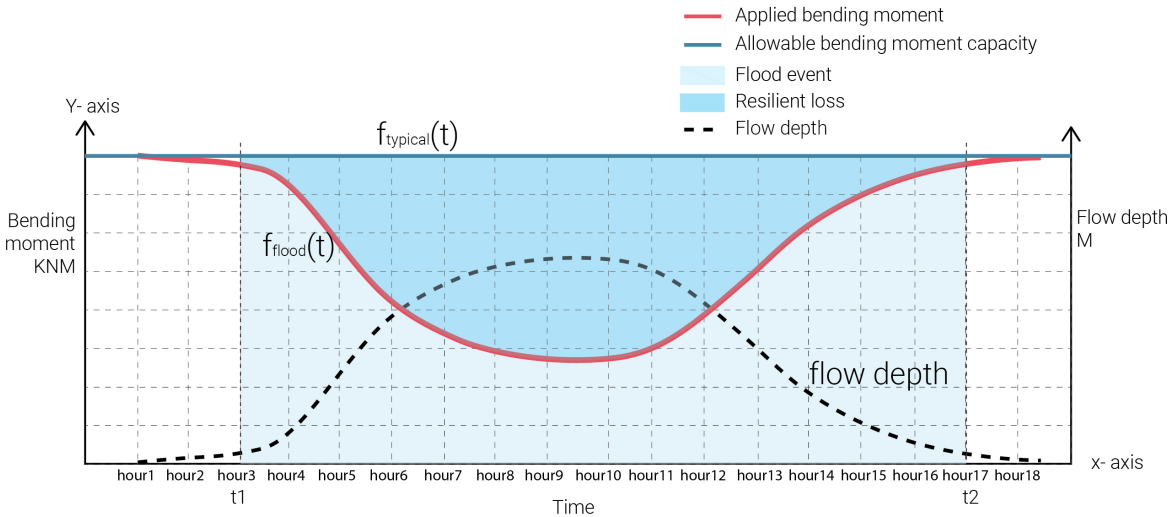


Figure 4.19: Graphical representation of quantification of flood resilience (Source: Author)

The resilience loss can be expressed as:

$$\text{Resilience loss} = \int_{t_1}^{t_2} (f_{\text{typical}}(t) - f_{\text{flood}}(t)) dt$$

Overall flood resilience matrix workflow

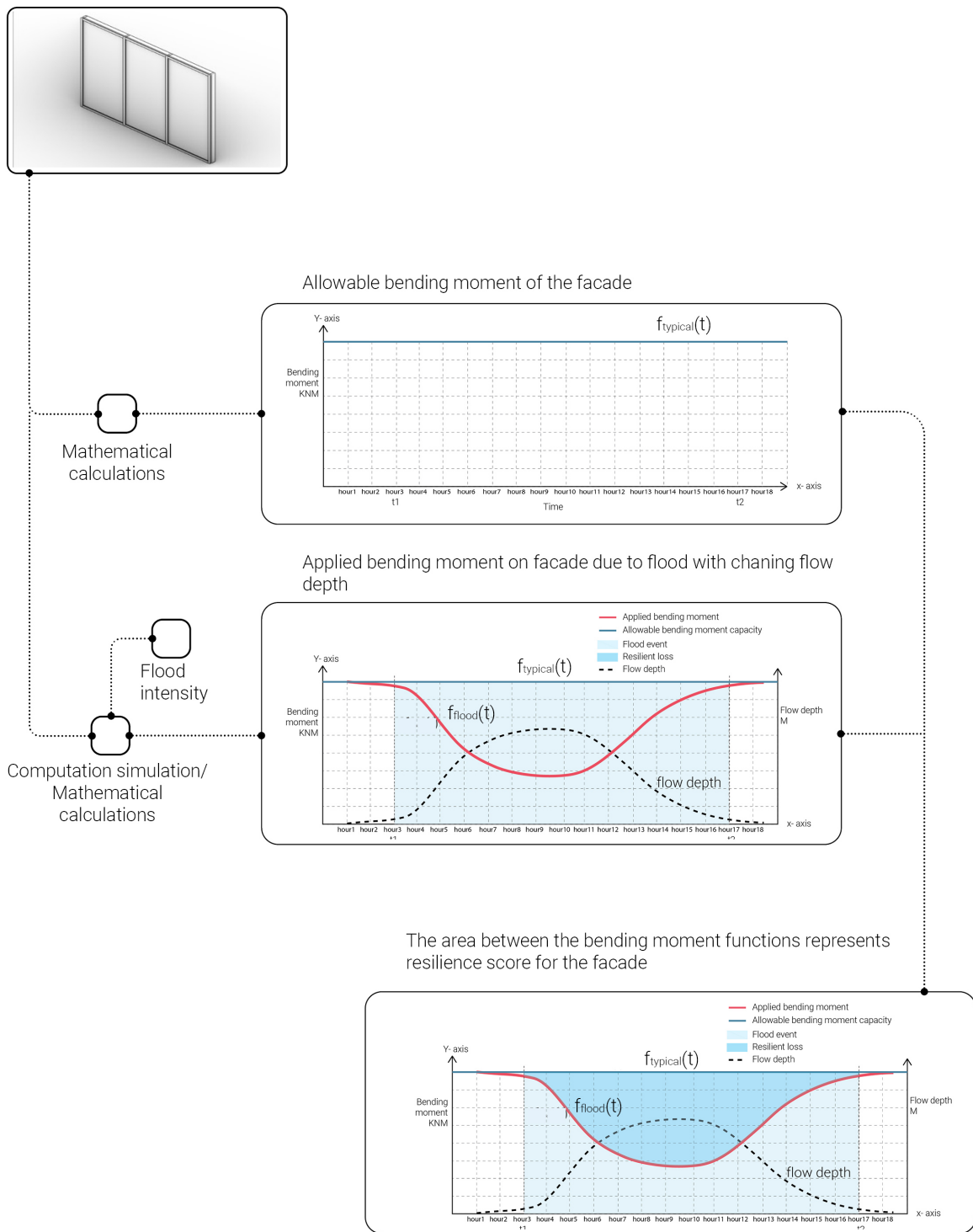


Figure 4.20: Graphical representation of flood resilience matrix workflow (Source: Author)

5

Multi-hazard resilience model

5.1. Multi-hazard resilience model

Adopting a multi-hazard strategy is essential in building design in order to address the diverse array of disruptive events that buildings may encounter. In contemporary urban environments, cities often face multiple types of disruptive events. Consequently, focusing on a single hazard and designing a structure to be resilient to only that specific hazard is insufficient.

The increasing frequency and severity of natural hazards such as floods, along with climate change-induced events like heatwaves, highlight the necessity of multi-hazard resilience quantification. This approach requires considering all potential disasters that could occur in a location, whether simultaneously or sequentially. Designers need to evaluate the impacts of different hazards and develop designs that account for these diverse impacts.

5.1.1. Multi-hazard resilience model for facade system

Designing building facades to withstand a variety of hazards is critical in order to provide comprehensive protection and adaptability in the face of diverse disruptive events. By considering a range of potential threats while design a facade, including natural disasters and human-made hazards, it can enhance safety of occupants, assets, and infrastructure. As climate change is contributing to an increased frequency and severity of extreme weather occurrences, buildings need to be designed in a way that can withstand extreme temperatures, high winds, heavy precipitation, and other environmental challenges. Investing in multi-hazard resilience facade design can be more cost-effective in the long run, minimizing the need for costly retrofits or repairs following a disaster. Furthermore, resilient facades contribute to overall sustainability by reducing the environmental impact of disasters and ensuring continuity of essential services and functions during and after emergencies. In essence, designing for multi-hazard resilience is essential for protecting lives, property, and the environment while promoting sustainability and maintaining functionality in the face of diverse threats. The principle of facade resilience emphasizes the importance of building designs that anticipate future uncertainties, meaning they should not be limited to specific weather conditions but should be adaptable to various circumstances (Patterson et al., 2017).

Given the contradictory nature of floods and heatwaves, this study assumes that these events will not occur concurrently. Nevertheless, it focuses on quantifying both thermal and flood resilience for a facade system within separate frameworks. Although these events can happen at different times, they can have severe impacts on facades, necessitating resilience in both scenarios.

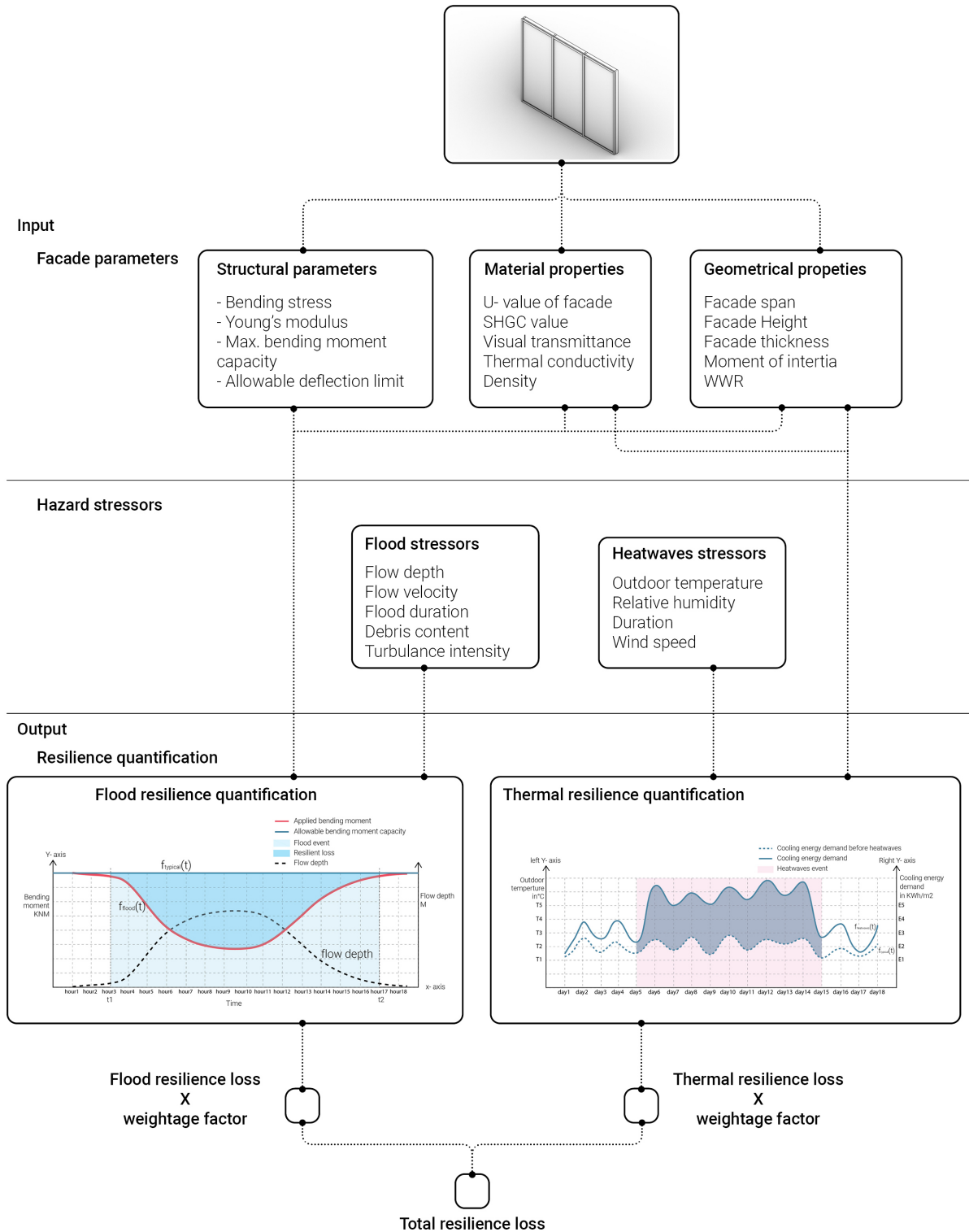


Figure 5.1: Graphical representation of Multi-hazard facade resilience design framework (Source: Author)

Based on all input parameters, including structural characteristics, material properties, and geometrical attributes of the facade system, along with the intensity of hazard stressors such as floods and heatwaves, the resilience of the facade can be calculated (as shown in Figure 5.1). These assessment processes occur independently, as these hazards will not occur simultaneously.

To define a single resilience loss for the facade, the flood resilience loss and thermal resilience loss are multiplied

by their respective weightage factors and then summed. The weightage factor depends on various conditions. For example, if in a particular location the likelihood of heatwaves is higher than that of floods, then the weightage factor for thermal resilience will be greater. Additionally, the weightage factor depends on the building condition. If a building has one floor and is shaded by its surroundings, the severity of a flood may be greater than that of heatwaves, leading to a higher weightage factor for flood resilience. Conversely, if the facade is located on an upper floor where it is unaffected by floods, the weightage factor for heatwave resilience will be higher. Overall, the weightage factors depend on the building typology, facade location, building condition, and geographical context (refer Table 5.1).

Table 5.1: Table presenting resilience loss assessment for different facade types

Facade type	Heatwaves resilience loss	Flood resilience loss	Total resilience loss	Weightage factor
Facade 1	HR1	FR1	0.7HR1 + 0.3FR1	70% likelihood of heatwaves and 30% likelihood of floods
Facade 2	HR2	FR2	0.4HR2 + 0.6FR2	40% likelihood of heatwaves and 60% likelihood of floods
Facade 3	HR3	FR3	0.5HR3 + 0.5FR3	50% likelihood of heatwaves and 50% likelihood of floods

5.1.2. Total resilience for three types of facade : Casestudy

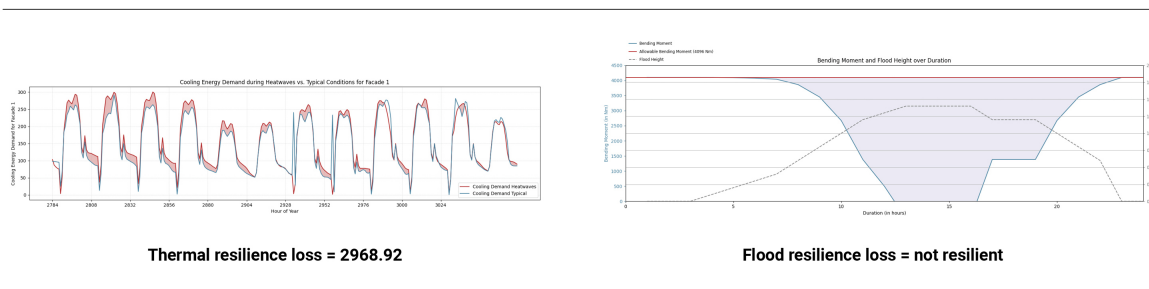
Facade 1 - Single glazed facade

Facade input parameters

Geometrical properties	Material properties	Structural parameters
- Facade span 3 m - Facade Height 3.5 m - Facade thickness 0.016m - Moment of inertia 0.000001024 m4 - WWR 75%	- U- value of facade 5.2 W/m2.K - SHGC value 0.9 - Visual transmittance 0.8 - Thermal conductivity 0.8 W/m.K	- Bending stress - Young's modulus 32 MPa - Max. bending moment capacity 72 GPa 9.216 KNm

Hazard intensity

Flood stressors	Heatwaves stressors
Flow depth 0 - 1.5m Flow velocity 2 m/s Flood duration 20 hours Debris content 1800 kg/m3	Outdoor temperature Chennai heatwaves Relative humidity 2021 weather data (EPW file) Duration Wind speed



Total resilience = 2968.92

According to the flood resilience graph, a single-glazed facade cannot withstand the intensity of the flood. Therefore, this facade system is resilient only against heatwaves.

Note: Total resilience score can not defined that facade is resilient for both the hazard.

Figure 5.2: Graphical representation of total resilience for single glazed facade (Source: Author)

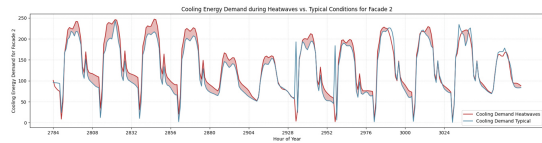
Facade 2 - Double glazed facade

Facade input parameters

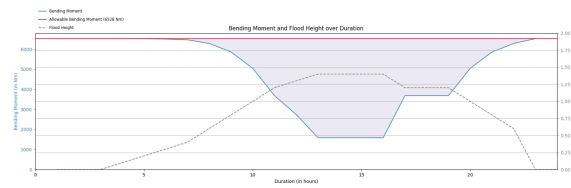
Geometrical properties	Material properties	Structural parameters
- Facade span 2 m	- U- value of facade 3.2 W/m ² .K	- Bending stress 34 MPa
- Facade Height 4.5 m	- SHGC value 0.5	- Young's modulus 72 GPa
- Facade thickness 0.024m	- Visual transmittance 0.5	- Max. bending moment 6.528 KNm
- Moment of inertia 0.000002304m ⁴	- Thermal conductivity 0.8 W/m.K	capacity
- WWR 75%		

Hazard intensity

Flood stressors	Heatwaves stressors
Flow depth 0 - 1.5m	Outdoor temperature Chennai heatwaves
Flow velocity 2 m/s	Relative humidity 2021 weather data
Flood duration 20 hours	Duration (EPW file)
Debris content 1800 kg/m ³	Wind speed



Thermal resilience loss = 2836.90



Flood resilience loss = 39764.70

Total resilience

Condition 1: If the facade is located on the ground floor and the building facade is shaded within its surrounding context, and if the likelihood of floods is higher than that of heatwaves, then the weightage factors for these hazards can be considered as 0.7 for floods and 0.3 for heatwaves.

$$\text{Total resilience} = 2836.90 \times 0.3 + 39764.70 \times 0.7 = 28685.87$$

Condition 3: If the facade is situated on an upper floor that is inaccessible during floods, then the weightage factor for heatwaves can be considered as 1.

$$\text{Total resilience} = 2836.90 \times 1 = 2836.90$$

Note: Total resilience score can not defined that facade is resilient for both the hazard.

Figure 5.3: Graphical representation of total resilience for double glazed facade (Source: Author)

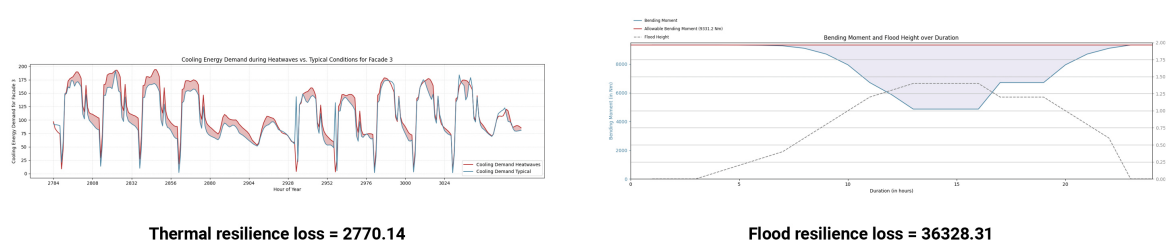
Facade 3 - Triple glazed facade

Facade input parameters

Geometrical properties	Material properties	Structural parameters
- Facade span: 1.2 m	- U-value of facade: 0.8 W/m ² .K	- Bending stress: 36 MPa
- Facade Height: 3 m	- SHGC value: 0.1	- Young's modulus: 72 GPa
- Facade thickness: 0.036m	- Visual transmittance: 0.1	- Max. bending moment: 9.331 KNm
- Moment of inertia: 0.0000466 m ⁴	- Thermal conductivity: 0.8 W/m.K	capacity
- WWR: 75%		

Hazard intensity

Flood stressors	Heatwaves stressors
Flow depth: 0 - 1.5m	Outdoor temperature: Chennai heatwaves
Flow velocity: 2 m/s	Relative humidity: 2021 weather data
Flood duration: 20 hours	Duration: (EPW file)
Debris content: 1800 kg/m ³	Wind speed



Thermal resilience loss = 2770.14

Flood resilience loss = 36328.31

Total resilience = 2770.14

Condition 1: If the likelihood of floods is lower than that of heatwaves, then the weightage factors for these hazards can be considered as 0.2 for floods and 0.8 for heatwaves.

$$\text{Total resilience} = 2770.14 \times 0.8 + 36328.31 \times 0.2 = 9481.77$$

Condition 3: If the facade is situated on an upper floor that is inaccessible during floods, then the weightage factor for heatwaves can be considered as 1.

$$\text{Total resilience} = 2770.14 \times 1 = 2770.14$$

Note: Total resilience score can not defined that facade is resilient for both the hazard.

Figure 5.4: Graphical representation of total resilience for triple glazed facade (Source: Author)

5.1.3. Comparison of resilience of different facade systems

In order to compare the resilience of different facade systems against floods and heatwaves, an optimal facade system must be defined. The optimal facade system exhibits low resilience loss while providing maximum functionality under both conditions. This study compares three facade systems with varying parameters, ranging from minimum to maximum values (as shown in Figure 5.2, 5.3, 5.4), to evaluate their flood and thermal resilience. The facade system that demonstrates the least resilience loss is identified as the optimal facade system. The resilience losses of the other two systems are then compared to this optimal facade system.

Table 5.2: Table presenting the comparison of different facade systems

Facade type	Cooling demand in KWh during heatwaves	Allowable bending moment in NM	Remark
Single glazed facade	44583.71	4096	
Double glazed facade	39039.04	6528	
Triple glazed facade	30131.33	9331.2	Optimal facade

Table 5.2 presents data on cooling energy demand during heatwaves and allowable bending moment capacity for

single, double, and triple glazed facade systems. Cooling energy demand were calculated for 12 days (As per Chennai heatwaves 2021 weather data). Using triple glazed facade system (refer input parameters from Figure 5.4) in building has lower cooling demand and higer allowable bending moment capacity (As illustrated in Table 5.2). Therefore, the triple glazed facade is identified as an optimal solution and its resilience loss is compared with other two facade for decision making process.

Thermal resilience comparison between facade systems

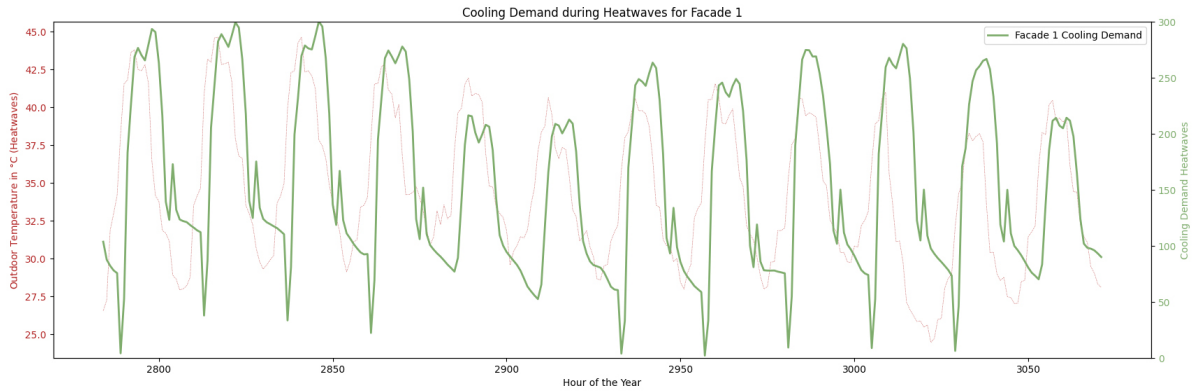


Figure 5.5: Graphical representation of Facade 1 outdoor temperature and cooling demand during heatwaves (Source: Author)

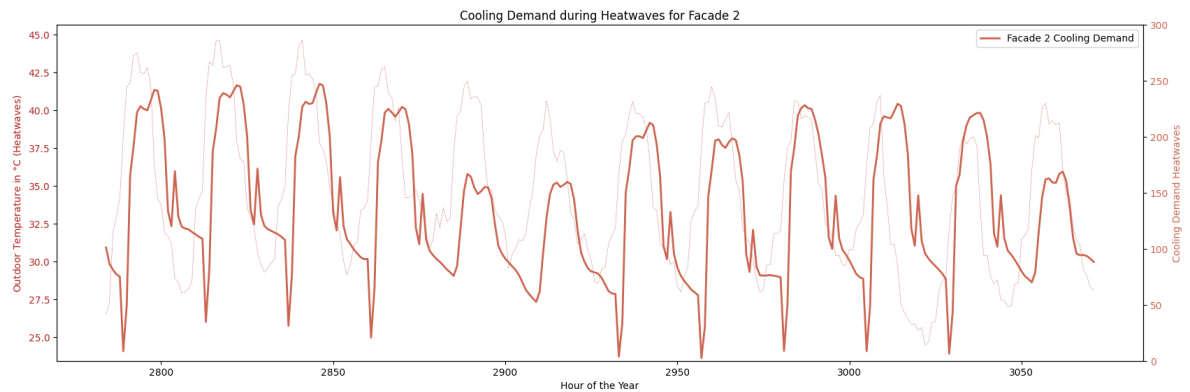


Figure 5.6: Graphical representation of Facade 2 outdoor temperature and cooling demand during heatwaves (Source: Author)

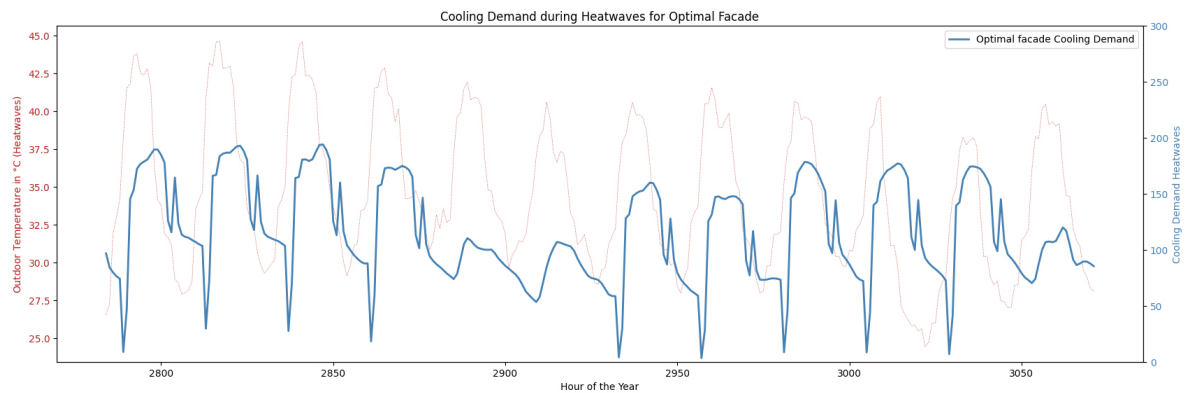


Figure 5.7: Graphical representation of Optimal facade outdoor temperature and cooling demand during heatwaves (Source: Author)

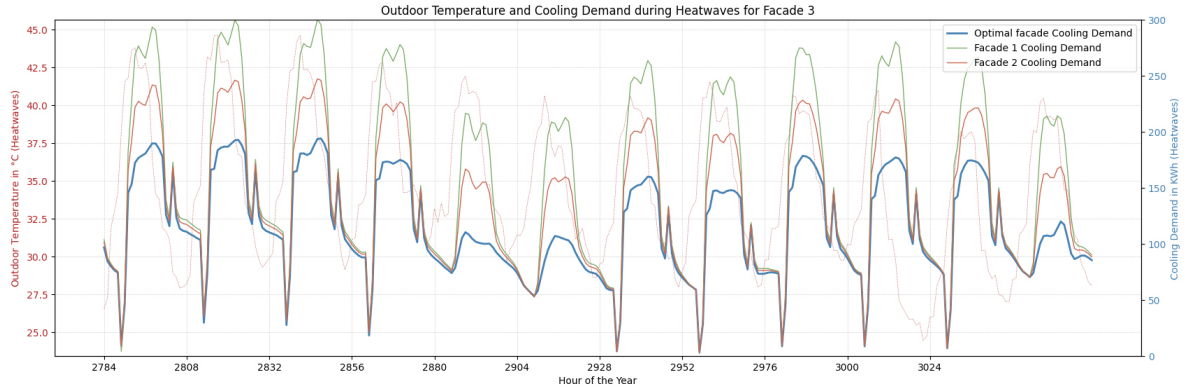


Figure 5.8: Graphical representation of All Facades outdoor temperature and cooling demand during heatwaves (Source: Author)

Resilience loss in the optimal facade scenario

$$\begin{aligned}
 \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{heatwaves}}(t) - f_{\text{typical}}(t)) dt \\
 &= 32901 - 30131 \\
 &= 2770
 \end{aligned}$$

Resilience loss in the single glazed facade scenario

$$\begin{aligned}
 \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{heatwaves}}(t) - f_{\text{typical}}(t)) dt \\
 &= 44583 - 30131 \\
 &= 14452
 \end{aligned}$$

Resilience loss in the double glazed facade scenario

$$\begin{aligned}
 \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{heatwaves}}(t) - f_{\text{typical}}(t)) dt \\
 &= 39039 - 30131 \\
 &= 8908
 \end{aligned}$$

Flood resilience comparison between facade systems

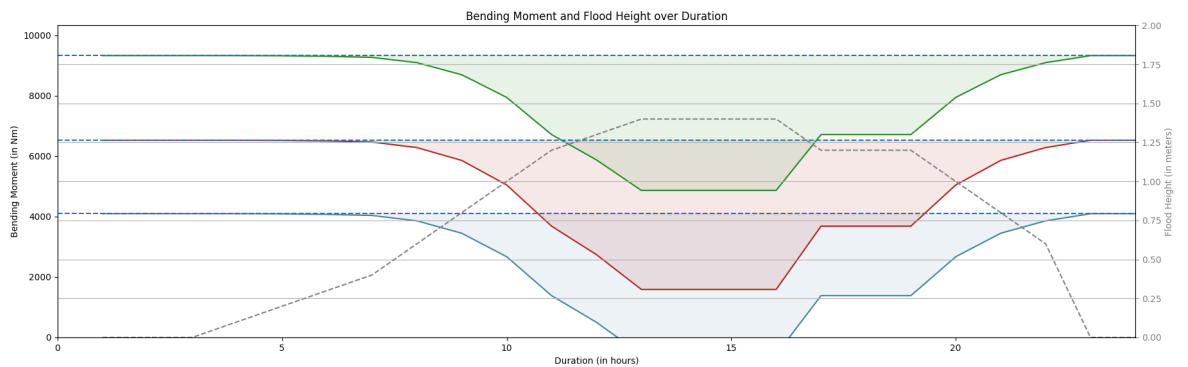


Figure 5.9: Graphical representation of All Facades flood height and bending moment during floods (Source: Author)

Resilience loss in the optimal facade scenario

$$\begin{aligned}
 \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{typical}}(t) - f_{\text{flood}}(t)) dt \\
 &= 167961.6 - 131633 \\
 &= 36328.4
 \end{aligned}$$

Resilience loss in the single glazed facade scenario

Resilience loss = Not resilient, as the applied bending moment exceeds the allowable limit

Resilience loss in the double glazed facade scenario

$$\begin{aligned}
 \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{typical}}(t) - f_{\text{floods}}(t)) dt \\
 &= 117504 - 77739 \\
 &= 39764.7
 \end{aligned}$$

Table 5.3: Table presenting total resilience loss for different facade types

Facade type	Heatwaves resilience loss (in %)	Flood resilience loss (in %)	Total resilience loss (in %)
Optimal facade	9.19 %	21.6 %	12.91 % (HR: FR = 0.7:0.3) 15.39 % (HR: FR = 0.5:0.5) 17.87 % (HR: FR = 0.3:0.7)
Single glazed facade	47.9 %	-	47.9 % (HR: FR = 1:0)
Double glazed facade	29.56 %	38 %	32.09 % (HR: FR = 0.7:0.3) 33.78 % (HR: FR = 0.5:0.5) 35.46 % (HR: FR = 0.3:0.7)

The Table 5.3 above illustrates the total resilience loss for all three facades based on their weighted values for heatwaves and flood occurrences. Designers can select the appropriate facade for different locations within the building to ensure maximum resilience.

5.1.4. Design suggestions from resilience quantification

After calculating the thermal and flood resilience, designers can enhance the resilience by making specific design decision:

For heatwaves resilience:

Use Horizontal and Vertical Shading Devices

Incorporating shading devices in building design significantly reduces cooling energy consumption by minimizing solar heat gain. These devices, such as overhangs, louvers, and shades, block direct sunlight, thereby lowering indoor temperatures and reducing the reliance on air conditioning systems. By preventing excessive heat infiltration, shading devices not only enhance occupant comfort but also contribute to energy efficiency of the building.

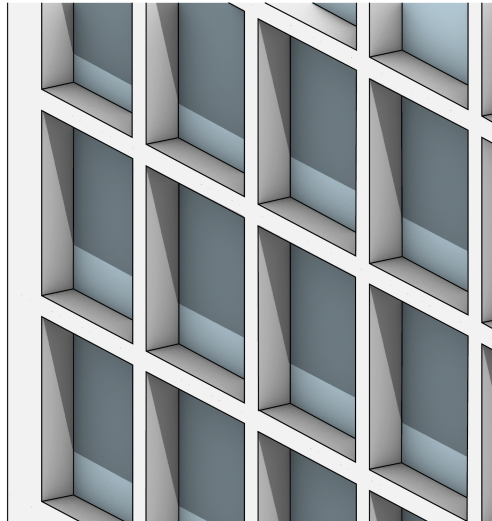


Figure 5.10: Graphical representation of shading device in building facade (Source: Author)

Use Automated blinds

Incorporating automated blinds into building design offers dual benefits: they significantly reduce cooling energy consumption by dynamically blocking sunlight during peak hours, thereby minimizing solar heat gain and decreasing reliance on air conditioning. This proactive shading not only enhances energy efficiency and reduces operational costs but also increases the resilience of the facade. By regulating solar exposure, automated blinds reduce thermal stress on building materials, extending their lifespan and lowering maintenance requirements.

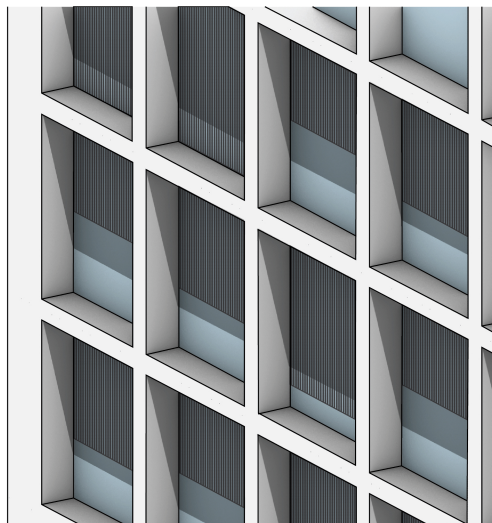


Figure 5.11: Graphical representation of automated blinds on facade (Source: Author)

Green Creepers on Facades

Using green creepers on building facades can help reduce cooling energy demand by providing natural insulation, shading the building from direct sunlight, and cooling the surrounding air through evapotranspiration. This approach not only promotes energy efficiency but also enhances the facade’s resilience.

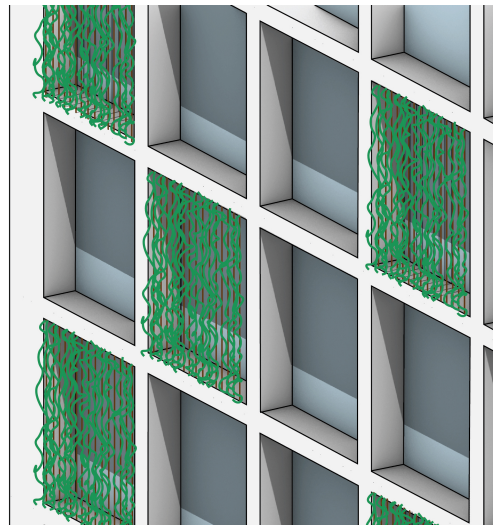


Figure 5.12: Graphical representation of green creepers on facades (Source: Author)

For flood resilience:

Use reinforced wall and reinforce glazing

Reinforced walls and reinforced glass facades enhance the bending moment capacity of buildings through strategic material reinforcement. Reinforced walls, typically reinforced with materials like steel or reinforced concrete, benefit from added tensile strength provided by the reinforcement (as shown in Figure 5.13. This enables them to withstand higher bending moments without compromising structural integrity. Additionally, incorporating interlocking wall systems further enhances bending moment capacity by distributing loads more efficiently across the structure (refer Figure 5.14. Interlocking systems, such as mechanically interlocked masonry or modular wall panels, improve the wall’s ability to resist bending forces by creating a cohesive and interconnected assembly.

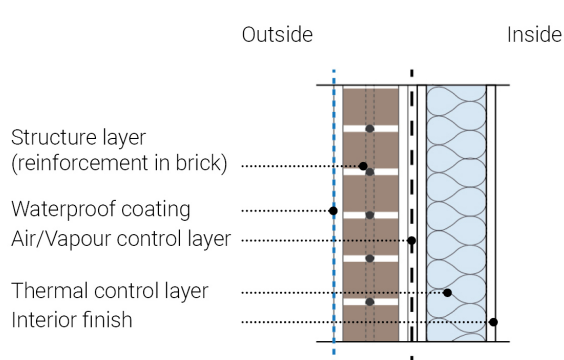


Figure 5.13: Graphical representation of reinforcement in opaque wall (Source: Author)

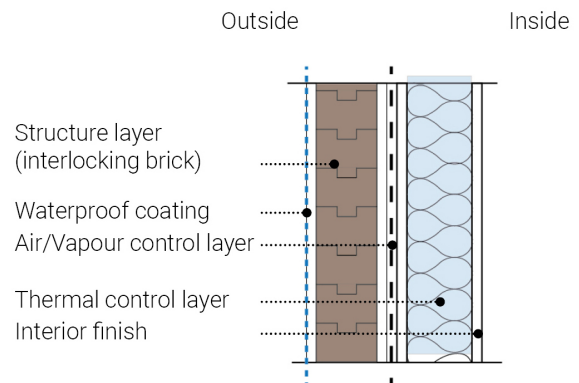


Figure 5.14: Graphical representation of interlocking bricks in opaque wall facade (Source: Author)

Similarly, reinforced glass facades, which can feature laminated or tempered glass supported by steel frames or fins, enhance overall stiffness and strength. The reinforcement in both cases redistributes forces effectively, allowing structures to support heavier loads and resist external pressures such as wind, thereby increasing overall resilience and durability.

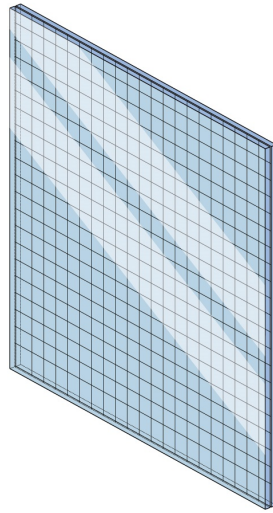


Figure 5.15: Graphical representation of reinforced laminated glass panel (Source: Author)

Use flood protection system in vulnerable points of the building

Flood protection at vulnerable points in buildings is crucial for minimizing damage and ensuring safety during flooding events. Key strategies include elevating critical systems above potential flood levels, applying waterproofing measures, and installing effective drainage systems. Using flood-resistant materials and incorporating permeable landscaping can also help manage water flow and reduce flood impact.

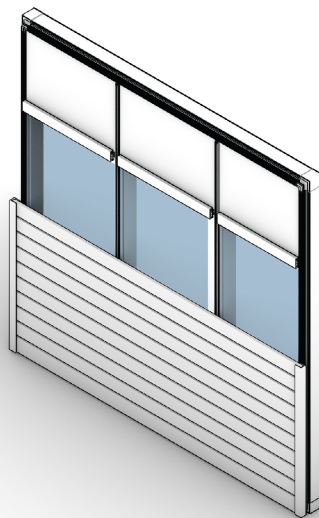


Figure 5.16: Graphical representation of flood protection system in front of facade (Source: Author)

5.1.5. Resilient facade design

A resilient facade design has been developed after evaluating various facade systems, including different glass materials and facade components. This design incorporates triple-glazed glass with a U-value of $0.8 \text{ W/m}^2\text{K}$, a Solar

Heat Gain Coefficient (SHGC) of 0.2, and a visible transmittance (T_{vis}) of 0.6. Additionally, the design features automated blinds that close when the radiation level exceeds 200 W/m^2 . Horizontal and vertical shading devices are also included to minimize direct heat gain from the sun.

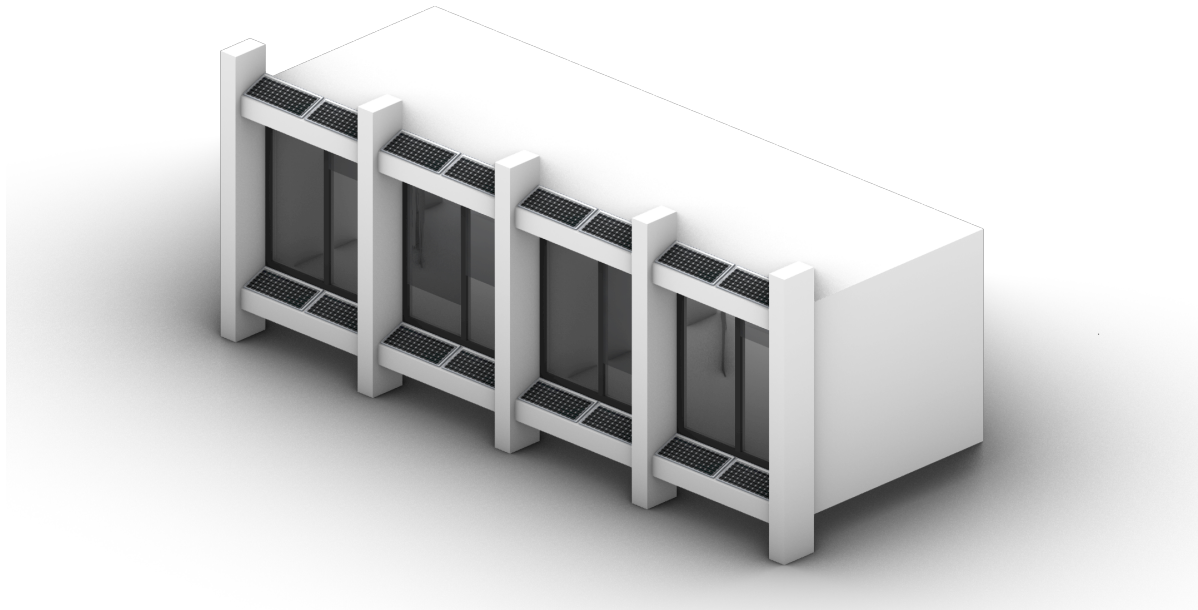


Figure 5.17: Graphical representation of resilient facade design (Source: Author)

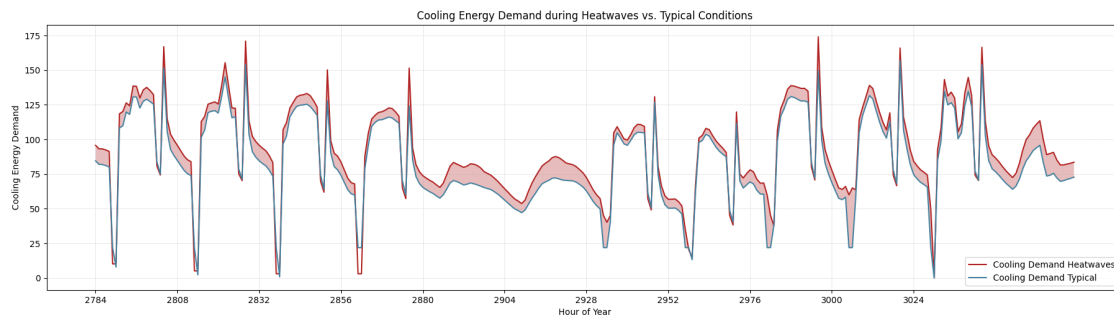


Figure 5.18: Graphical representation of resilience quantification of resilient facade design (Source: Author)

Resilience loss in designed facade

$$\begin{aligned}
 \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{heatwaves}}(t) - f_{\text{typical}}(t)) dt \\
 &= 26173.94 - 23805.02 \\
 &= 2368.92 \quad (\text{around } 11\% \text{ resilience loss})
 \end{aligned}$$

6

Case Study: Chennai, India

6.1. Thermal resilience calculations

6.1.1. Computational simulation

A hypothetical office building in Chennai is considered for this case study. The building is detached on all four sides to simulate a scenario of maximum heat gain. It features a double-glazed façade with a U-value of $1.5 \text{ W/m}^2\cdot\text{K}$. The analysis focuses on the sixth floor, which is divided into nine zones. The central zone is designated as the service core. The distance from the building envelope to the core is 13 meters on all sides, and the clear height is 3 meters. All other zones are designated as open office spaces. The input parameters for the study are illustrated in Figure X. The building's geometry was generated using Grasshopper software and then converted into HB (Honeybee) geometry for the analysis of thermal comfort and energy demand.

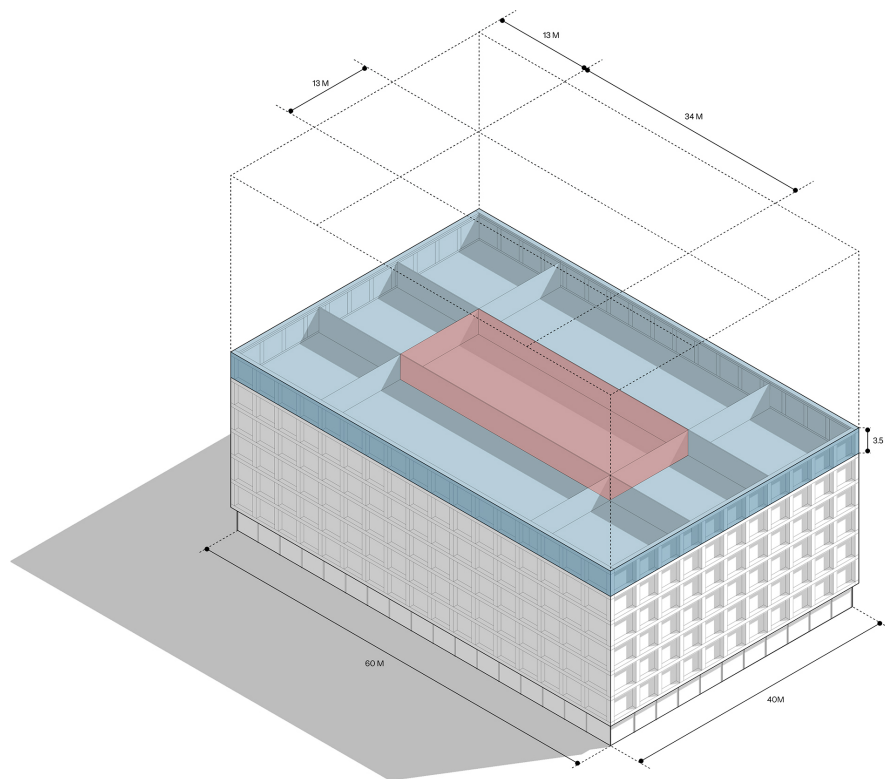


Figure 6.1: Graphical representation of office building for case study (Source: Author)

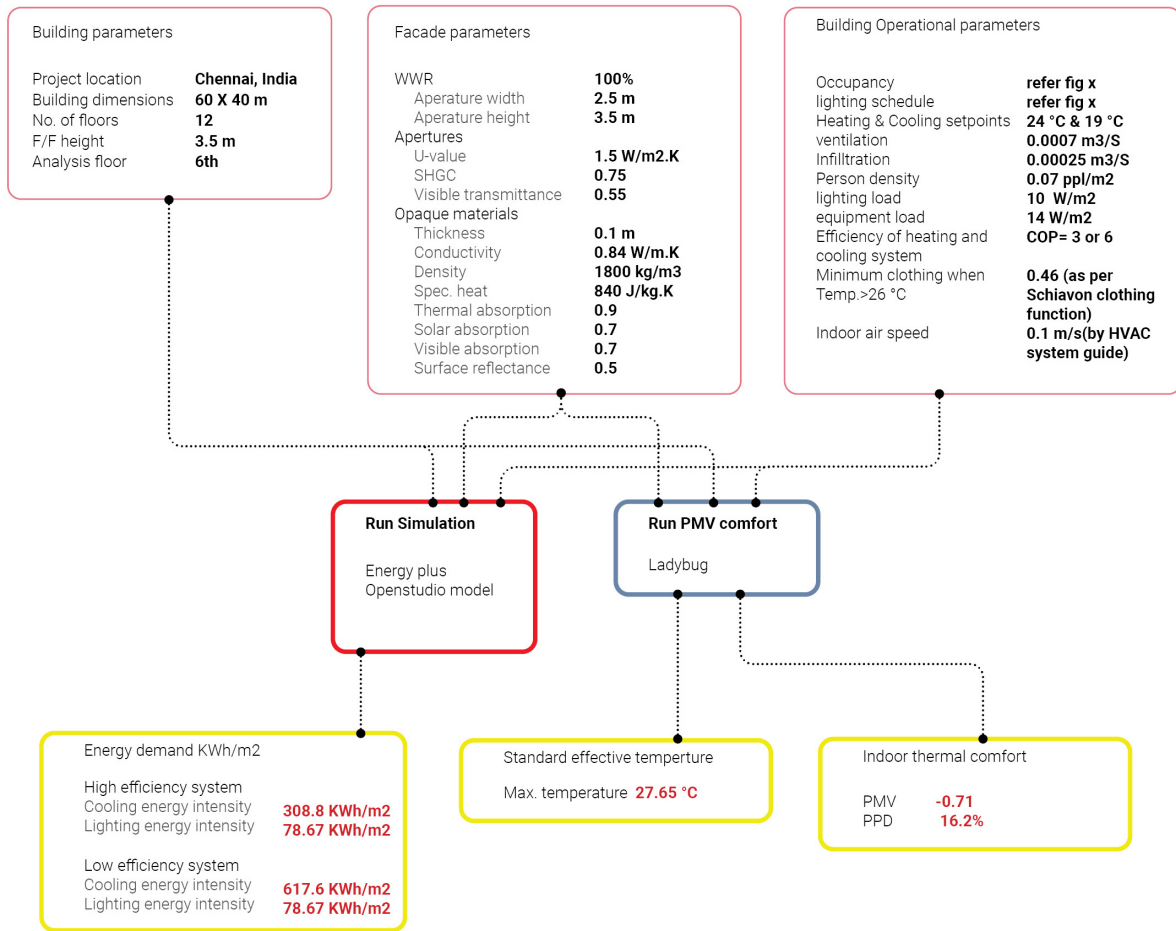


Figure 6.2: Graphical representation of heatwaves simulation workflow (Source: Author)

6.1.2. Resilience Calculation

In order to assess the resilience loss for the facade of this building, it is simulated under two different weather scenarios. The first scenario represents typical conditions without heatwaves, while the second scenario represents extreme conditions during a heatwave. According to the extreme weather (EPW file) of Chennai, several severe heatwaves occurred from April to June. However, this case study focuses on assessing the resilience loss from day 116 (2784th hour) to day 126 (3072nd hour), representing a continuous 12-day period during which heatwaves occurred. The outputs from the typical weather and extreme weather scenarios are shown in Figure X and Figure Y, respectively.

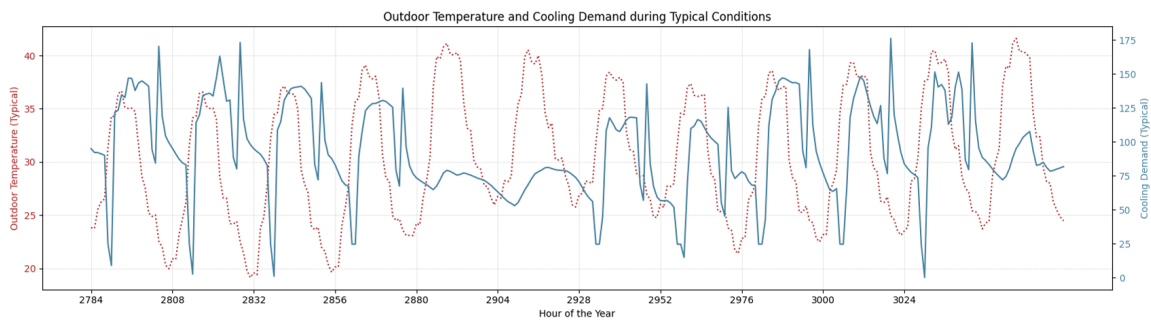


Figure 6.3: Graphical representation of outdoor temperature and cooling demand during typical conditions

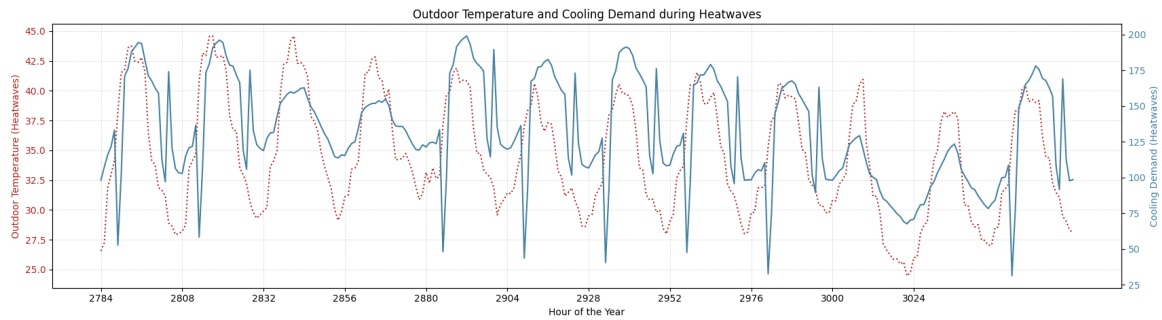


Figure 6.4: Graphical representation of outdoor temperature and cooling demand during heatwaves

As explained in Section 3.5, resilience loss can be depicted by calculating the area difference between the cooling demand functions of both scenarios (refer to Figure 6.5).

The resilience loss can be expressed as:

$$\begin{aligned} \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{heatwaves}}(t) - f_{\text{typical}}(t)) dt \\ &= 37931.638 - 26747.222 \\ &= 11184.416 \end{aligned}$$

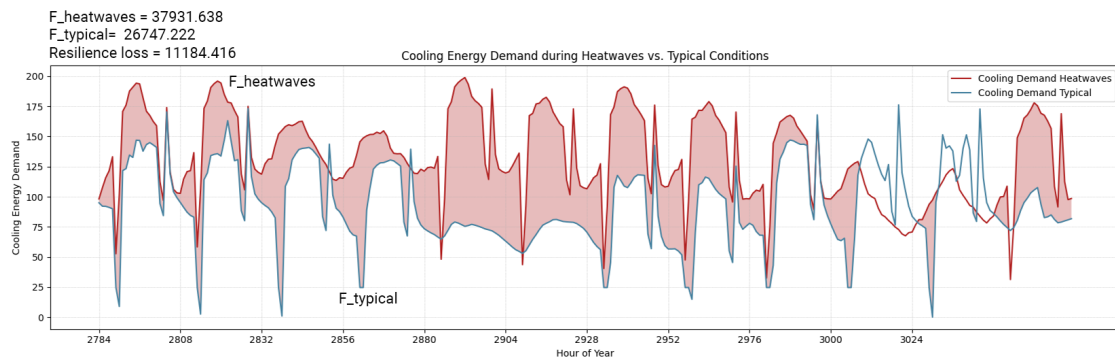


Figure 6.5: Graphical representation of resilience loss heatwaves (Source: Author)

6.2. Flood resilience calculations

6.2.1. Computational simulation

The assessment of flood resilience is conducted on the ground floor of the above mentioned building, which was previously utilized for thermal resilience calculations (as shown in Figure 6.6). This floor features a glass façade characterized by panels 2 meters wide and 4.5 meters in height, with a glass thickness of 20 mm. Utilizing pertinent façade parameters and material properties, such as bending strength (σ), the allowable bending moment capacity is determined through a mathematical model as detailed in Section 4.2.4.

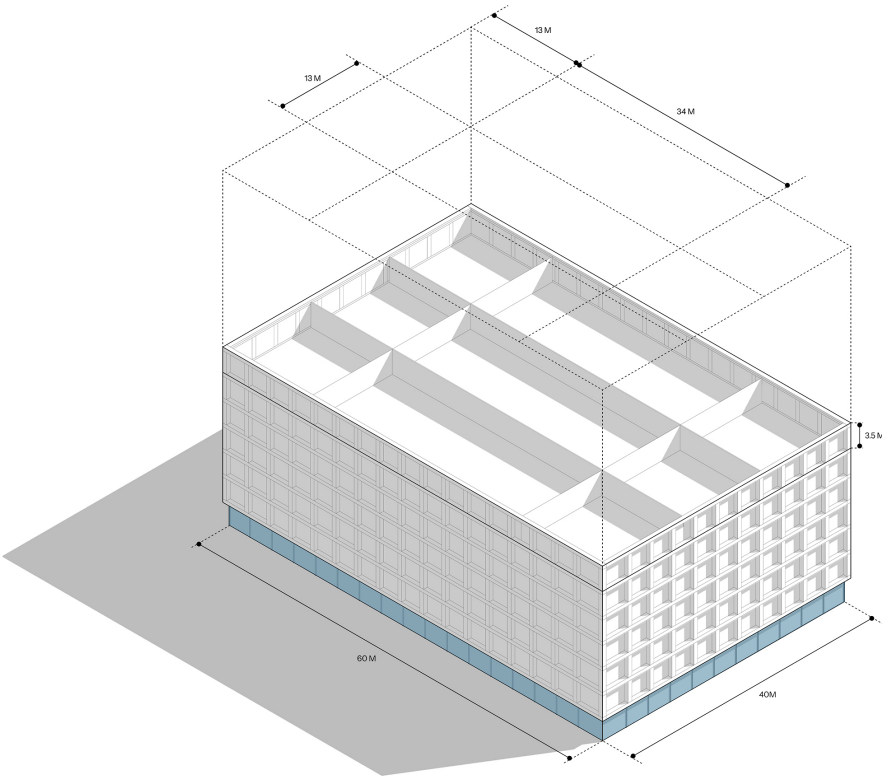


Figure 6.6: Graphical representation of office building (1st floor) case study (Source: Author)

The building geometry is modeled in 3D using Rhino software and subsequently imported into Ansys Fluent for hydraulic pressure simulation. Initially, the entire ground floor façade is simulated to ascertain the applied total hydraulic force and maximum bending moment on the façade, as depicted in Figure ???. Subsequently, to conduct a more detailed assessment, the façade is divided into two distinct sections: one with a flat surface (see Figure 6.8) and another comprising a corner façade (see Figure 6.9). This division allows for targeted analysis of these specific segments of the façade to discern localized effects and vulnerabilities.

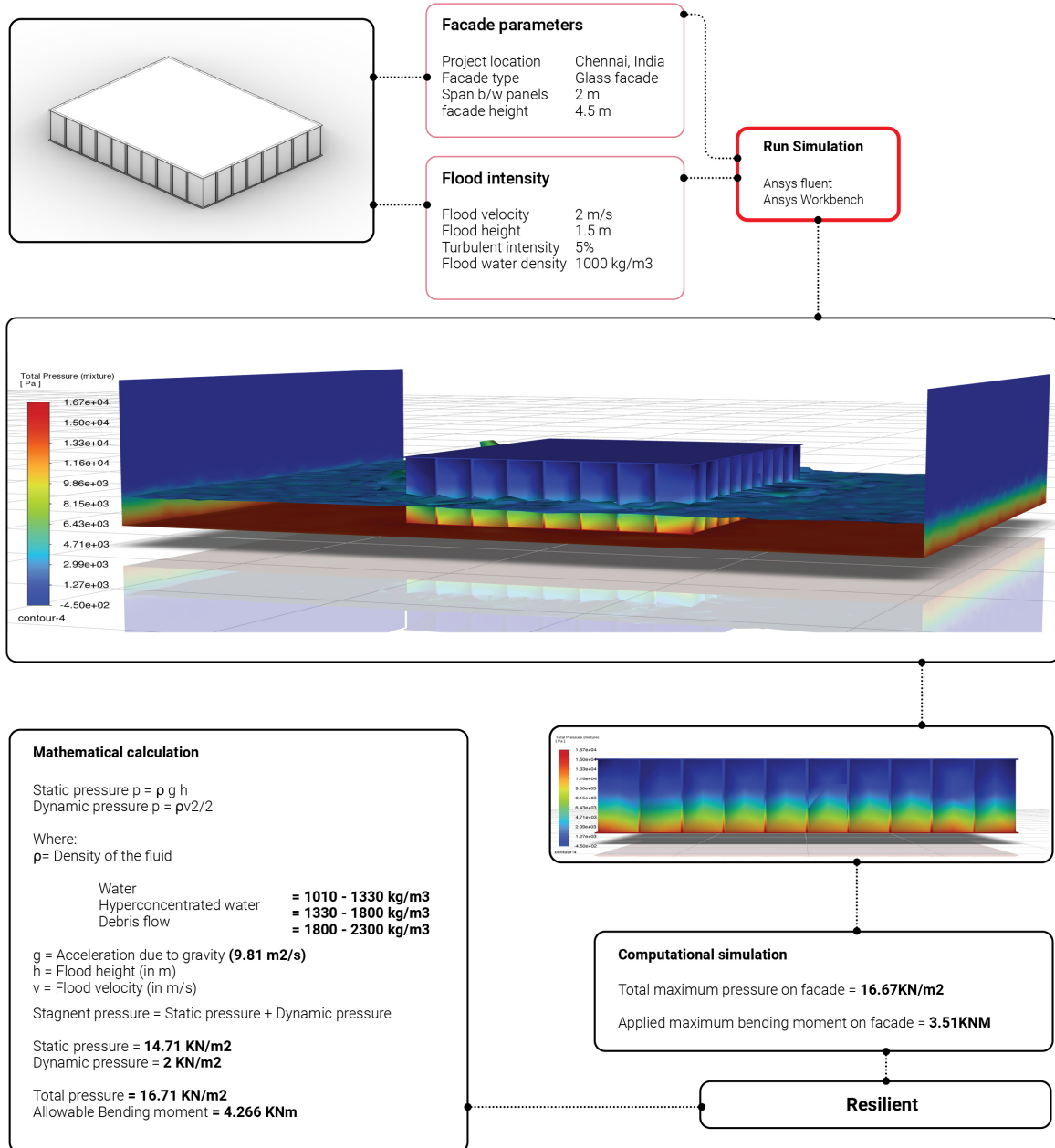


Figure 6.7: Graphical representation of ground floor facade flood simulation (Source: Author)

The figure 6.7 illustrates the hydraulic pressure on the entire ground floor façade. Computational simulations indicate that the maximum applied load is 16.67 kN/m², a value that corroborates the mathematical calculations. In terms of resilience indicators, the bending moment capacity analysis demonstrates that the applied bending moment is less than the allowable bending moment capacity of the facade. Therefore, this facade can withstand the flood intensity considered in this study.

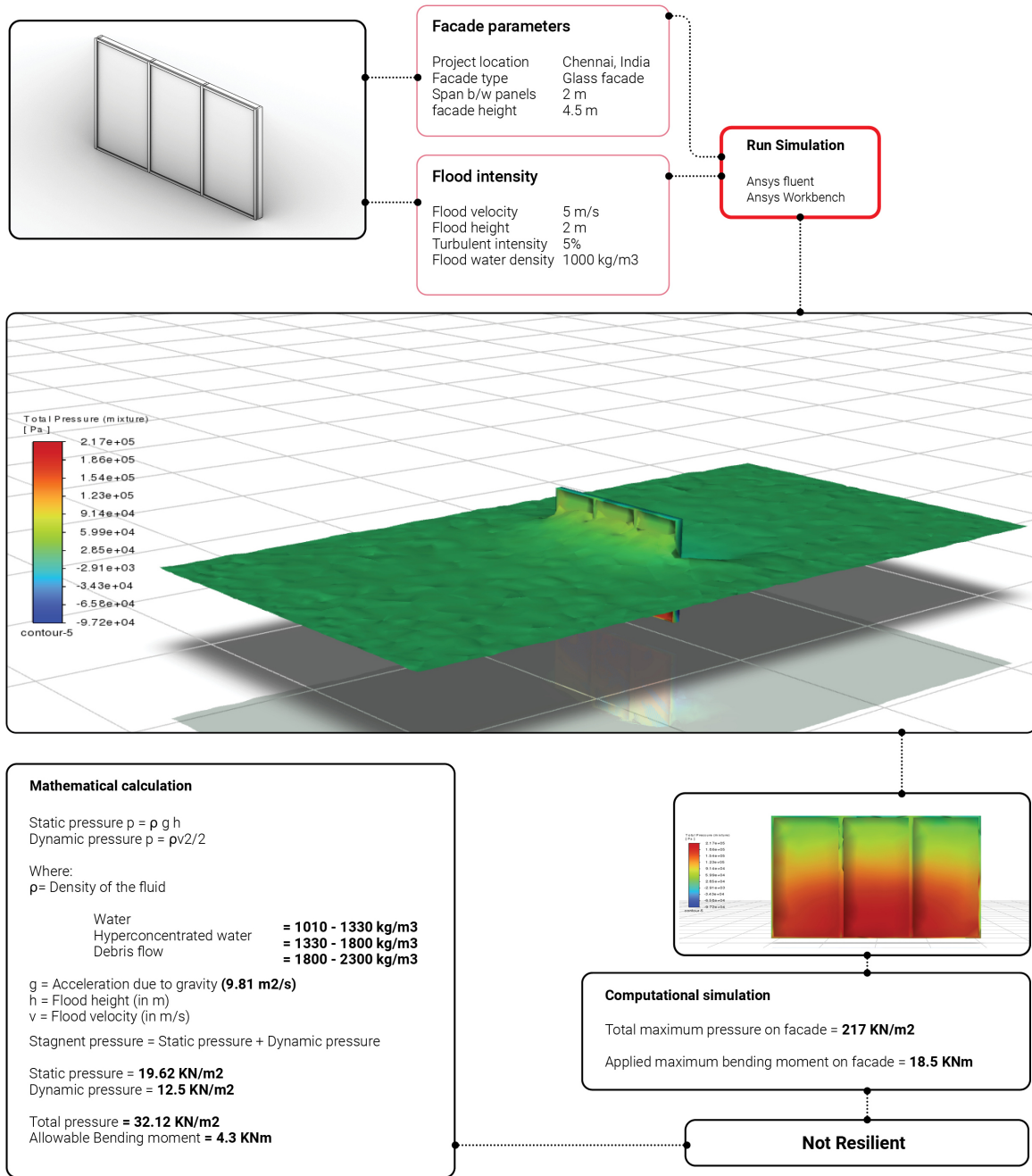


Figure 6.8: Graphical representation of flat surface facade flood simulation (Source: Author)

Figure 6.8 shows the hydraulic pressure on three panels of the facade. Computational simulations indicate that the maximum applied load is 217 kN/m² due to the high intensity of the flood. In terms of resilience indicators, the bending moment capacity analysis demonstrates that the applied bending moment is higher than the allowable bending moment capacity of the facade. Therefore, this facade is no longer resilient to this intensity of the hazard.

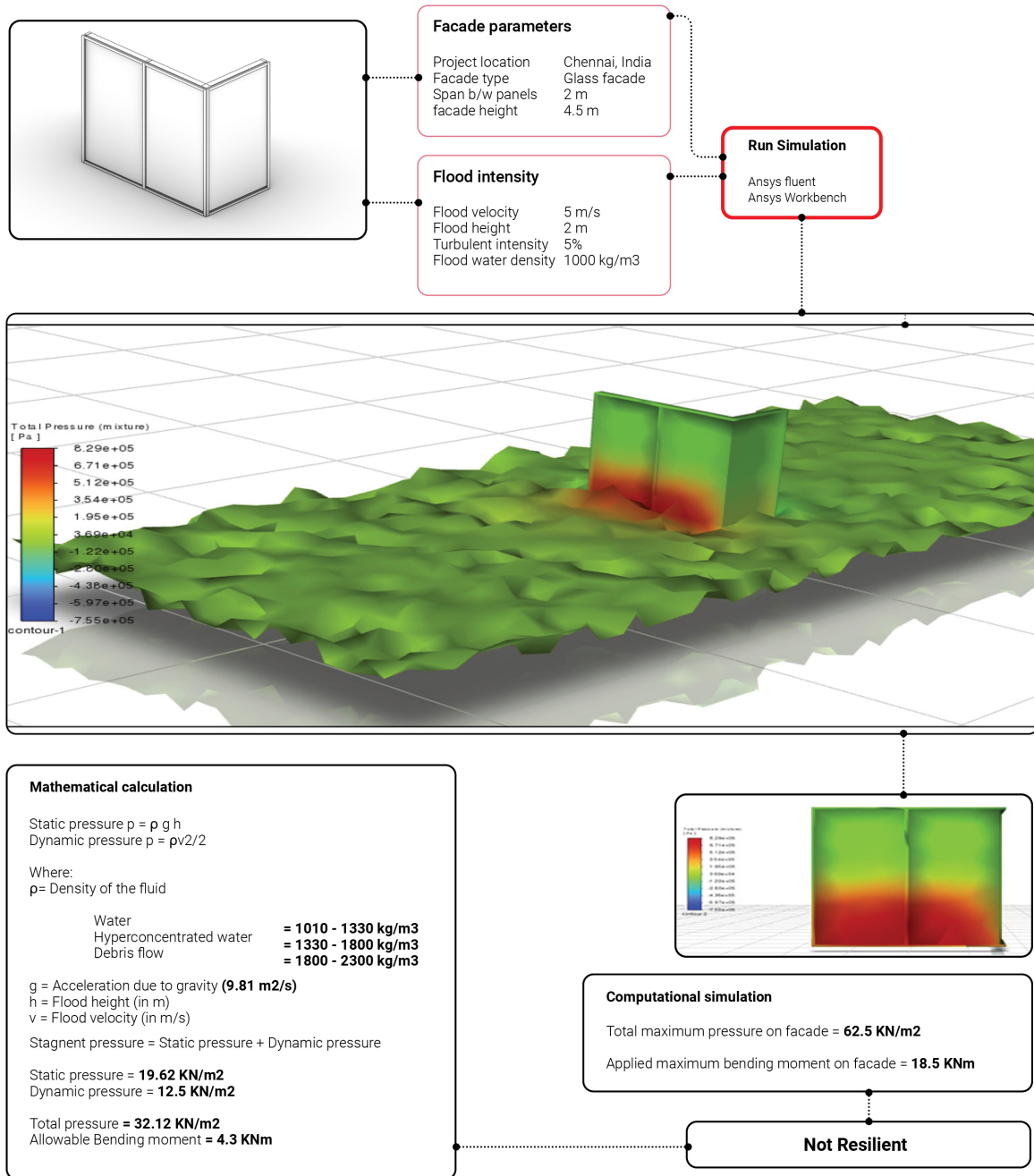


Figure 6.9: Graphical representation of corner facade flood simulation (Source: Author)

Figure 6.9 shows the hydraulic pressure on corner panels of the facade. Computational simulations indicate that the maximum applied load is 62.5 kN/m² due to the higher turbulence of the flood. In terms of resilience indicators, the bending moment capacity analysis demonstrates that the applied bending moment is higher than the allowable bending moment capacity of the facade. Therefore, this facade is no longer resilient to this intensity of the hazard.

6.2.2. Resilience Calculation

To calculate the resilience score of the building's facade, the bending moment capacity is used as an indicator of resilience. Initially, the allowable bending moment capacity of the facade is determined based on its specifications. This capacity represents the threshold beyond which the facade is no longer considered resilient. If the applied bending moment reaches or exceeds this threshold, the facade fails to maintain its resilience. Conversely, if the ap-

plied bending moment remains below the allowable limit, the difference between the applied and allowable bending moments indicates the facade's resilience. A greater difference signifies a higher resilience score for the facade.

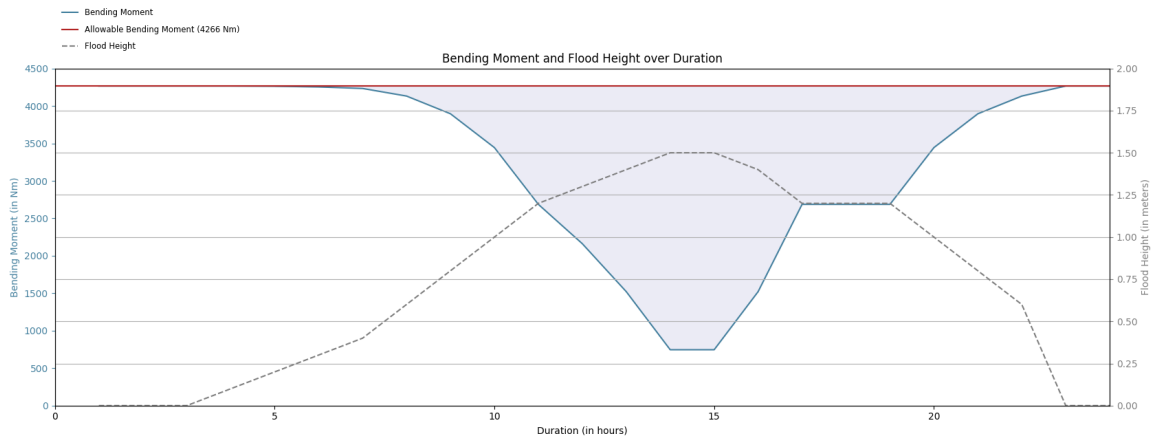


Figure 6.10: Graphical representation of Resilience score floods

In the graph 6.10, the bending moment is plotted on the left y-axis, the flood height is plotted on the right y-axis, and the duration is plotted on the x-axis. The red line represents the constant allowable bending moment limit. The blue line illustrates the applied bending moment, which varies over time in response to changes in the intensity of the flood. The highlighted part represents the resilience score of the facade.

The resilience score can be expressed as:

$$\begin{aligned}
 \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{typical}}(t) - f_{\text{flood}}(t)) dt \\
 &= 76788.0 - 53145.4 \\
 &= 23642.6
 \end{aligned}$$

7

Conclusion and Discussion

7.1. Conclusion

This thesis project has delved into the quantification of multi-hazard resilience, specifically focusing on heatwaves and floods, in building facades. The primary objective was to develop a methodology capable of assessing the impact of these hazards on building envelopes. Through extensive literature review, research gaps were identified, setting the stage for the development of a comprehensive framework to aid facade designers and engineers in making informed decisions regarding resilient facade systems.

In the pursuit of quantifying thermal resilience, this study commenced with a thorough examination of heatwave stressors and their implications for building facades and human comfort. Subsequently, over 7168 scenarios were simulated computationally, and various machine learning models were developed and compared to enhance prediction accuracy. Sensitivity analysis was conducted to ascertain the most influential input parameters on facade resilience. Finally, a resilience matrix was devised, utilizing cooling energy demand as a resilience indicator, thereby quantifying the facade's resilience loss under heatwave conditions.

Similarly, the quantification of flood resilience employed a parallel approach. Here, bending moment was designated as the resilience indicator, with the facade's material properties and parameters informing the calculation of its allowable bending moment capacity. Through computational fluid dynamics (CFD) simulations and mathematical modeling, the bending moment induced by hydraulic pressure on the facade was determined. The disparity between the two bending moments served as the resilience score, with greater differences indicating higher resilience.

This study culminated in a case study focusing on Chennai, a region susceptible to both heatwaves and floods. By addressing the multi-hazard resilience challenge through the definition of resilience metrics for each hazard, this research equips facade designers with the tools to prioritize input parameters effectively. By leveraging the findings of this study, designers can make informed decisions when designing resilient facade systems tailored to specific environmental contexts.

In summary, this thesis contributes to the advancement of knowledge in the field of building facade resilience by offering a robust methodology for quantifying resilience to heatwaves and floods. The insights gained from this research not only fill existing gaps in the literature but also provide practical guidance for enhancing the resilience of building facades in the face of increasingly complex and varied environmental hazards.

7.2. Answer to research questions

1. What are the most probable stressors associated with heatwaves and floods that should be considered in the research, and how do they impact building facades and indoor comfort?

In the context of heatwaves and floods, several stressors associated with these hazards are considered for this research:

Heatwaves

Outdoor Temperature

High outdoor temperatures can exacerbate thermal stress on building facade materials and systems, affecting their

functionality and indoor comfort. Increased outdoor temperatures can elevate the heat absorption of building facades, leading to higher energy demand for cooling.

Relative Humidity

Although relative humidity does not directly affect the structural integrity of the facade, it can exacerbate thermal discomfort for building occupants. Buildings experiencing high humidity during heatwaves often face increased cooling loads. Air conditioning systems must work harder to remove heat and excess moisture from the air, resulting in higher energy demand for cooling.

Wind Speed

High wind speeds during heatwaves can increase the rate of heat transfer from building exterior surfaces, which can lead to higher energy demand for cooling. Wind can also exert mechanical stress on facades, particularly on windows, doors, and other openings.

Duration

Prolonged exposure to extreme heat stress can cause thermal fatigue in building facade materials, leading to deterioration and reducing their functionality and lifespan.

Urban Heat Island Effect

Urban areas experience amplified heatwaves due to the Urban Heat Island (UHI) effect. These areas generally have low albedo surfaces (concrete, asphalt, etc.), which absorb more heat than natural surfaces. This contributes to higher temperatures and increased cooling energy demand to maintain indoor comfort.

Floods

Flow Depth

Greater flow depth can lead to more severe damage to facade structures. In sensitivity analysis, flow depth is identified as the most influential parameter, having a significant impact on facades. Increased flow depth will elevate the hydraulic pressure on facades, affecting the structural integrity of the building exterior.

Flow Velocity

High velocity can cause severe damage to facade systems by increasing dynamic pressure on the facade. Research indicates that a velocity above 2 m/s can cause total destruction to a building Clausen, 1989.

Debris Content

Debris in floodwaters can significantly impact building facades by striking them. In this research, debris content is considered as the density of the flow. If the flow contains debris, its density is assumed to be between 1800-2300 kg/m³ Clausen, 1989. Debris-laden flows can strike large objects against the facade, such as wood or vehicles, affecting the structure of the facade.

Duration

Prolonged flooding can lead to more extensive damage to facade materials, including mold growth and material deterioration. This reduces the functionality of the building envelope and the aesthetic appeal of the building exterior.

This study identifies all the hazard stressors and ranks them based on their impact on building facades.

2. What existing methodologies or frameworks are available for assessing the resilience of building envelopes/-facades, and how do they address multiple hazards?

The assessment of resilience has become crucial due to climate change, with various methodologies and frameworks developed to evaluate resilience across different scales and hazards. At the building scale, methodologies such as the AHP multi-criteria evaluation method are employed for flood resilience, focusing on properties like compressive strength, water permeability, and thermal conductivity (Klijn et al., 2015). Multi-hazard resilience for facades is addressed by combining qualitative assessments of floods, windstorms, and heatwaves to calculate risk ratings (Favoio et al., 2022). Computational simulations are also used to analyze fluid flow impacts on building structures during floods (Mazzorana et al., 2014).

At an urban scale, GIS-based methods and AHP are used for flood mapping and vulnerability classification, considering factors such as topographic elevation, coastal proximity, and building maintenance (Shahri et al., 2020) and (Afifah, Sani & Hizbaron, Dyah Rahmawati, 2020). For heatwaves, Ouzeau's method and IDA ICE software are used for thermal resilience assessment (Flores-Larsen et al., 2023) and (Homaei & Hamdy, 2021).

Specific to facades, quantitative multi-criteria decision methods evaluate heatwave impacts, considering operative temperature and wind speed (Lassandro & Di Turi, 2019). The MIVES methodology combined with MCDM and GIS modeling assesses urban resilience to heatwaves, taking into account factors like albedo, vegetation index, and accessibility (Quesada-Ganuza et al., 2023). Each methodology provides unique approaches, emphasizing tailored criteria and methods for effective resilience evaluation.

As mentioned above, despite ongoing efforts to evaluate resilience at broader geographic scales such as city, district, and region, existing studies exhibit significant gaps and limitations, particularly in assessing resilience and performance at the facade level during extreme events. The lack of a dedicated tool or method tailored to this specific scale poses a substantial challenge. Additionally, the absence of comprehensive tools for multi-hazard impact assessment, integrating both floods and heatwaves, hinders a holistic understanding of risks and vulnerabilities. This limitation is particularly concerning as even minor flood events can disproportionately impact building facades, leading to economic losses. Consequently, there is a pressing need for a tool that conducts a thorough assessment considering the nuanced effects of small-scale flooding on facade resilience. Moreover, the prevalent reliance on qualitative assessments in the literature underscores a significant gap in quantitative evaluation tools. The dearth of such tools highlights the necessity to develop instruments that provide designers with quantitative data, empowering them to make informed decisions during the design process. Addressing these gaps is crucial for enhancing the efficacy of resilience assessments and fostering more robust design practices.

3. What input parameters (including facade parameters and hazard stressors) have the most significant impact on the output?

To assess which input parameters (facade parameters and hazard stressors) have the most significant impact, sensitivity analysis is employed. Sensitivity analysis involves estimating how target variables (performance indicators) change in relation to changes in input variables (stressors) and determining which input variables have the strongest impact on target variables. This process is crucial for enhancing the robustness of the proposed methodology for assessing facade resilience in the context of multi-hazard events, specifically heatwaves.

Following the computational simulations and training of the machine learning model aimed at simulating the impact of stressors on the facade, sensitivity analysis becomes a critical step in discerning the relative importance and influence of each stressor on the performance indicators. By systematically varying input parameters and observing the corresponding changes in performance metrics, sensitivity analysis provides valuable insights into the sensitivity of the facade resilience model. This analysis not only highlights the most influential factors affecting facade performance but also aids in optimizing design solutions by prioritizing interventions that address the most critical stressors.

The benefit of sensitivity analysis in this research lies in its ability to inform targeted and efficient design decisions, ensuring that the proposed digital tool accurately captures the nuances of multi-hazard resilience. Through this systematic examination, the research aims to enhance the precision and applicability of the tool, ultimately contributing to the development of more resilient building facades capable of withstanding the complex challenges posed by heatwaves.

In the context of quantifying facade resilience against floods, the input variables include facade parameters and hazard stressors. Conducting this analysis helps identify which input parameter has a greater impact on the output. This assists facade designers in prioritizing influential variables when designing the building envelope. This research explores correlation matrix and Sobol's method for sensitivity analysis.

4. How can we quantify the flood and thermal resilience of building facades?

Following the acquisition of output values from input parameters via computational simulation, the dataset (comprising input and output values) is utilized to train a machine learning model. This model establishes a functional relationship between the input and output values. Subsequently, these values are employed in sensitivity analysis to identify the most impactful input parameters.

Heatwave Resilience Quantification

In the context of heatwave resilience quantification, the cooling energy demand of a building serves as an indicator of thermal resilience. As outdoor temperatures rise, the cooling energy demand increases, necessitating more energy to maintain a comfortable indoor temperature. A graph is plotted to illustrate the relationship between cooling energy demand, outdoor temperature, and time. The left Y-axis represents outdoor temperature, while the right Y-axis represents cooling energy demand, with time plotted on the X-axis.

To assess resilience, a facade with consistent specifications was simulated under two scenarios. The first scenario represents conditions prior to a hazard, with outdoor temperatures ranging typically between 30–35°C as per the EPW weather file. The second scenario simulates extreme heat stress, where temperatures exceed 40°C.

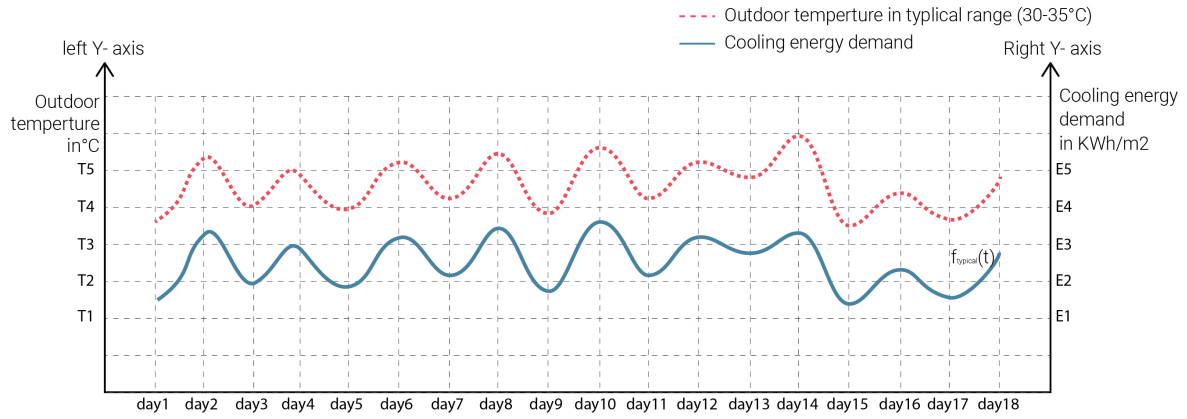


Figure 7.1: Graphical representation of temperature-cooling demand in typical conditions (Source: Author)

In the first scenario, the facade system operates normally, exhibiting a typical cooling demand (as shown in Figure 7.1). However, under heatwave conditions, the facade system experiences increased stress, leading to a higher cooling demand to maintain indoor comfort levels. In this scenario, outdoor temperature and cooling energy demand are plotted before the hazard. In the second scenario, these variables are plotted during the heat stress event, which begins on day 5 and ends on day 15 (depicted in Figure 7.2). On day 5, when the heatwave starts, the temperature increases significantly, necessitating a corresponding increase in cooling energy demand to maintain indoor comfort.

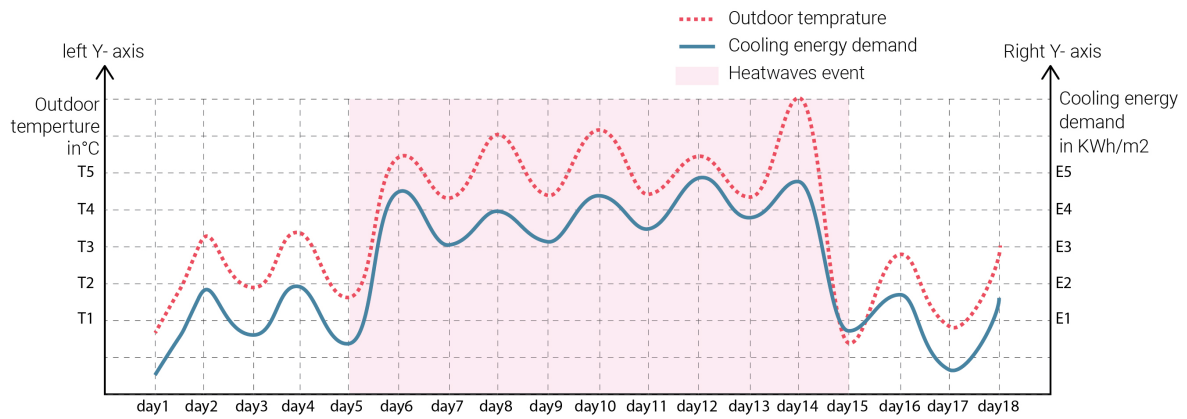


Figure 7.2: Graphical representation of temperature-cooling demand in heatwaves conditions (Source: Author)

The graph in Figure 7.3 compares the cooling demand in both scenarios: before the heatwave (typical conditions, denoted as $f_{\text{typical}}(t)$) and during heatwaves (denoted as $f_{\text{heatwaves}}(t)$). It quantifies the difference in terms of the additional cooling energy required during the extreme heat stress period. This difference is referred to as the resilience loss of the facade system.

The resilience loss can be expressed as:

$$\text{Resilience loss} = \int_{t_1}^{t_2} (f_{\text{heatwaves}}(t) - f_{\text{typical}}(t)) dt$$

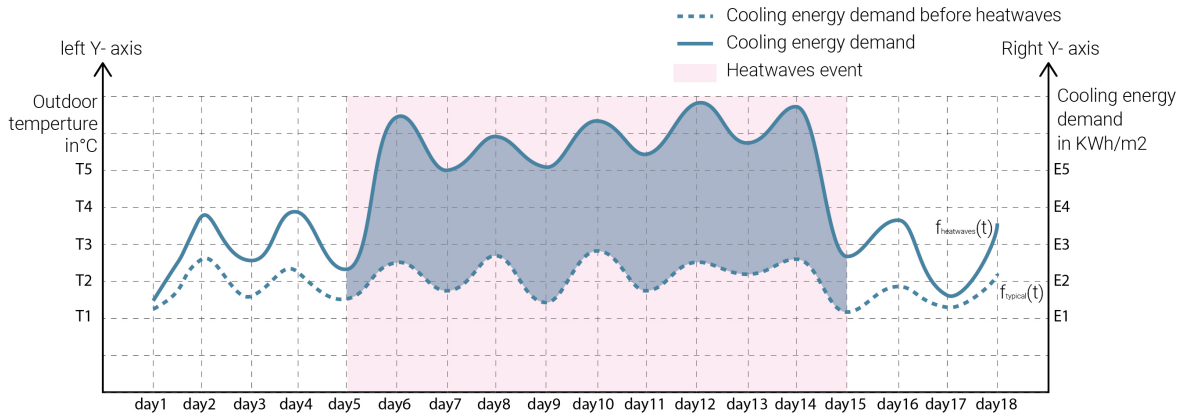


Figure 7.3: Graphical representation of resilience calculation by cooling demand

Flood Resilience Quantification

The development of a resilience matrix for assessing facade resilience against floods involves a systematic approach aimed at evaluating and enhancing the ability of facade elements to withstand flood events. The bending moment is defined as a resilience indicator. Through sensitivity analysis, flood height is identified as the most influential parameter affecting the bending moment (output).

Both output values (applied bending moment and allowable bending moment) are plotted on a graph. The x-axis represents time, the left y-axis represents the bending moment, and the right y-axis represents the flood height (refer Figure 7.4). The allowable bending capacity is depicted as a straight line, indicating the bending moment limit. As the flood height increases, the applied bending moment also rises and can reach this allowable limit, at which point the facade is no longer considered resilient. The area difference between these two functions (outputs) represents the resilience score of the facade, with a larger area indicating higher resilience.

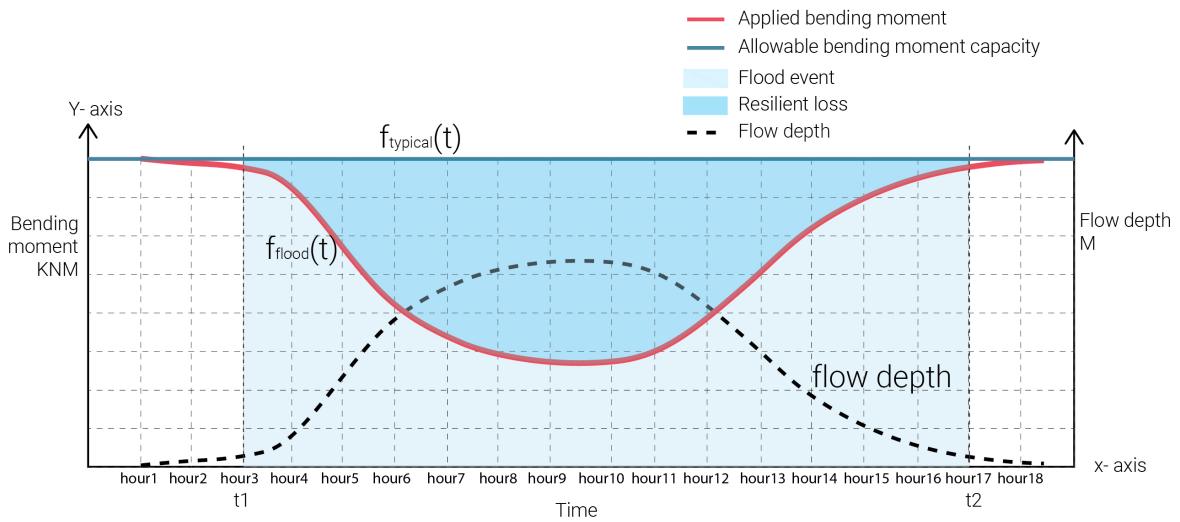


Figure 7.4: Graphical representation of quantification of flood resilience (Source: Author)

The resilience loss can be expressed as:

$$\text{Resilience loss} = \int_{t_1}^{t_2} (f_{\text{typical}}(t) - f_{\text{flood}}(t)) dt$$

5. How can we define the total resilience loss, including heatwave and flood resilience loss, for a façade system using a multi-criteria decision-making process?

Designing building facades to withstand a variety of hazards is critical in order to provide comprehensive protection and adaptability in the face of diverse disruptive events. By considering a range of potential threats while design a facade, including natural disasters and human-made hazards, it can enhance safety of occupants, assets, and infrastructure. As climate change is contributing to an increased frequency and severity of extreme weather occurrences, buildings need to be designed in a way that can withstand extreme temperatures, high winds, heavy precipitation, and other environmental challenges. Investing in multi-hazard resilience facade design can be more cost-effective in the long run, minimizing the need for costly retrofits or repairs following a disaster. Furthermore, resilient facades contribute to overall sustainability by reducing the environmental impact of disasters and ensuring continuity of essential services and functions during and after emergencies. In essence, designing for multi-hazard resilience is essential for protecting lives, property, and the environment while promoting sustainability and maintaining functionality in the face of diverse threats. The principle of facade resilience emphasizes the importance of building designs that anticipate future uncertainties, meaning they should not be limited to specific weather conditions but should be adaptable to various circumstances (Patterson et al., 2017).

Given the contradictory nature of floods and heatwaves, this study assumes that these events will not occur concurrently. Nevertheless, it focuses on quantifying both thermal and flood resilience for a facade system within separate frameworks. Although these events can happen at different times, they can have severe impacts on facades, necessitating resilience in both scenarios.

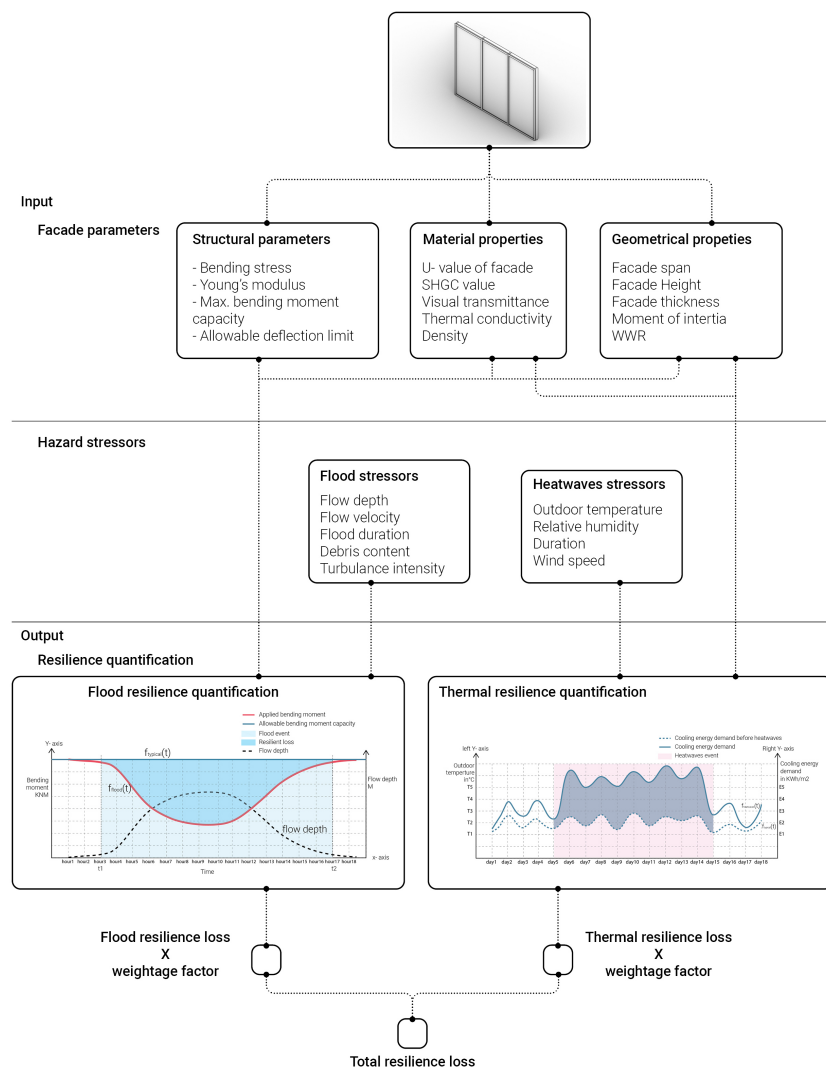


Figure 7.5: Graphical representation of Multi-hazard facade resilience design framework (Source: Author)

Based on all input parameters, including structural characteristics, material properties, and geometrical attributes of the facade system, along with the intensity of hazard stressors such as floods and heatwaves, the resilience of the facade can be calculated (as shown in Figure 7.5). These assessment processes occur independently, as these hazards will not occur simultaneously.

To define a single resilience loss for the facade, the flood resilience loss and thermal resilience loss are multiplied by their respective weightage factors and then summed. The weightage factor depends on various conditions. For example, if in a particular location the likelihood of heatwaves is higher than that of floods, then the weightage factor for thermal resilience will be greater. Additionally, the weightage factor depends on the building condition. If a building has one floor and is shaded by its surroundings, the severity of a flood may be greater than that of heatwaves, leading to a higher weightage factor for flood resilience. Conversely, if the facade is located on an upper floor where it is unaffected by floods, the weightage factor for heatwave resilience will be higher. Overall, the weightage factors depend on the building typology, facade location, building condition, and geographical context (refer Table 7.1).

Table 7.1: Table presenting resilience loss assessment for different facade types

Facade type	Heatwaves resilience loss	Flood resilience loss	Total resilience loss	Weightage factor
Facade 1	HR1	FR1	$0.7HR1 + 0.3FR1$	70% likelihood of heatwaves and 30% likelihood of floods
Facade 2	HR2	FR2	$0.4HR2 + 0.6FR2$	40% likelihood of heatwaves and 60% likelihood of floods
Facade 3	HR3	FR3	$0.5HR3 + 0.5FR3$	50% likelihood of heatwaves and 50% likelihood of floods

Main research question:

How can we identify the optimal facade system that is resilient against heatwaves and floods?

To identify the optimal facade combination that is resilient against both floods and heatwaves, designers must determine the weightage factor for each hazard specific to the location. For instance, if the facade is designed for the ground floor, it can be affected by both heatwaves and floods. Conversely, for an upper floor facade, the weightage factor for heatwaves would be higher than for floods. Once the weightage factors are defined, designers can calculate the resilience loss for different facade systems by plotting their resilience graphs. The facade system that exhibits the lowest resilience loss is considered more resilient than the others.

Case Study:

To compare the resilience of different facade systems against floods and heatwaves, an optimal facade system must be identified. This optimal system should exhibit low resilience loss while providing maximum functionality under both conditions. This study compares three facade systems with varying parameters, ranging from minimum to maximum values (as shown in Figures 5.2, 5.3, and 5.4), to evaluate their flood and thermal resilience. The facade system demonstrating the least resilience loss is identified as the optimal facade system. The resilience losses of the other two systems are then compared to this optimal system.

In order to compare the resilience of different facade systems against floods and heatwaves, an optimal facade system must be defined. The optimal facade system exhibits low resilience loss while providing maximum functionality under both conditions. This study compares three facade systems with varying parameters, ranging from minimum to maximum values to evaluate their flood and thermal resilience. The facade system that demonstrates the least resilience loss is identified as the optimal facade system. The resilience losses of the other two systems are then compared to this optimal facade system.

Table 7.2: Table presenting the comparison of different facade systems

Facade type	Cooling demand in KWh during heatwaves	Allowable bending moment in NM	Remark
Single glazed facade	44583.71	4096	
Double glazed facade	39039.04	6528	
Triple glazed facade	30131.33	9331.2	Optimal facade

Table 7.2 presents data on cooling energy demand during heatwaves and allowable bending moment capacity for single, double, and triple glazed facade systems. Cooling energy demand were calculated for 12 days (As per Chennai heatwaves 2021 weather data). Using triple glazed facade system in building has lower cooling demand and higer allowable bending moment capacity (As illustrated in Table 7.2).Therefore, the triple glazed facade is identified as an optimal solution and its resilience loss is compared with other two facade for decision making process.

Thermal resilience comparison between facade systems

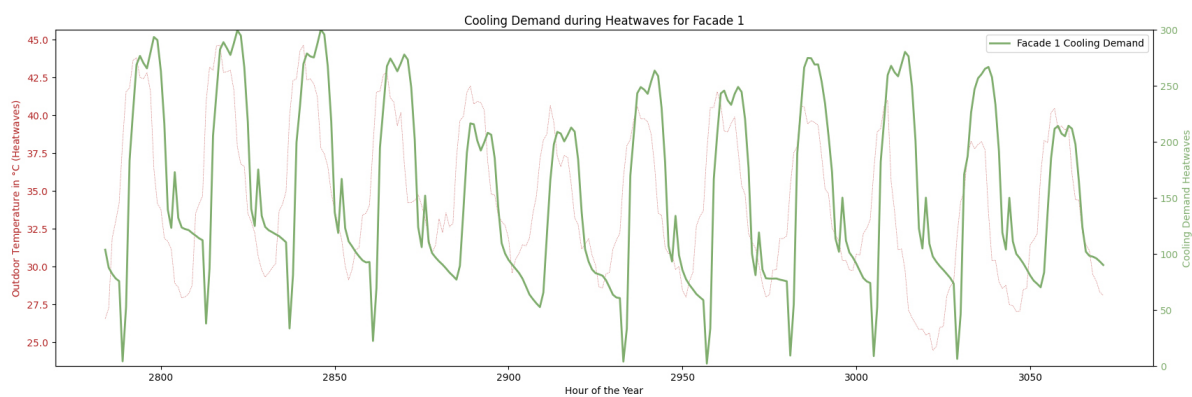


Figure 7.6: Graphical representation of Facade 1 outdoor temperature and cooling demand during heatwaves (Source: Author)

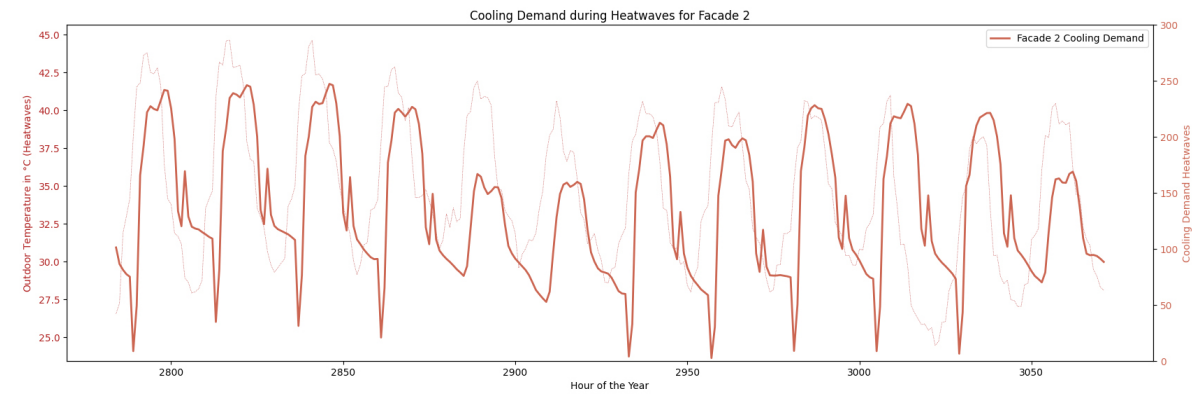


Figure 7.7: Graphical representation of Facade 2 outdoor temperature and cooling demand during heatwaves (Source: Author)

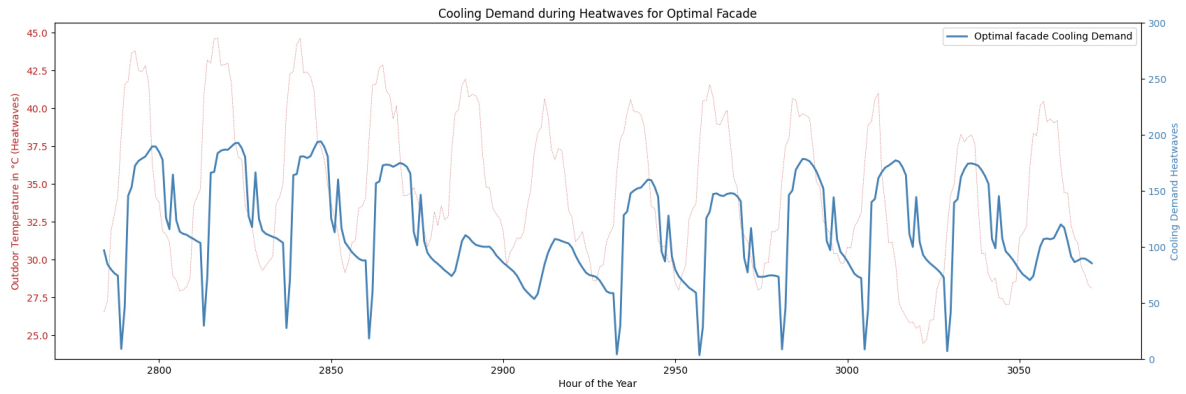


Figure 7.8: Graphical representation of Facade 3 outdoor temperature and cooling demand during heatwaves (Source: Author)

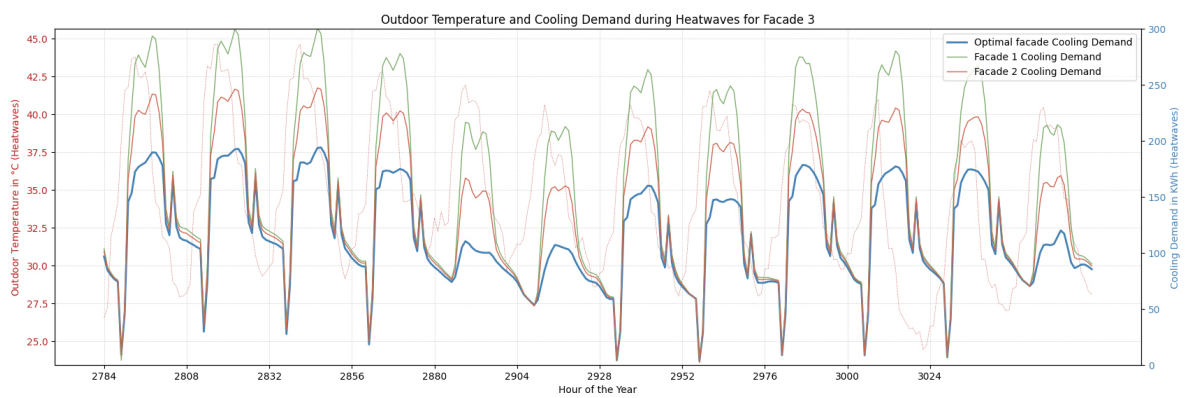


Figure 7.9: Graphical representation of All Facades outdoor temperature and cooling demand during heatwaves (Source: Author)

Resilience loss in the triple glazed facade scenario

$$\begin{aligned}
 \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{heatwaves}}(t) - f_{\text{typical}}(t)) dt \\
 &= 32901 - 30131 \\
 &= 2770
 \end{aligned}$$

Resilience loss in the single glazed facade scenario

$$\begin{aligned}
 \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{heatwaves}}(t) - f_{\text{typical}}(t)) dt \\
 &= 44583 - 30131 \\
 &= 14452
 \end{aligned}$$

Resilience loss in the double glazed facade scenario

$$\begin{aligned}
 \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{heatwaves}}(t) - f_{\text{typical}}(t)) dt \\
 &= 39039 - 30131 \\
 &= 8908
 \end{aligned}$$

Flood resilience comparison between facade systems

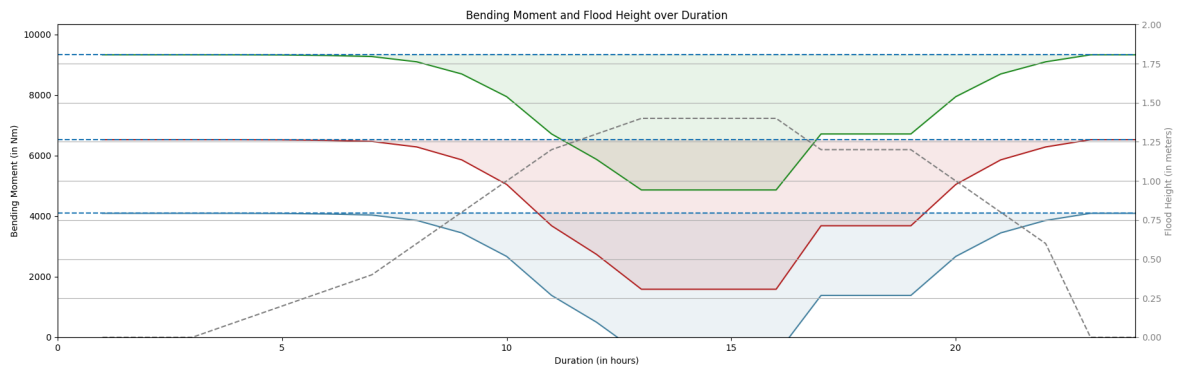


Figure 7.10: Graphical representation of All Facades flood height and bending moment during floods (Source: Author)

Resilience loss in the triple glazed facade scenario

$$\begin{aligned} \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{typical}}(t) - f_{\text{flood}}(t)) dt \\ &= 167961.6 - 131633 \\ &= 36328.4 \end{aligned}$$

Resilience loss in the single glazed facade scenario

Resilience loss = Not resilient, as the applied bending moment exceeds the allowable limit

Resilience loss in the double glazed facade scenario

$$\begin{aligned} \text{Resilience loss} &= \int_{t_1}^{t_2} (f_{\text{typical}}(t) - f_{\text{floods}}(t)) dt \\ &= 117504 - 77739 \\ &= 39764.7 \end{aligned}$$

Table 7.3: Table presenting total resilience loss for different facade types

Facade type	Heatwaves resilience loss (in %)	Flood resilience loss (in %)	Total resilience loss (in %)
Triple glazed facade	9.19 %	21.6 %	12.91 % (HR: FR = 0.7:0.3)
			15.39 % (HR: FR = 0.5:0.5)
			17.87 % (HR: FR = 0.3:0.7)
Single glazed facade	47.9 %	-	47.9 % (HR: FR = 1:0)
Double glazed facade	29.56 %	38 %	32.09 % (HR: FR = 0.7:0.3)
			33.78 % (HR: FR = 0.5:0.5)
			35.46 % (HR: FR = 0.3:0.7)

The Table 7.3 above illustrates the total resilience loss for all three facades based on their weighted values for heatwaves and flood occurrences. Designers can select the appropriate facade for different locations within the building to ensure maximum resilience.

7.3. Further development

Based on the conducted research and findings, this study can be further developed in the following aspects:

Development of a Tool/Webpage:

Based on the conducted research and findings, a significant advancement can be achieved by developing an interactive tool or webpage. This platform would integrate the machine learning model employed in the project, enabling designers and architects to input specific facade parameters and hazard intensities to generate resilience loss graphs. This innovation offers several key benefits. First, by creating a user-friendly interface, designers can easily access and utilize the model without needing extensive technical expertise, making the tool accessible to a wider range of users. The platform allows users to input precise parameters relevant to their specific projects, ensuring that the generated resilience loss graphs are highly tailored to the specific needs of each project. The automated process of generating these graphs significantly reduces the time and effort required for manual calculations and assessments, enabling designers to quickly compare different facade systems and make informed decisions efficiently. Additionally, the graphical representation of resilience losses allows for an intuitive understanding and comparison of different facade systems, supporting better decision-making by clearly highlighting the most resilient options. The tool can be designed to integrate updated climate and hazard data, ensuring that assessments remain accurate and relevant over time. Furthermore, it can serve as an educational resource for students and professionals in architecture and engineering, illustrating the importance of resilience in facade design and demonstrating how different factors influence resilience outcomes. The foundational structure of the tool can be expanded in the future to include additional hazards, materials, and building types, ensuring its continued value as new research and technologies emerge. By developing this tool or webpage, the research can have a more substantial impact, transforming theoretical findings into practical applications that enhance the resilience and sustainability of building designs worldwide.

Urban Scale Application

Currently, this study focuses on assessing the resilience of building facades. However, the methodology can be expanded to quantify resilience at an urban scale. Applying this study to an urban level will provide a comprehensive multi-hazard risk assessment tool, aiding governing authorities in making urgent decisions regarding vulnerable buildings. By identifying buildings that are more susceptible to hazards, authorities can prioritize and implement retrofitting measures before disasters strike. This proactive approach enhances the overall resilience of urban areas, safeguarding lives and reducing potential economic losses. Expanding this research to an urban scale will thus have significant implications for urban planning and disaster management, ensuring that cities are better prepared to withstand and recover from various hazards.

Inclusion of More Hazards

Currently, this tool assesses thermal and flood resilience. However, expanding its scope to include additional hazards, such as earthquakes and windstorms, would significantly enhance its utility. By incorporating a broader range of hazards, designers can comprehensively verify the resilience of their designs against multiple potential threats. This multi-hazard approach would provide a more robust and holistic assessment, ensuring that buildings are not only protected against the specific hazards of heatwaves and floods but also resilient to other natural and man-made disasters. This enhancement would further support the creation of safer, more sustainable, and resilient built environments.



Reflection

What is the relation between your graduation topic, the studio topic, master track Building Technology, and master programme (MSc AUBS)?

My graduation topic is “A digital design tool for floods and heatwaves resilient façade system” which is a subset of the Studio topic “Digital design tool for climate resilient structures”. This research specifically focuses on the quantification of façade resilience in a multi-hazard scenario, taking into account both floods and heatwaves. 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 the risk management methodology derived from natural hazard engineering. The outcome of this project is expected to provide valuable insights for designers, architects, and decision makers involved in the design of building envelopes. Ultimately, it aims to enhance overall resilience in the face of environmental challenges.

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

The literature study provides a strong foundation for the development of this design tool. The research explores several existing methodologies and current advancements in this field. It also compares these methodologies to evaluate their impact on resilience quantification. By identifying and analyzing these methodologies, the research highlights key findings and research gaps in this area. The integration of the literature review offers valuable information on hazard stressors, such as the impact of heatwaves and floods on building facades and human comfort. Additionally, the research adapts certain methods for analyzing large datasets, which are applied in this thesis project. Thus, the literature study significantly aids in understanding hazards and their impacts, guiding the design and recommendations.

Conversely, the design and recommendations significantly influenced the direction and focus of this thesis research. By establishing clear design goals and criteria, specific areas requiring deeper investigation were identified. This iterative process highlighted the need for more detailed analysis of certain methodologies and datasets, leading to a more comprehensive understanding of thermal and flood resilience. The practical application of design principles also prompted the exploration of novel approaches and tools, which were then incorporated into the research. Furthermore, feedback from the design phase helped refine research questions and objectives, ensuring that the study remained aligned with real-world challenges and practical solutions. Overall, the interplay between design and research enriched both aspects, resulting in a more robust and relevant thesis project.

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

To assess the value of the approach, methods, and methodology used in this thesis, several criteria can be considered:

Effectiveness

This study effectively develops a digital tool for resilience quantification of the building facades against floods and heatwaves. By integrating the interdisciplinary approach and employing a robust quantitative methodology, including detailed computational simulation, the research isolates critical facade parameters and uses machine learning

model to predict the output. This digital tool will assist facade designers and engineers in making informed decisions while designing the resilient facade system.

Efficiency

The digital tool helps designers save time by streamlining the comprehensive and time-consuming analysis required for resilient facade design. By simplifying complex steps, it enhances efficiency in the design process.

Innovation

After conducting a comprehensive literature review, the primary discovery was the absence of a tool capable of assessing the impact of building facades across multiple hazard scenarios in the current world. Existing studies predominantly focus on quantifying resilience at the urban, city, or building levels. Consequently, a tool is required that offers a streamlined approach for designers to assess resilience at the building facade level, given that facades serve as the initial point of contact in any hazardous event.

Impact

The development of this digital tool stands to have a profound impact both within academic circles and in real-world applications. Academically, it represents a significant advancement in the understanding of resilient facade design, particularly in the face of multi-hazard events like floods and heatwaves. By introducing innovative approach such as computational simulations and machine learning model, it paves the way for further research and experimentation in the field. Moreover, it serves as a valuable educational resource, offering students and researchers hands-on experience with advanced analysis techniques. In practical terms, the tool aims to revolutionize the design process, allowing architects and designers to expedite the creation of resilient facades while minimizing the complexity of analysis. This efficiency not only translates to cost savings for architectural firms and construction projects but also contributes to the creation of buildings better equipped to withstand and recover from natural disasters.

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

Currently, the world is experiencing severe climate change, leading to numerous devastating hazards. Floods and heatwaves are among those with the most profound impact on infrastructure, human health, and ecosystems. Various projects are currently ongoing to assess resilience at broader geographic scales, i.e., city, district, and region. However, there is still a need for a tool or method specifically designed to evaluate resilience and performance at the facade level during extreme events.

My graduation work, focused on developing a digital design tool for a facade system resilient to floods and heatwaves, holds profound relevance in broader social, professional, and scientific contexts. On a social level, it directly contributes to community resilience by ensuring buildings can withstand multiple hazards, enhancing public safety during extreme weather events. Professionally, architects, engineers, and decision-makers benefit from the integrated methodologies, advancing design practices and supporting informed decision-making in urban planning and construction. Scientifically, the multidisciplinary approach of the project, incorporating structural design, facade design, and risk management, contributes to the understanding of creating climate-resilient structures, with potential implications for further studies in the field.

In essence, my work addresses pressing societal needs, improves professional practices, and contributes valuable knowledge to the scientific community.

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

The primary objective of this study is to quantify the resilience of building facades against heatwaves and floods. This project employs a streamlined methodology for calculating facade resilience, which includes identifying hazard stressors (in this case, heatwaves and flood stressors) and determining their impact on the building envelope and human comfort. The methodology involves several key steps: identifying the hazard stressors, conducting computational simulations, applying machine learning models, performing sensitivity analysis, and ultimately calculating the resilience score of the facade.

The aforementioned workflow is versatile and can be adapted to other hazard scenarios, such as wind storms or earthquakes, with modifications to the computational simulations. By altering the weather files and adjusting local input values, this tool can be applied to any location worldwide to quantify facade resilience. Therefore, with appropriate adjustments, this tool can be adapted to different hazard scenarios and various locations, making it a valuable resource for resilience assessment globally.

How this project contribute to the sustainable development?

This thesis makes a significant contribution to sustainable development by providing an assessment strategy for facade resilience. In the current world, the frequency of devastating hazards has significantly increased, directly affecting infrastructure, human life, and ecosystems. This tool assists designers and facade engineers in making informed decisions when designing resilient facade systems. Resilient facades are better able to withstand severe hazards, experience less impact, and recover more quickly after disruptions.

Using this tool, designers can evaluate all critical parameters and configure facades based on the hazard intensity of a given site, thereby minimizing destruction during disruptive events. Consequently, employing this tool will directly contribute to the sustainable development of society by enhancing the resilience of buildings and reducing the adverse effects of natural hazards.

Did you encounter any challenges during this study, and how did you address them?

Unavailability of Hydraulic Simulation Tool for Flood Impact on Facades:

As discussed in Chapter 4, the digital tool developed in this study aims to quantify the impact of floods on facades. However, simulating the flood-facade interactions computationally proved difficult due to the lack of suitable software and the complexity involved. It took three months of trial and error with various simulation tools, including OpenFOAM, SimScale, Flow Design, SolidWorks, and Butterfly CFD, before reliable results were achieved. Ultimately, the computational simulations were successfully conducted using ANSYS Fluent. Due to the complexity and time required for each simulation, it was impractical to simulate all 163,840 scenarios. To address this, a mathematical model was developed to calculate the outputs for these scenarios, and the results were verified with ANSYS Fluent.

Modification of Heatwave Hazard Data:

Typically, weather files (EPW files) for any location contain standard data, such as dry bulb temperature, relative humidity, and wind speed. However, this thesis focused on extreme heatwave conditions, necessitating modifications to the weather data. Several tools, including CCWorldWeatherGen and EnergyPlus Weather Converter, were tested for this modification. However, the generated EPW files were incompatible with the Grasshopper script used for computational simulations. Eventually, extreme heatwave weather data were extracted from nearby weather stations and incorporated into the typical weather file using Dragonfly, a Grasshopper plugin, to effectively simulate extreme conditions.

These challenges underscore the complexity and innovative aspects of this research, highlighting the need for adaptable tools and methodologies in resilience assessment.

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A

Grasshopper script

Grasshopper scripts that are used for heatwaves and Flood simulation are presented

Grasshopper script for heatwaves simulation

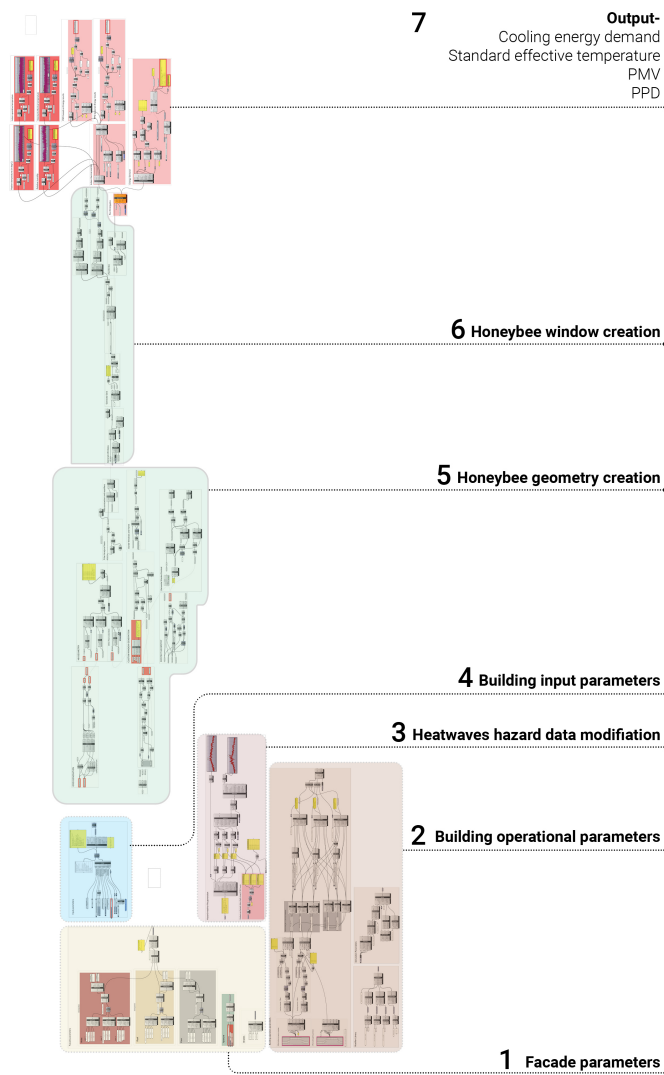


Figure A.1: Graphical representation of heatwaves simulation GH script (Source: Author)

1. Facade parameters

Facade parameters

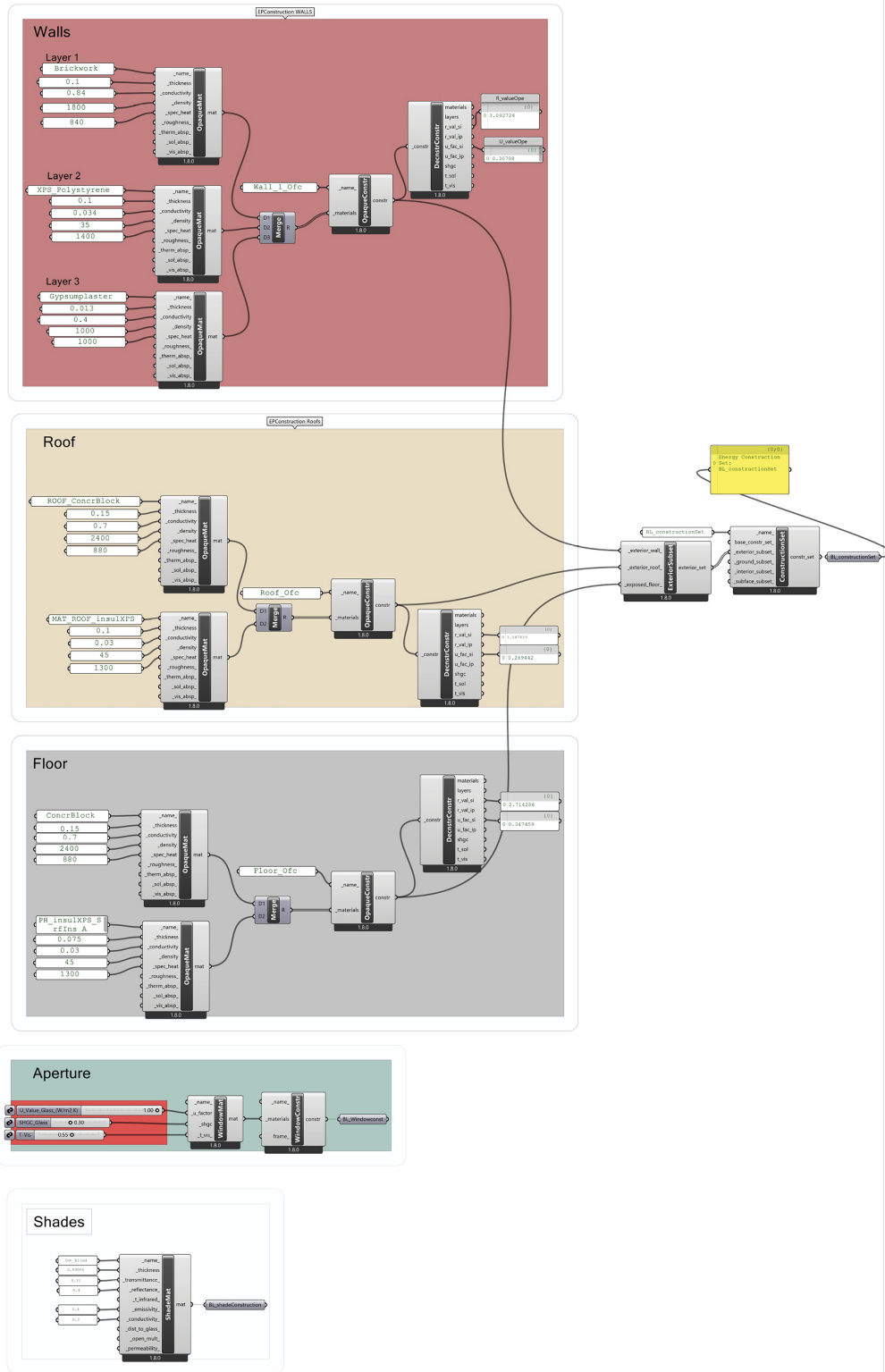


Figure A.2: Graphical representation of heatwaves simulation facade parameters GH script (Source: Author)

2. Building operational parameters

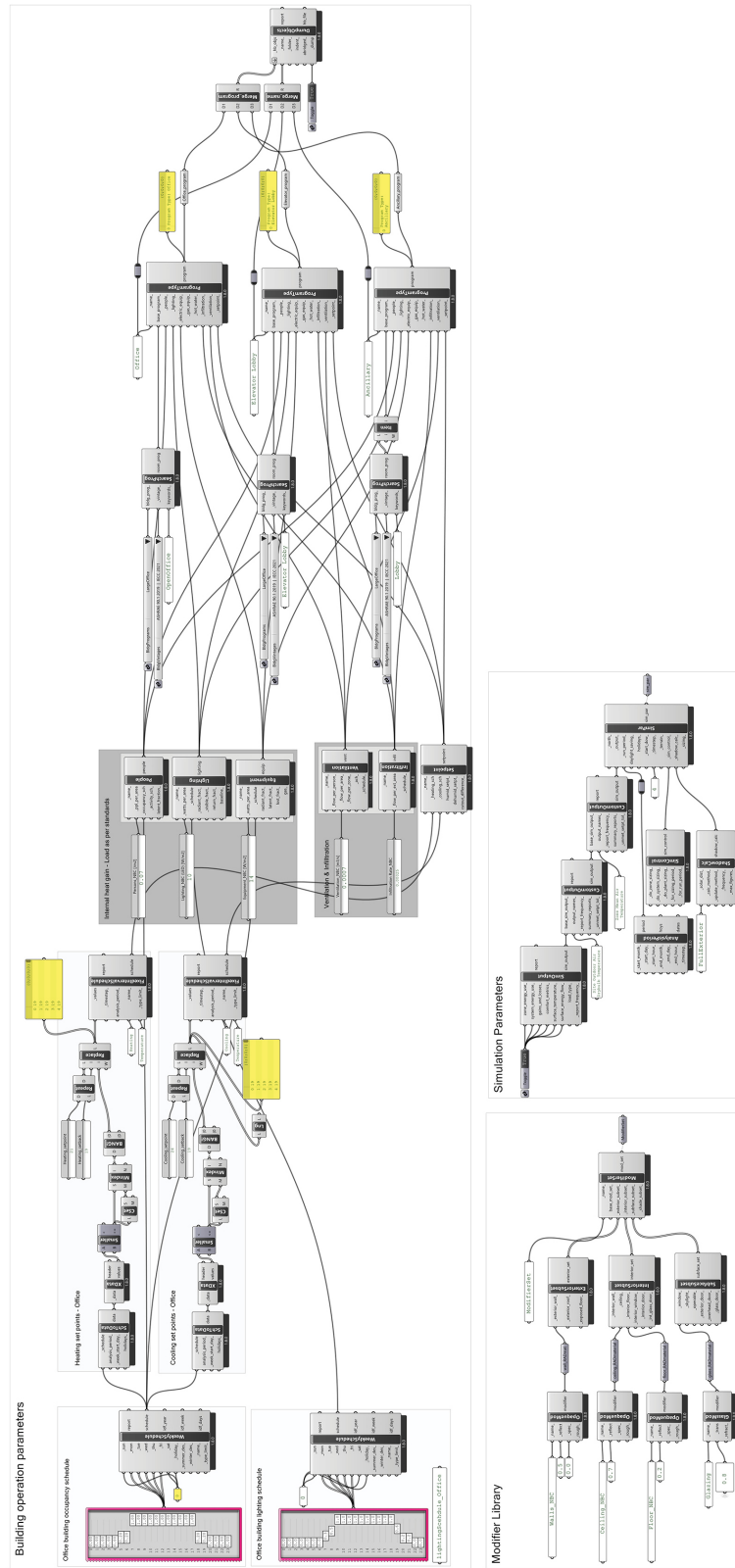


Figure A.3: Graphical representation of heatwaves simulation building operational parameters GH script (Source: Author)

3. Heatwaves hazard data modification

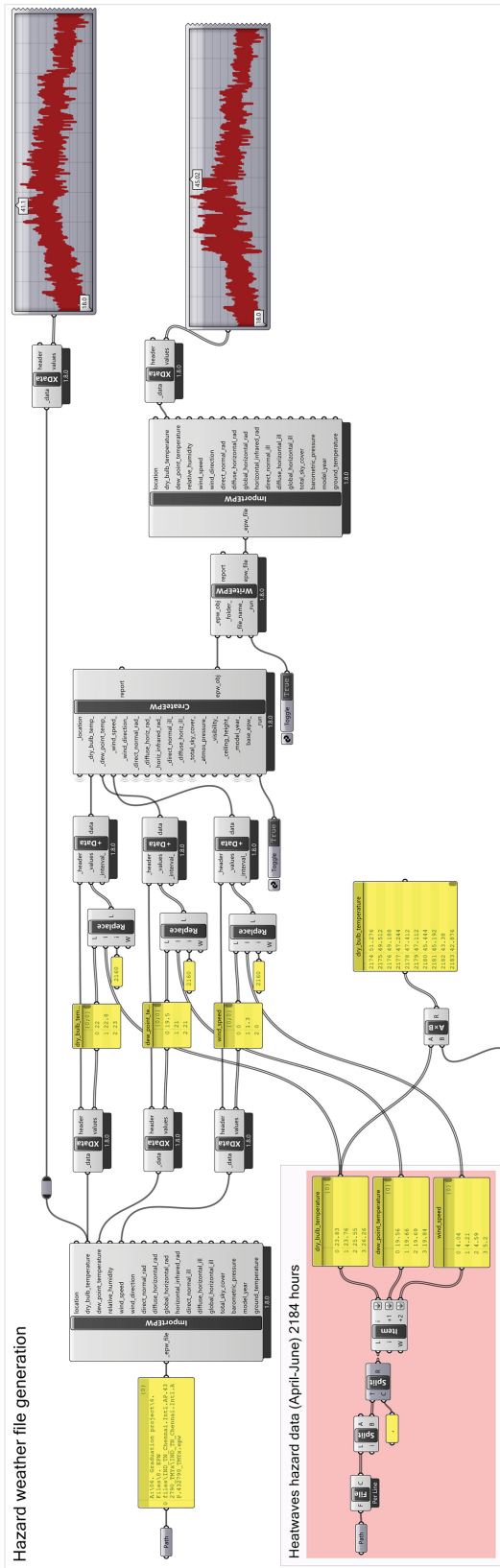


Figure A.4: Graphical representation of heatwaves simulation hazard data modification GH script (Source: Author)

4. Building input parameters

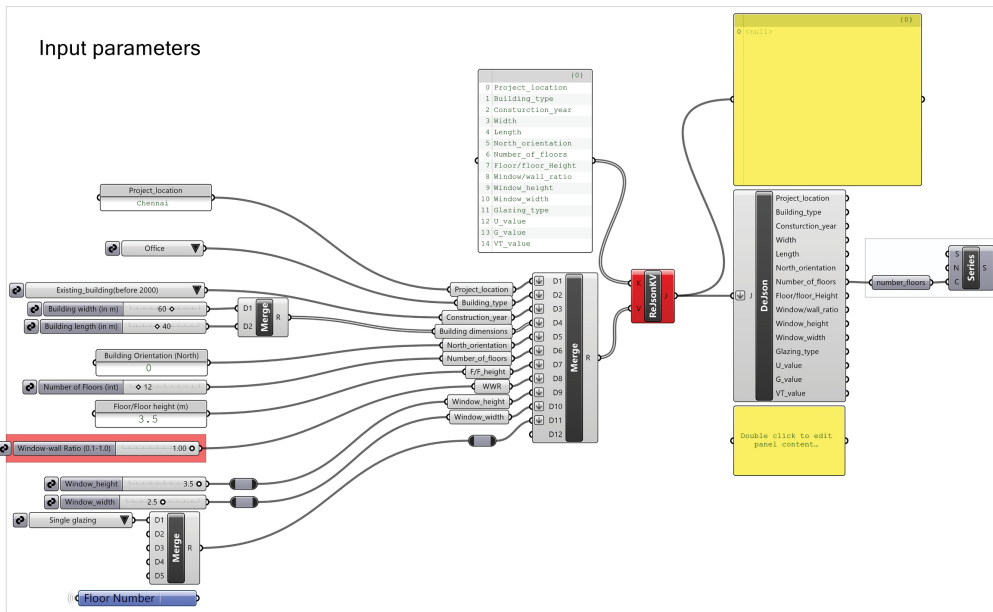


Figure A.5: Graphical representation of heatwaves simulation building input parameters GH script (Source: Author)

5. Honeybee geometry creation

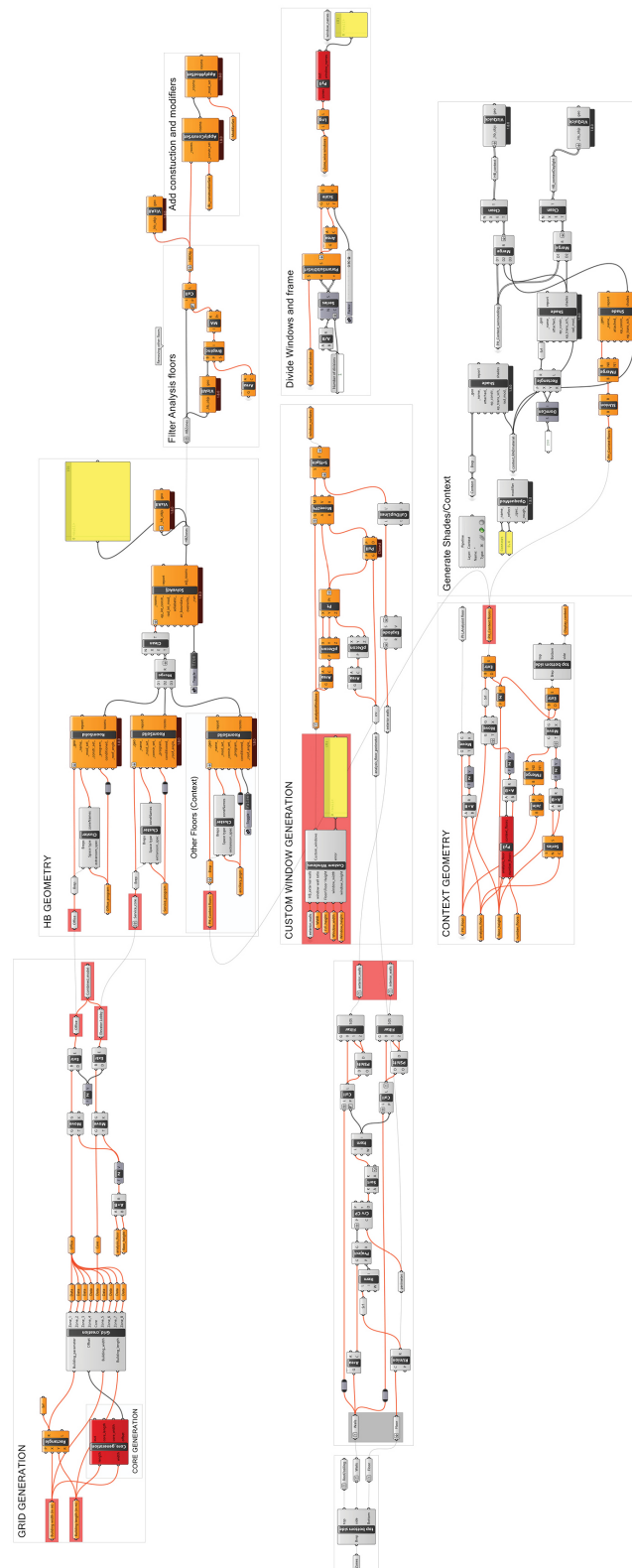


Figure A.6: Graphical representation of heatwaves simulation Honeybee geometry creation (Source: Author)

6. Honeybee window creation

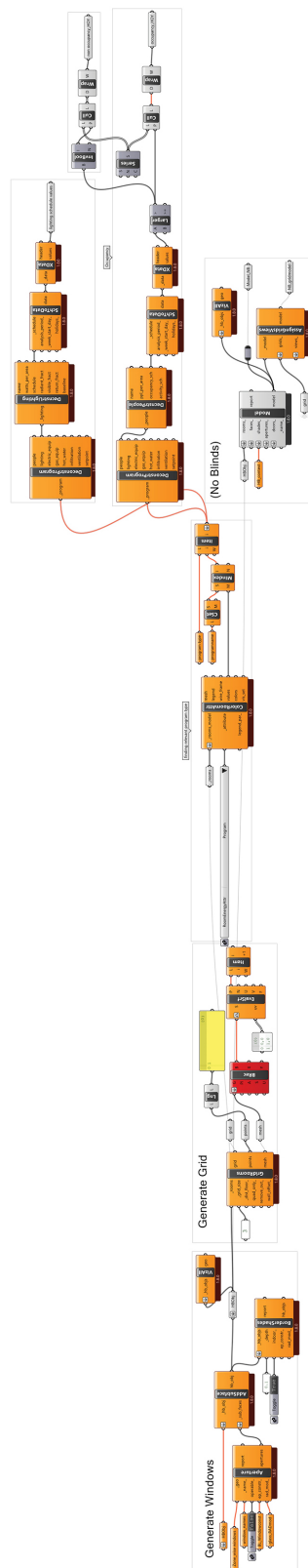


Figure A.7: Graphical representation of heatwaves simulation Honeybee window creation GH script (Source: Author)

7. Output

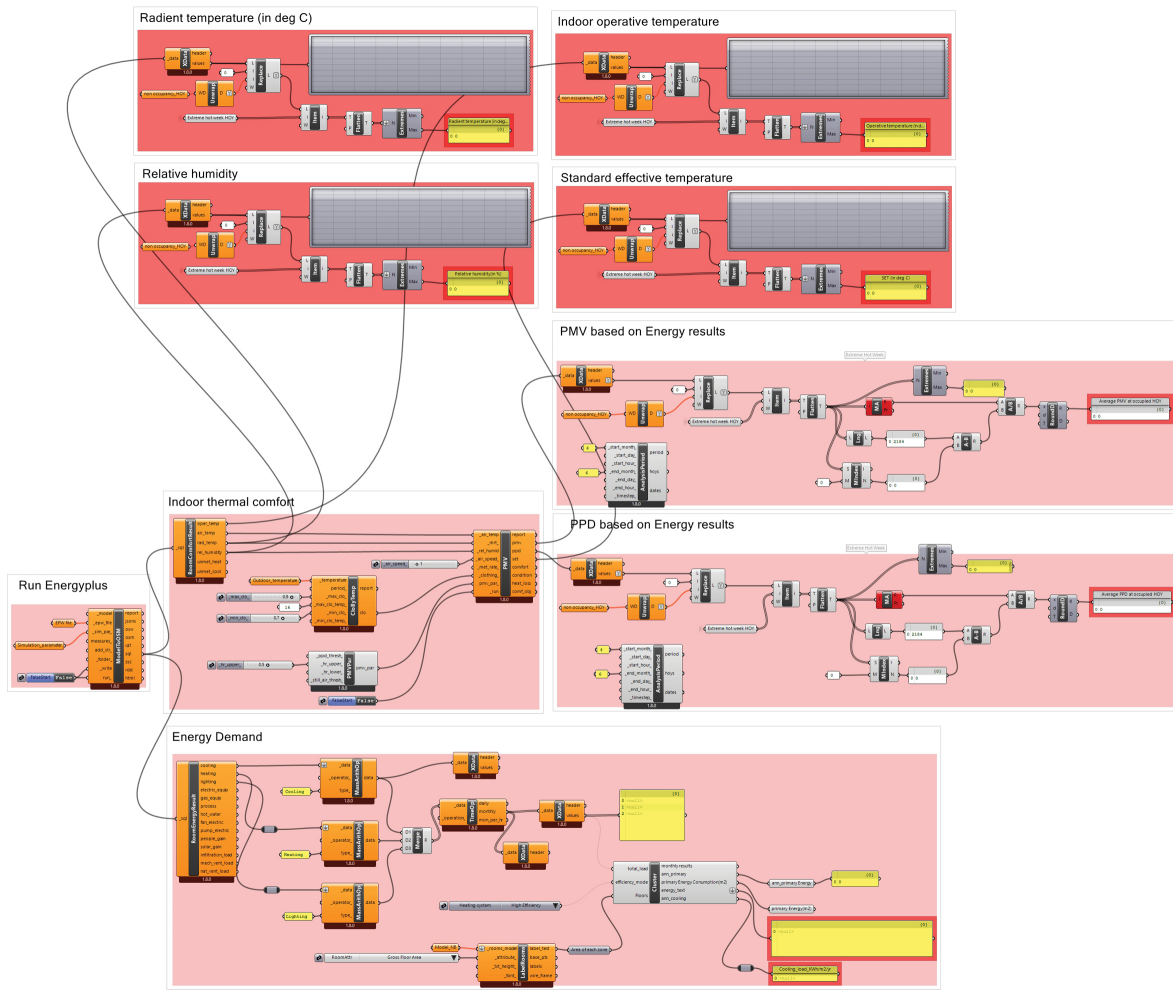


Figure A.8: Graphical representation of heatwaves simulation outputs GH script (Source: Author)

Grasshopper script for flood impact calculation

1. Flood impact calculation

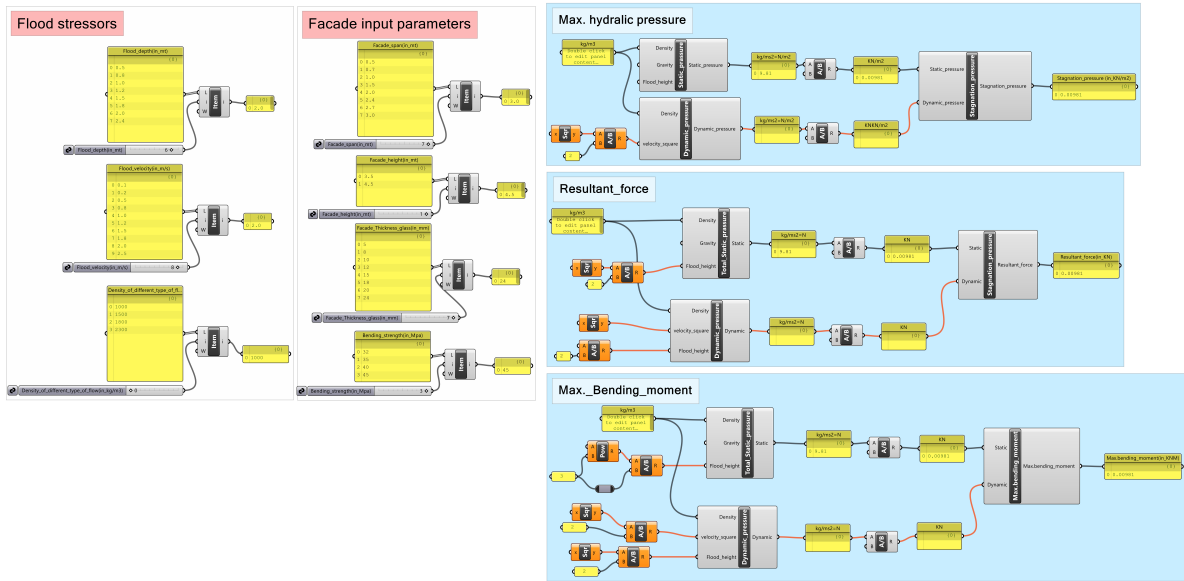


Figure A.9: Graphical representation of flood impact calculation GH script (Source: Author)

2. Flood stressors & Facade input parameters

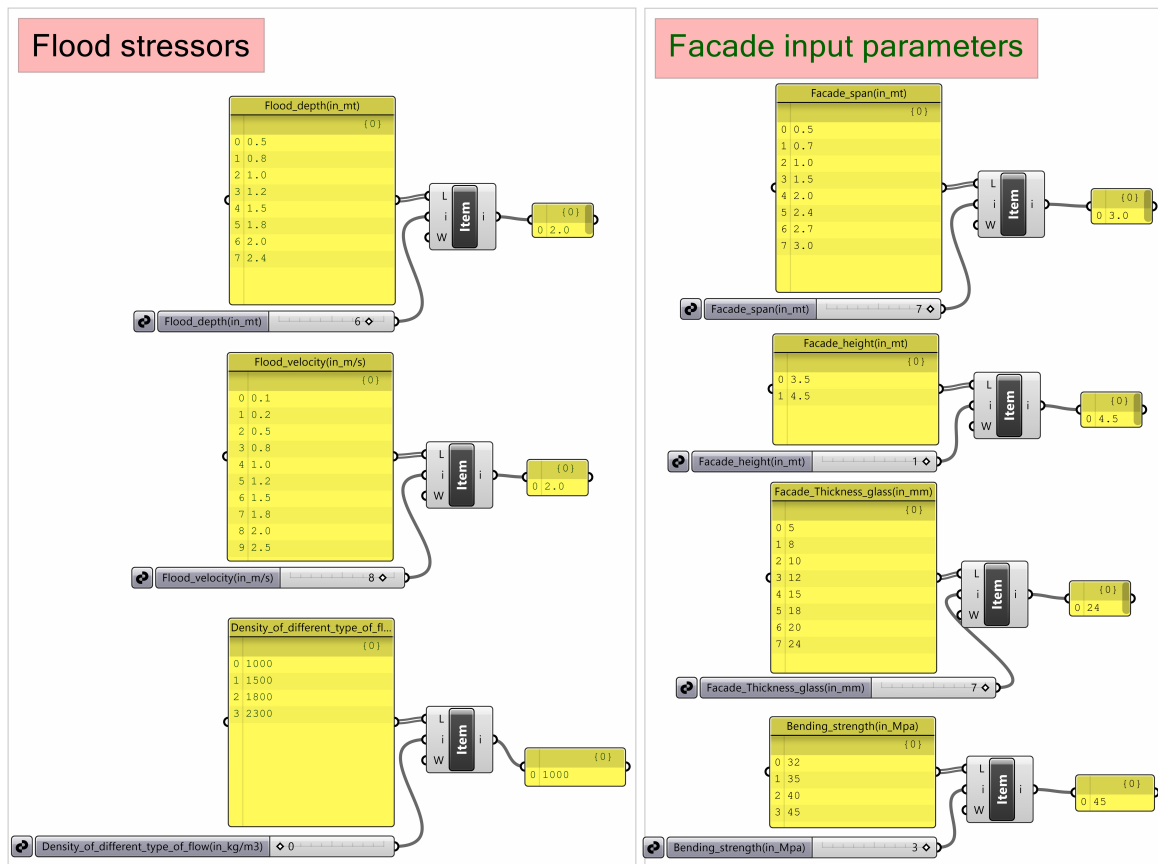


Figure A.10: Graphical representation of flood stressors and facade input parameters GH script (Source: Author)

2. Output

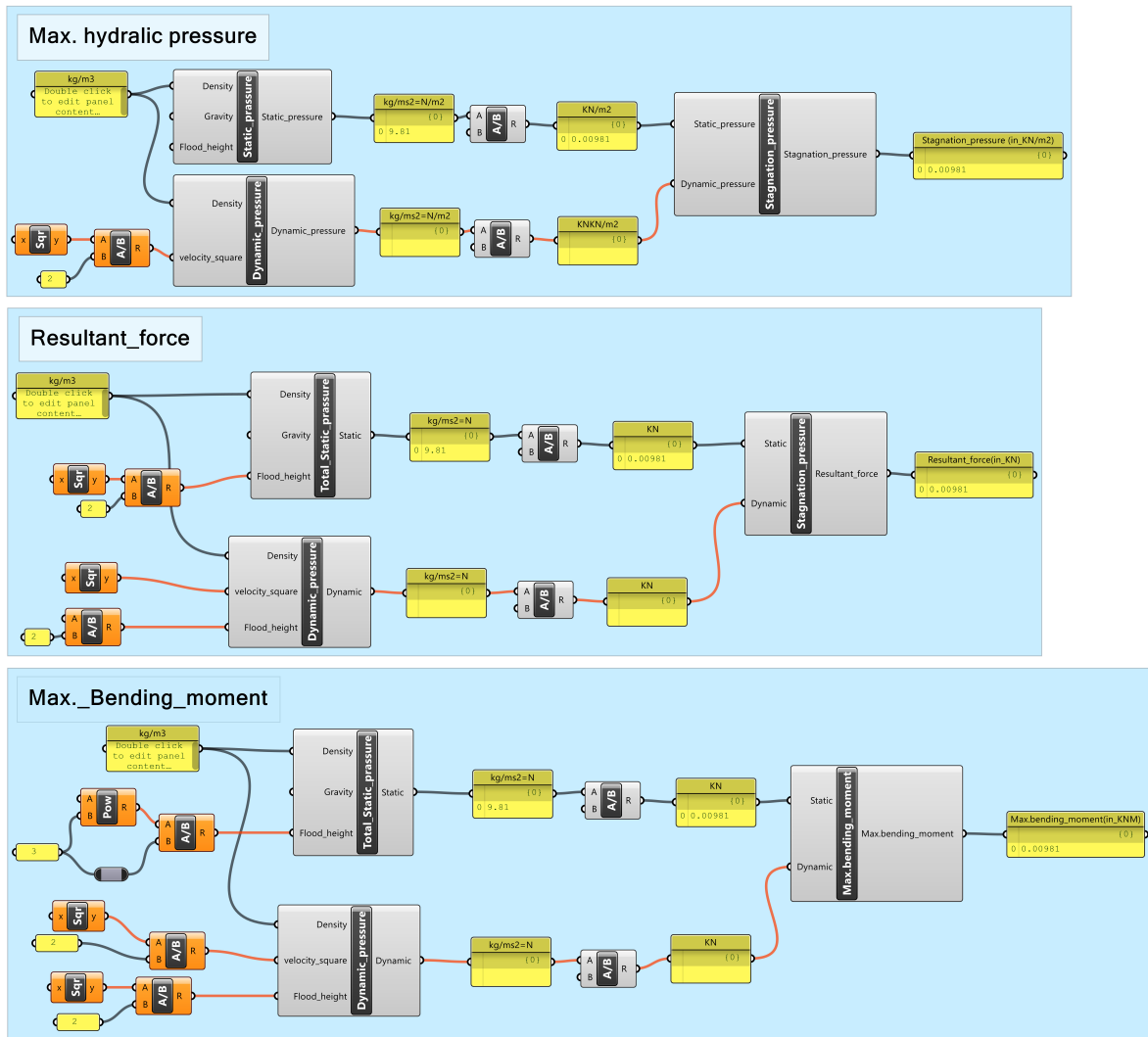


Figure A.11: Graphical representation of flood calculation output (Source: Author)

B

Python script

Python script for heatwaves resilience quantification

```
1 .....
2 Import Libraries
3 .....
4
5 import SALib
6 import pandas as pd
7 import numpy as np
8 import matplotlib.pyplot as plt
9 import seaborn as sns
10 from scipy.stats import uniform
11 from sklearn.gaussian_process import GaussianProcessRegressor
12 from sklearn.gaussian_process.kernels import RBF
13 from SALib.sample import saltelli
14 from SALib.analyze import sobol
15 from sklearn.model_selection import train_test_split
16 from sklearn.preprocessing import StandardScaler
17 from sklearn.neural_network import MLPRegressor
18 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
19 import csv
20 from math import ceil
21 from SALib.test_functions import Ishigami, Sobol_G
22 from sklearn.ensemble import RandomForestRegressor
23 from matplotlib.colors import LinearSegmentedColormap
24 .....
25 Import Simulation Outcomes
26 Load input and output data from CSV file
27 .....
28 .....
29 .....
30 .....
31 # data = pd.read_csv("./20240513_Heatwaves_Simulations_3584_check.csv") # read the data
32 data = pd.read_csv("./heatwaves/20240530_New_Heatwaves_Dataset_7168.csv") # read the data
33 .....
34 print(data) # print the dataframe
35 .....
36 .....
37 # Get input names from the first row of the data DataFrame
38 input_names = list(data.columns[:6])
39 output_names = list(data.columns[6:7])
40 .....
41 print(input_names)
42 print(output_names)
43 .....
44 # Step 2: Extract input and output columns
45 inputs = data.iloc[:, :6] # Assuming the first six columns are inputs
46 outputs = data.iloc[:, 6:] # Assuming columns after the first six are outputs
47 .....
48 print(outputs)
```

```

49
50 print(inputs.shape)
51 print(outputs.shape)

```

```

    in:T-Vis  in:Thickness_ins  in:SHGC_Glass  ...  out:Relative humidity(in %)  out:Average PMV at occupied HOY  out:Average PPD at occupied HOY
0      0.1      0.034      0.1  ...      89.130000      -0.81      19.38
1      0.1      0.034      0.1  ...      89.100000      -0.81      19.28
2      0.1      0.034      0.1  ...      88.640000      -0.81      19.25
3      0.1      0.034      0.1  ...      88.630000      -0.81      19.14
4      0.1      0.034      0.1  ...      88.630000      -0.81      19.10
...      ...      ...      ...      ...      ...      ...
7163    0.8      0.068      0.7  ...      89.083566      -0.82      19.67
7164    0.8      0.238      0.7  ...      89.032035      -0.83      20.00
7165    0.8      0.272      0.7  ...      89.026695      -0.83      20.02
7166    0.8      0.068      0.7  ...      89.083569      -0.82      19.67
7167    0.8      0.238      0.7  ...      89.032034      -0.83      20.00

[7168 rows x 13 columns]
['in:T-Vis', 'in:Thickness_ins', 'in:SHGC_Glass', 'in:R_Value_Opqueuewall', 'in:U_Value_Glass_(W/m2 K)', 'in:MWR']
['out:Cooling_load_KWh/m2/yr']
    out:Cooling_load_KWh/m2/yr  out:Operative temperature (in deg C)  ...  out:Average PMV at occupied HOY  out:Average PPD at occupied HOY
0      260.17      28.960000  ...      -0.81      19.38
1      260.45      28.990000  ...      -0.81      19.28
2      260.65      29.080000  ...      -0.81      19.25
3      261.27      29.370000  ...      -0.81      19.14
4      261.46      29.270000  ...      -0.81      19.10
...      ...      ...      ...      ...      ...
7163    257.24      28.876862  ...      -0.82      19.67
7164    252.53      28.797131  ...      -0.83      20.00
7165    252.27      28.792367  ...      -0.83      20.02
7166    257.25      28.876974  ...      -0.82      19.67
7167    252.54      28.797212  ...      -0.83      20.00

[7168 rows x 7 columns]
(7168, 6)
(7168, 7)

```

Figure B.1: Graphical representation of input and output columns heatwaves (Source: Author)

```

1
2
3 Compute the correlation between each input and output variable
4
5
6 correlation_matrix = pd.DataFrame(index=inputs.columns, columns=outputs.columns)
7
8 for input_col in inputs.columns:
9     for output_col in outputs.columns:
10        correlation = np.corrcoef(inputs[input_col], outputs[output_col])[0, 1]
11        correlation_matrix.loc[input_col, output_col] = correlation
12
13 # Create a custom colormap
14 greyish_red = (178/255, 34/255, 34/255)
15 custom_blue = (70/255, 130/255, 160/255)
16 custom_cmap = LinearSegmentedColormap.from_list('custom_cmap', [greyish_red, 'white',
17        custom_blue], N=256)
18
19 # Plot the correlation matrix
20 plt.figure(figsize=(12, 10), dpi=100)
21 sns.heatmap(correlation_matrix.astype(float), cmap=custom_cmap, vmin=-1, vmax=1, annot=True,
22        fmt=".2f", square=True, cbar_kws={"shrink": 0.8}, annot_kws={"size": 10})
23
24 # Set axis labels and title
25 plt.xlabel('Output Variables', fontsize=12)
26 plt.ylabel('Input Variables', fontsize=12)
27 plt.title('Correlation Matrix between Inputs and Outputs', fontsize=14)
28
29 plt.tight_layout() # Adjust layout to prevent clipping of labels
30 plt.show()

```

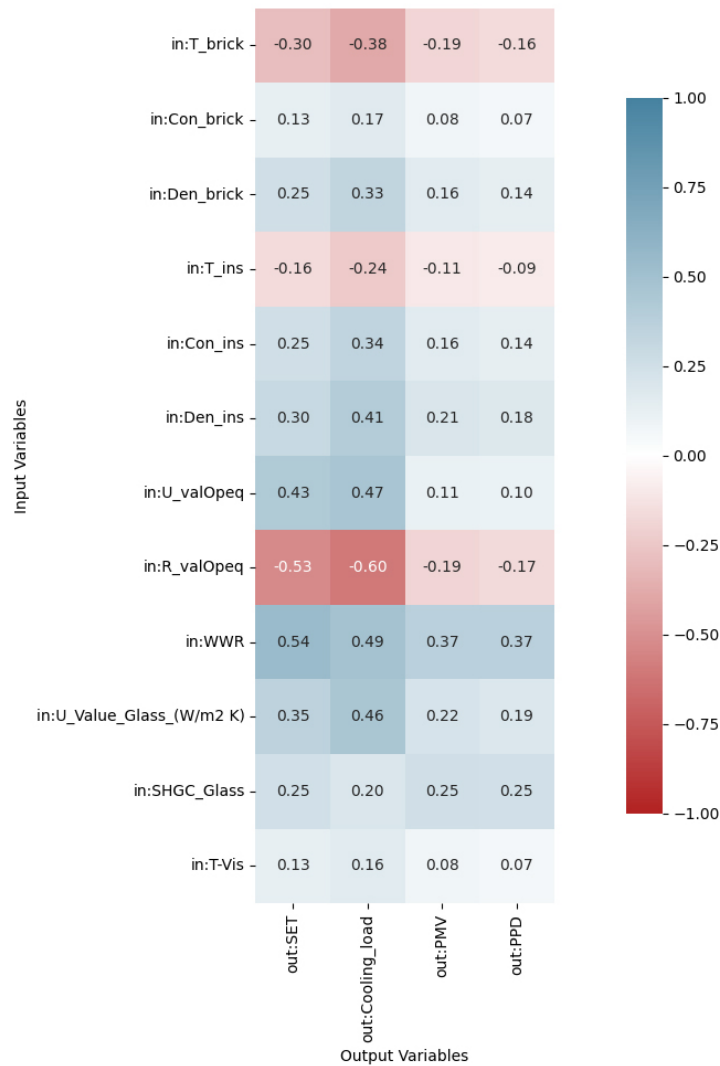



Figure B.2: Graphical representation of correlation matrix with 12 input variables (Source: Author)

```

1  """
2  Create a separate list of (min, max) tuples for each input variable
3  """
4  bounds = [(inputs.iloc[:, i].min(), inputs.iloc[:, i].max()) for i in range(inputs.shape[1])]
5
6  print(bounds)
7
8  """
9  Create an empty list to store the distribution curves
10 """
11 distribution_curves = []
12
13 """
14 Plot histograms with density in Y axis for each input variable
15 """
16 sns.set_style("whitegrid", {'axes.grid': True, 'grid.color': 'lightsteelblue', 'grid.
17     linewidth': 0.5})
18
19 # Create a grid of subplots with a fixed number of columns
20 num_cols = 2
21 num_rows = (len(input_names) + num_cols - 1) // num_cols
22 fig, axs = plt.subplots(nrows=num_rows, ncols=num_cols, figsize=(15, 15))
23 axs = axs.flatten()
24 for i, name in enumerate(input_names):

```

```

25 # Plot the histogram with density curve using the specified color code
26 sns.histplot(data=data, x=name, kde=True, stat='density', ax=axes[i], color='#5ca0ce',
27               line_kws={'color': '#5ca0ce'}) # Using the color code for both histogram
                and density curve
28 axes[i].set_ylabel('Density')
29 axes[i].set_xlabel(name)
30
31 # Add thin gridlines with blueish gray color inside the subplot
32 axes[i].grid(True, linewidth=0.5)
33
34 for j in range(len(input_names), len(axes)):
35     axes[j].axis('off')
36
37 plt.tight_layout()
38 plt.show()

```

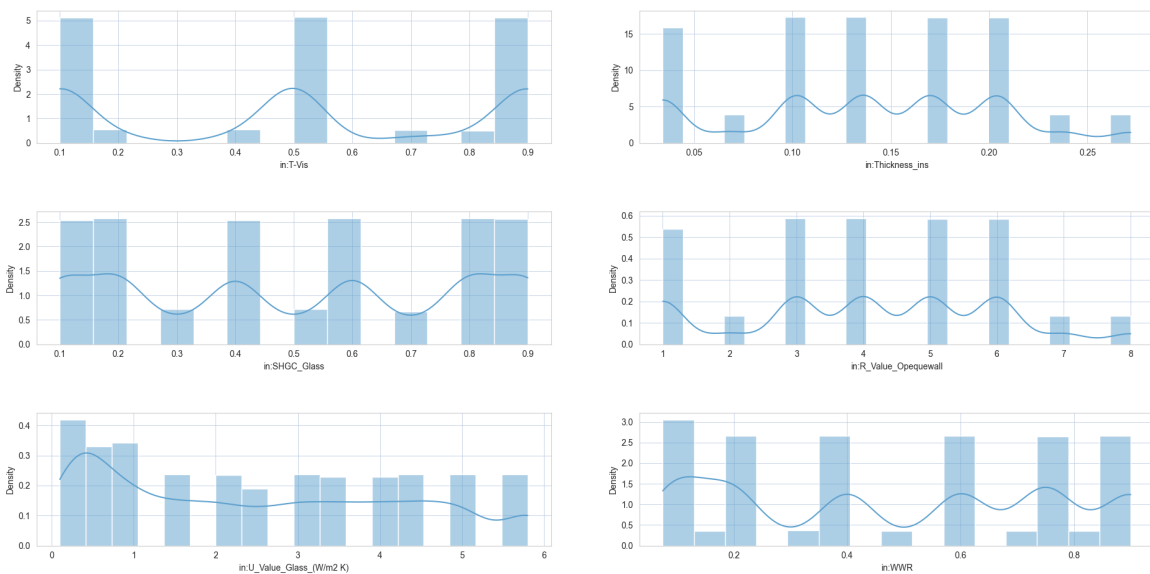


Figure B.3: Graphical representation of histograms with density in Y axis for each input variable (Source: Author)

```

1
2
3 Preparing prediction data for machine learning models (Artificial regression model)
4
5 # Separate the input data and output variable
6 X = data.iloc[:, :6].values
7 y = data.iloc[:, 6].values # Predicting only the 7th column, so no slicing with :7
8
9 print("y",y)
10 print("y_shape",y.shape)
11
12 # Split the data into training and testing sets
13 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=100)
14
15 # Standardize the features by scaling each feature to a mean of 0 and a standard deviation of
16 1
17 scaler = StandardScaler()
18 X_train_scaled = scaler.fit_transform(X_train)
19 X_test_scaled = scaler.transform(X_test)
20
21 # Create the ANN regression model
22 model = MLPRegressor(hidden_layer_sizes=(100,100,50), activation='relu', solver='adam',
23                       random_state=100)
24
25 # Fit the model to the training data
26 model.fit(X_train_scaled, y_train)

```

```
25
26 # Make predictions on the testing data
27 y_pred = model.predict(X_test_scaled)
28
29 # Calculate mean squared error (MSE)
30 mse = mean_squared_error(y_test, y_pred)
31
32 # Calculate root mean squared error (RMSE)
33 rmse = np.sqrt(mse)
34
35 # Calculate R-squared (coefficient of determination)
36 r2 = r2_score(y_test, y_pred)
37
38 # Print evaluation metrics
39 print("Mean Squared Error (MSE):", mse)
40 print("Root Mean Squared Error (RMSE):", rmse)
41 print("R-squared (Coefficient of Determination):", r2)
42
43 # Set the RGB color
44 color = (70/255, 130/255, 160/255)
45
46 # Create a scatter plot of predicted vs. actual values
47 plt.figure(facecolor='white') # Set background color to white
48 plt.scatter(y_test, y_pred, color=color)
49 plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='black', linestyle
50         = '--', linewidth=1) # Plotting the ideal line
51 plt.xlabel('Actual Values')
52 plt.ylabel('Predicted Values')
53 plt.title('Accuracy of ANN Regression Model')
54 plt.grid(color='lightgrey', linestyle='-', linewidth=0.5) # Set grid properties
55
56 # Convert R-squared to percentage accuracy
57 accuracy_percentage = r2 * 100
58
59 # Display accuracy percentage on the graph
60 plt.text(0.05, 0.9, f'Accuracy: {accuracy_percentage:.2f}%', transform=plt.gca().transAxes)
61 plt.show()
62
63 # Print accuracy percentage
64 print("Accuracy Percentage:", accuracy_percentage)
65
66 # Set the RGB color for the scatter plot points
67 color = (70/255, 130/255, 160/255)
68
69 # Create a scatter plot of predicted vs. actual values
70 plt.figure(facecolor='white') # Set background color to white
71 plt.scatter(y_test, y_pred, color=color, label='Predicted Values')
72 plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='black', linestyle
73         = '--', linewidth=1, label='Ideal Line') # Plotting the ideal line
74 plt.xlabel('Actual Values')
75 plt.ylabel('Predicted Values')
76 plt.title('Accuracy of ANN Regression Model')
77 plt.grid(color='lightgrey', linestyle='-', linewidth=0.5) # Set grid properties
78
79 # Convert R-squared to percentage accuracy
80 accuracy_percentage = r2 * 100
81
82 # Display accuracy percentage on the graph
83 plt.text(0.05, 0.9, f'Accuracy: {accuracy_percentage:.2f}%', transform=plt.gca().transAxes)
84
85 # Show legend
86 plt.legend()
87 plt.show()
88
89 # Print accuracy percentage
90 print("Accuracy Percentage:", accuracy_percentage)
```



Figure B.4: Graphical representation of ANN model accuracy (Source: Author)

```
Mean Squared Error (MSE): 5.6970471689025235
Root Mean Squared Error (RMSE): 2.3868487947296795
R-squared (Coefficient of Determination): 0.9855029754662792
```

Figure B.5: Graphical representation of evaluation metrics (Source: Author)

```
1
2
3 Preparing prediction data for machine learning models (Randomforest regression model)
4
5 # Split input and output variables
6 X = data.iloc[:, :6] # Input variables
7 y = data.iloc[:, 6] # Output variables
8
9 # Split data into training and testing sets (80% for training, 20% for testing)
10 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
11
12 # Check the shapes of training and testing sets
13 print("Training set shapes - Input:", X_train.shape, "Output:", y_train.shape)
14 print("Testing set shapes - Input:", X_test.shape, "Output:", y_test.shape)
15
16 # Train the model
17 regressor_Dataset = RandomForestRegressor()
18 regressor_Dataset.fit(X_train, y_train)
19
20 # Make predictions
21 y_pred = regressor_Dataset.predict(X_test)
22 print(y_pred)
23
24 # Convert Y to a pandas DataFrame
25 Y_df = pd.DataFrame(y_pred)
26
27 # Export Y to an Excel file
28 Y_df.to_excel('NEW6.xlsx', index=False)
29
30 # Calculate and print the accuracy
31 mae_Dataset = mean_absolute_error(y_test, y_pred)
32 Prediction_Model_Accuracy = round((1 - mae_Dataset) * 100, 1)
33 print(f"Prediction_Model_Accuracy: {Prediction_Model_Accuracy:.2f}%")
```

```
34
35
36 # Load the trained model
37 trained_model = RandomForestRegressor()
38 trained_model.fit(X_train, y_train)
39
40 # Set the color
41 scatter_color = (70/255, 130/255, 160/255)
42
43 # Calculate and print the accuracy
44 mae_Dataset = mean_absolute_error(y_test, y_pred)
45 Prediction_Model_Accuracy = round((1 - mae_Dataset) * 100, 1)
46 print(f"Prediction_Model_Accuracy: {Prediction_Model_Accuracy:.2f}%")
47
48 # Calculate Mean Squared Error (MSE)
49 mse = mean_squared_error(y_test, y_pred)
50
51 # Calculate Root Mean Squared Error (RMSE)
52 rmse = np.sqrt(mse)
53
54 # Calculate R-squared (R2)
55 r_squared = r2_score(y_test, y_pred)
56
57 print("Mean Squared Error (MSE):", mse)
58 print("Root Mean Squared Error (RMSE):", rmse)
59 print("R-squared (R2):", r_squared)
60
61 # Set the color
62 scatter_color = (70/255, 130/255, 160/255)
63
64 # Create a scatter plot of predicted vs. actual values
65 plt.figure(figsize=(8, 6), facecolor='white') # Set the figure size and background color
66 plt.scatter(y_test, y_pred, color=scatter_color, alpha=0.7) # Set the color and transparency
67 plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='black', linestyle
68         = '--', linewidth=1) # Plotting the ideal line
69 plt.xlabel('Actual Values')
70 plt.ylabel('Predicted Values')
71 plt.title('Accuracy of Random Forest Regression Model\nAccuracy: {:.2f}'.format(
72         Prediction_Model_Accuracy))
73 plt.grid(color='lightgrey', linestyle='-', linewidth=0.5) # Set grid properties
74
75 # Display accuracy percentage on the graph
76 plt.text(0.05, 0.9, f'Accuracy: {Prediction_Model_Accuracy:.2f}%', transform=plt.gca().
77         transAxes)
78 plt.show()
```

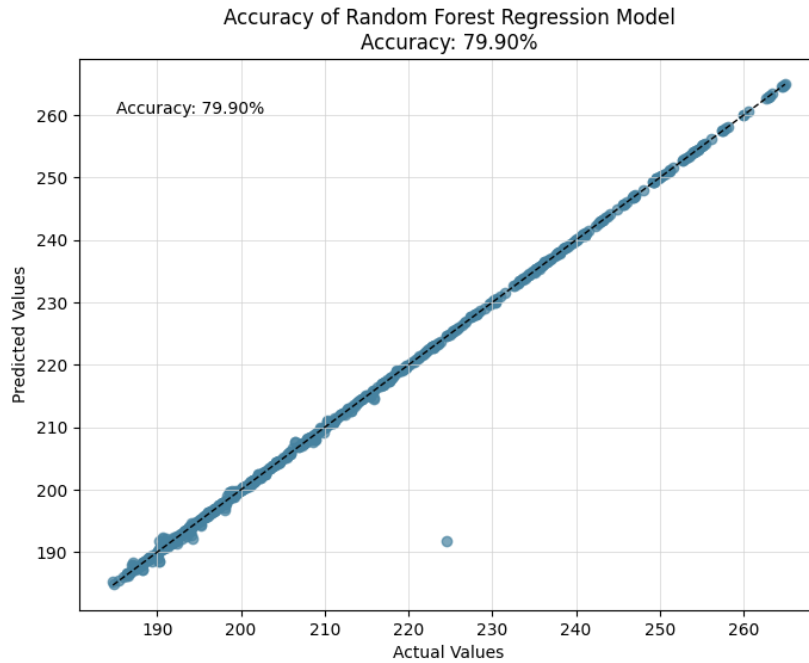


Figure B.6: Graphical representation of RFB model accuracy (Source: Author)

```
Prediction_Model_Accuracy: 68.40%
Mean Squared Error (MSE): 8.565389525922168
Root Mean Squared Error (RMSE): 2.92666867375215
R-squared (R2): 0.9790472300115709
```

Figure B.7: Graphical representation of evaluation metrics RFB (Source: Author)

```
1
2
3 Preparing prediction data for machine learning models (Gaussian Regression model)
4
5 # Separate the input data and output variable
6 X = data.iloc[:, :6].values
7 y = data.iloc[:, 6].values
8
9 # Create the Gaussian regression model
10 kernel = RBF(length_scale=1.0)
11
12 model = GaussianProcessRegressor(kernel=kernel)
13
14 # Fit the model to the data
15 model.fit(X, y)
16
17 print(X)
18 print(y)
19
20 # Convert X and y to DataFrames
21 X_df = pd.DataFrame(X)
22 y_df = pd.DataFrame(y)
23
24 # Export X to Excel
25 X_df.to_excel("X_data.xlsx", index=False)
26
27 # Export y to Excel
28 y_df.to_excel("y_data.xlsx", index=False)
29
30
```

```

31 Check Error and accuracy
32 """
33 # Make predictions on the training data
34 y_pred = model.predict(X)
35 print("y_pred", y_pred)
36
37 # Calculate mean squared error (MSE)
38 mse = mean_squared_error(y, y_pred)
39
40 # Calculate root mean squared error (RMSE)
41 rmse = np.sqrt(mse)
42
43 # Calculate R-squared (coefficient of determination)
44 r2 = r2_score(y, y_pred)
45
46 print("Mean Squared Error (MSE):", mse)
47 print("Root Mean Squared Error (RMSE):", rmse)
48 print("R-squared (Coefficient of Determination):", r2)
49
50 # Calculate the accuracy (assuming the calculation is similar to the previous example)
51 mae_Dataset = mean_absolute_error(y, y_pred)
52 Prediction_Model_Accuracy = round((1 - mae_Dataset) * 100, 1)
53 print(f"Prediction_Model_Accuracy: {Prediction_Model_Accuracy:.2f}%")
54
55 # Set the color
56 scatter_color = (70/255, 130/255, 160/255)
57
58 # Create a scatter plot of predicted vs. actual values
59 plt.figure(figsize=(8, 6), facecolor='white') # Set the figure size and background color
60 plt.scatter(y, y_pred, color=scatter_color, alpha=0.7) # Set the color and transparency
61 plt.plot([y.min(), y.max()], [y.min(), y.max()], color='black', linestyle='--', linewidth=1)
62 # Plotting the ideal line
63 plt.xlabel('Actual Values')
64 plt.ylabel('Predicted Values')
65 plt.title('Accuracy of Gaussian Regression Model\nAccuracy: {:.2f}%'.format(
66     Prediction_Model_Accuracy))
67 plt.grid(color='lightgrey', linestyle='-', linewidth=0.5) # Set grid properties
68
69 # Display accuracy percentage on the graph
70 plt.text(0.05, 0.9, f'Accuracy: {Prediction_Model_Accuracy:.2f}%', transform=plt.gca().
71     transAxes)
72
73 plt.show()
74
75 """
76 Check Fitting
77 """
78 # Generate test points for prediction
79 X_test = data.iloc[:, :6]. values
80
81 # Predict the mean and standard deviation of the output at test points
82 y_mean , y_std = model.predict(X_test , return_std=True)
83
84 # Plot the predicted mean with uncertainty
85 plt.figure(figsize =(20, 6))
86 plt.plot(y_mean , color='blue', lw=0.1, label='Predicted Mean')
87 plt.xlabel('Sample Index')
88 plt.ylabel('Output')
89 plt.title('Fitting of the Gaussian Regression Model')
90 plt.legend()
91 plt.show()

```

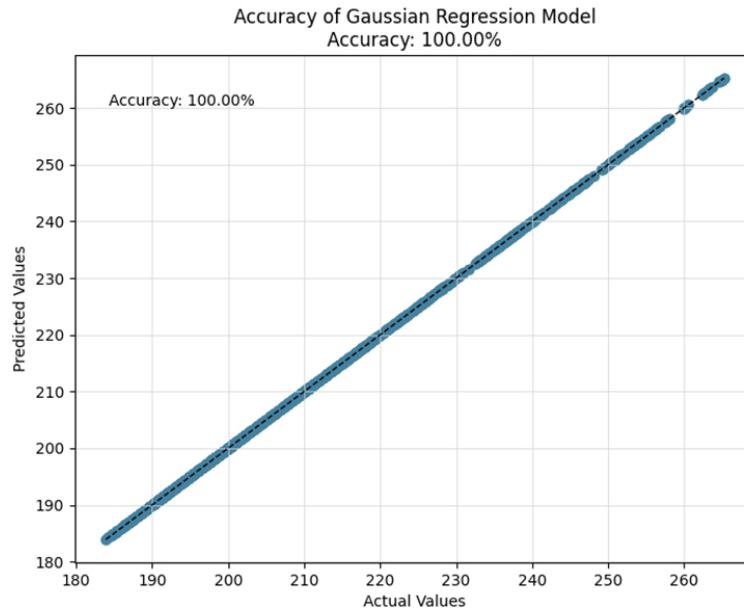


Figure B.8: Graphical representation of Gaussian regression model accuracy (Source: Author)

```
Mean Squared Error (MSE): 7.723992925083653e-16
Root Mean Squared Error (RMSE): 2.779207247594834e-08
R-squared (Coefficient of Determination): 1.0
Prediction_Model_Accuracy: 100.00%
```

Figure B.9: Graphical representation of evaluation metrics GRM (Source: Author)

```

1
2
3 Sensitivity Analysis by using Sobol's indices
4
5 # Define the problem definition for sensitivity analysis
6 problem = {
7     'num_vars': X.shape[1] ,
8     'names':  ['in:T-Vis','in:Thickness_insulation_(in_mt)','in:SHGC_Glass','in:
9     'bounds': [(inputs.iloc[:, i].min(), inputs.iloc[:, i].max()) for i in range(inputs.shape
10     'dists' : ['unif','unif','unif','unif','unif','unif']]
11 }
12
13 # Sampling Parameter Values Using Saltelli's Method
14 param_values = saltelli.sample(problem, 1024)
15
16 print("paramevalue", param_values)
17 print("paramevalueshape", param_values.shape)
18
19 # Evaluate the model with the adjusted sample size
20
21 # Y = model.predict(param_values)
22
23 # Y = regressor_Dataset.predict(param_values)
24 Y = model.predict(param_values)
25 y_pred = model.predict(X)
26
27 print("Y",Y)
28 print("X",X)
29 print("y_pred",y_pred)
30
31 print("paramevalue", param_values)

```



```

32 print("paramevalueshape", param_values.shape)
33
34 # Check the shape of Y
35 print("Shape_of_Y:", Y.shape)
36 print("Shape_of_X:", X.shape)
37 print("y_pred_shape", y_pred.shape)
38
39 # Perform sensitivity analysis using Sobol indices
40 Si = sobol.analyze(problem, Y)
41
42 # Extract the first-order indices, total indices, and second-order indices
43
44 first_order_indices = Si['S1']
45 total_order_indices = Si['ST']
46
47 # # second_order_indices = Si['S2']
48
49 print("First-Order-Indices:", Si['S1'])
50 print("Total-Order-Indices:", Si['ST'])
51
52 # Create figure and axis objects for first-order indices
53 fig, ax = plt.subplots(figsize=(10, 6))
54
55 # Plot first-order indices
56 ax.barh(input_names, first_order_indices, color=(70/255, 130/255, 160/255))
57 ax.set_xlabel('Sensitivity_Index_Value')
58 ax.set_ylabel('Input_Variables')
59 ax.set_title('First-order_Sensitivity_Analysis_Results')
60
61 # Show plot for first-order indices
62 plt.show()
63
64 # Create figure and axis objects for total-order indices
65 fig, ax = plt.subplots(figsize=(10, 6))
66
67 # Plot total-order indices
68 ax.barh(input_names, total_order_indices, color=(70/255, 130/255, 160/255))
69 ax.set_xlabel('Sensitivity_Index_Value')
70 ax.set_ylabel('Input_Variables')
71 ax.set_title('Total-order_Sensitivity_Analysis_Results')
72
73 # Show plot for total-order indices
74 plt.show()

```

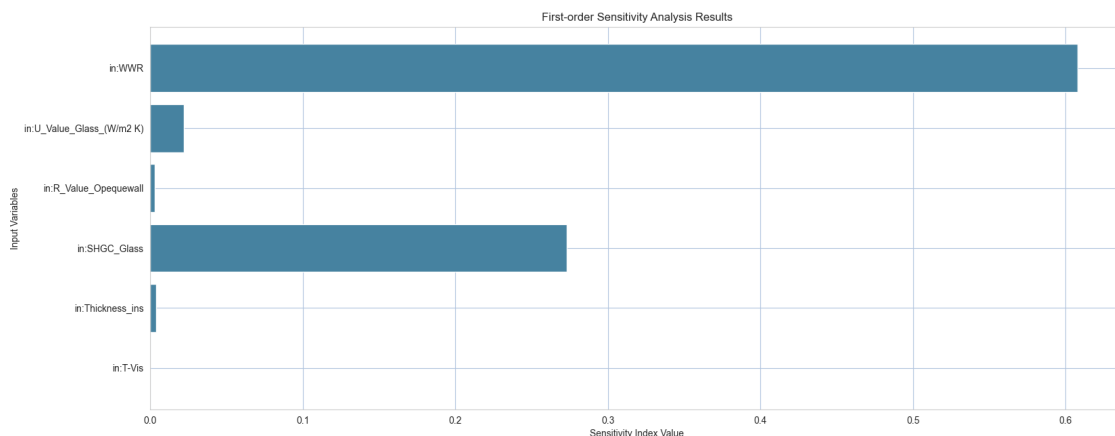


Figure B.10: Graphical representation of first-order indices (Source: Author)

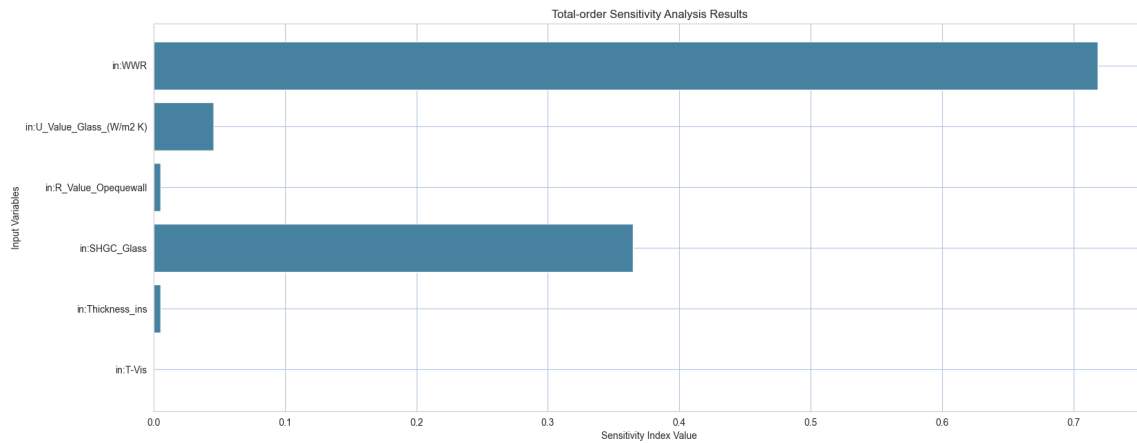


Figure B.11: Graphical representation of total-order indices (Source: Author)

```

1
2
3 Resilience matrix heatwaves
4
5 # Load the data from CSV file
6 data = pd.read_csv('./Heatwaves/Resilience_matrix_dataset_heatwaves.csv')
7
8 print(data)
9
10 # Extracting the columns
11 hour_of_year = data.iloc[:, 0]
12 outdoor_temp_heatwaves = data.iloc[:, 1]
13 cooling_demand_heatwaves = data.iloc[:, 2]
14 outdoor_temp_typical = data.iloc[:, 3]
15 cooling_demand_typical = data.iloc[:, 4]
16
17 # Calculate the area under Cooling Energy demand during Heatwaves and typical weather
18   condition
19 F_heatwaves = np.trapz(np.abs(cooling_demand_heatwaves), dx=1)
20 print("f_heatwaves", F_heatwaves)
21
22 F_typical = np.trapz(np.abs(cooling_demand_typical), dx=1)
23 print("f_typical", F_typical)
24
25 # Calculate the area between Cooling Energy demand during Heatwaves and typical weather
26   condition
27 Resilience_loss = F_heatwaves - F_typical
28 print("Resilience_loss", Resilience_loss)
29
30 # Define RGB colors
31 color_right_y_axis = (70/255, 130/255, 160/255) # RGB(70, 130, 160)
32 color_left_y_axis = (178/255, 34/255, 34/255) # RGB(178, 34, 34)
33
34 # First graph: heatwaves
35 fig, ax1 = plt.subplots()
36
37 ax1.set_xlabel('Hour_of_the_Year')
38 ax1.set_ylabel('Outdoor_Temperature_(Heatwaves)', color=color_left_y_axis)
39 ax1.plot(hour_of_year, outdoor_temp_heatwaves, color=color_left_y_axis, linestyle=':')
40 ax1.tick_params(axis='y', labelcolor=color_left_y_axis)
41
42 ax2 = ax1.twinx()
43 ax2.set_ylabel('Cooling_Demand_(Heatwaves)', color=color_right_y_axis)
44 ax2.plot(hour_of_year, cooling_demand_heatwaves, color=color_right_y_axis)
45 ax2.tick_params(axis='y', labelcolor=color_right_y_axis)
46
47 # Add grid with thin dotted lines to the plot background
48 ax1.grid(True, which='both', linestyle=':', linewidth=0.5)

```

```

47
48 # Set x-axis ticks from 2784 to 3024
49 plt.xticks(np.arange(2784, 3025, step=24))
50
51 fig.tight_layout()
52 plt.title('Outdoor Temperature and Cooling Demand during Heatwaves')
53 plt.show()
54
55 # Second graph: typical conditions
56 fig, ax1 = plt.subplots()
57
58 ax1.set_xlabel('Hour of the Year')
59 ax1.set_ylabel('Outdoor Temperature (Typical)', color=color_left_y_axis)
60 ax1.plot(hour_of_year, outdoor_temp_typical, color=color_left_y_axis, linestyle=':')
61 ax1.tick_params(axis='y', labelcolor=color_left_y_axis)
62
63 ax2 = ax1.twinx()
64 ax2.set_ylabel('Cooling Demand (Typical)', color=color_right_y_axis)
65 ax2.plot(hour_of_year, cooling_demand_typical, color=color_right_y_axis)
66 ax2.tick_params(axis='y', labelcolor=color_right_y_axis)
67
68 # Add grid with thin dotted lines to the plot background
69 ax1.grid(True, which='both', linestyle=':', linewidth=0.5)
70
71 # Set x-axis ticks from 2784 to 3024
72 plt.xticks(np.arange(2784, 3025, step=24))
73
74 fig.tight_layout()
75 plt.title('Outdoor Temperature and Cooling Demand during Typical Conditions')
76 plt.show()
77
78 # Define RGB colors
79 color_heatwaves = (178/255, 34/255, 34/255) # RGB(178, 34, 34)
80 color_typical = (70/255, 130/255, 160/255) # RGB(70, 130, 160)
81
82 # Plot the cooling energy demand for both heatwaves and typical conditions
83 plt.figure(figsize=(12, 6))
84 plt.plot(hour_of_year, cooling_demand_heatwaves, label='Cooling Demand Heatwaves', color=
85         color_heatwaves)
86 plt.plot(hour_of_year, cooling_demand_typical, label='Cooling Demand Typical', color=
87         color_typical)
88
89 # Highlight the positive area difference between the two curves
90 plt.fill_between(hour_of_year, cooling_demand_heatwaves, cooling_demand_typical,
91                 where=(cooling_demand_heatwaves > cooling_demand_typical),
92                 facecolor=color_heatwaves, alpha=0.3, interpolate=True)
93
94 # Add labels and legend
95 plt.xlabel('Hour of Year')
96 plt.ylabel('Cooling Energy Demand')
97 plt.title('Cooling Energy Demand during Heatwaves vs. Typical Conditions')
98 plt.legend()
99
100 # Add grid with thin dotted lines to the plot background
101 plt.grid(True, which='both', linestyle=':', linewidth=0.5)
102
103 # Set x-axis ticks from 2784 to 3024
104 plt.xticks(np.arange(2784, 3025, step=24))
105
106 # Show the plot
107 plt.show()

```

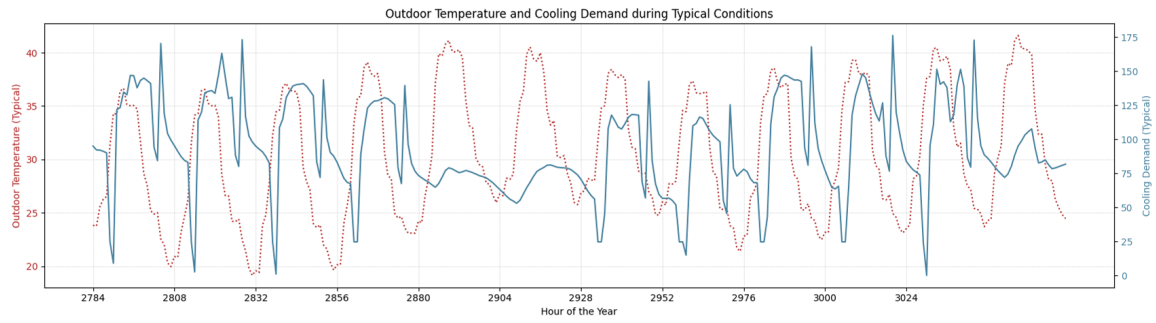


Figure B.12: Graphical representation of outdoor temperature and cooling demand during typical conditions

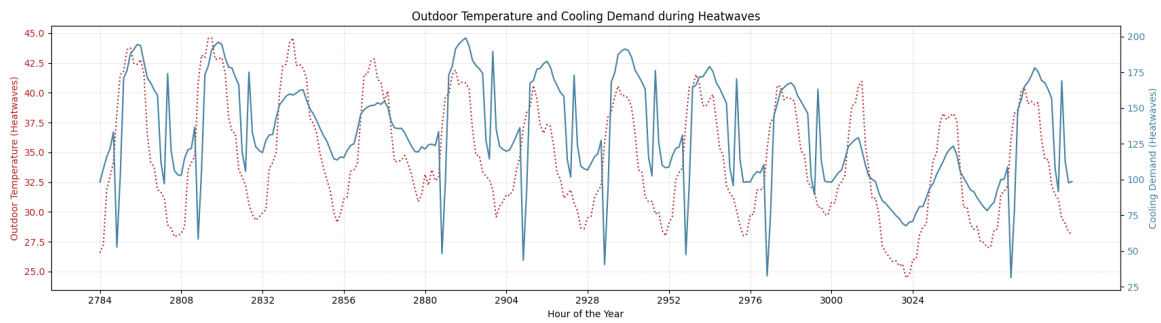


Figure B.13: Graphical representation of outdoor temperature and cooling demand during heatwaves

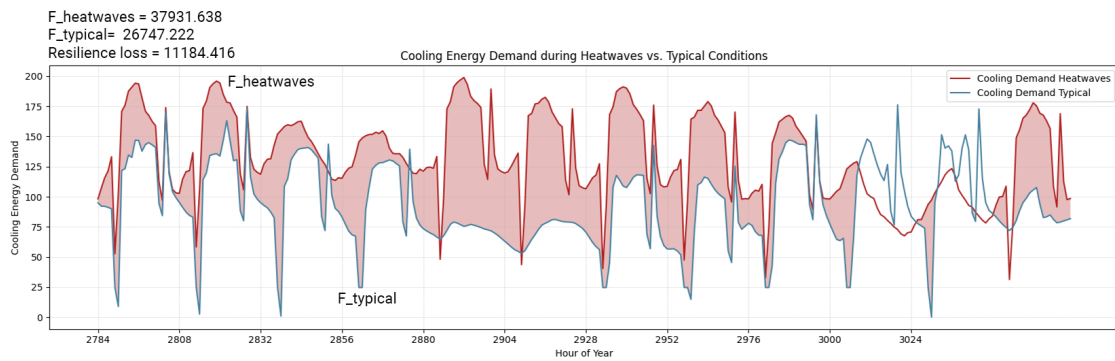


Figure B.14: Graphical representation of resilience loss heatwaves (Source: Author)

```
f_heatwaves 37931.6389015
f_typical 26747.222
Resilience_loss 11184.4169015
```

Figure B.15: Graphical representation of Resilience loss heatwaves calculation

Python script for flood resilience quantification

```

1  """
2  Import Libraries
3  """
4  import SALib
5  import pandas as pd
6  import numpy as np
7  import matplotlib.pyplot as plt
8  import seaborn as sns
9  from scipy.stats import uniform
10 from sklearn.gaussian_process import GaussianProcessRegressor
11 from sklearn.gaussian_process.kernels import RBF
12 from SALib.sample import saltelli
13 from SALib.analyze import sobol
14 from sklearn.model_selection import train_test_split
15 from sklearn.preprocessing import StandardScaler
16 from sklearn.neural_network import MLPRegressor
17 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
18 import csv
19 from math import ceil
20 from SALib.test_functions import Ishigami, Sobol_G
21 from sklearn.ensemble import RandomForestRegressor
22 from matplotlib.colors import LinearSegmentedColormap
23 from tensorflow.keras.models import Sequential
24 from tensorflow.keras.layers import Dense
25
26 """
27 Import Simulation Outcomes
28 Load input and output data from CSV file
29 """
30 data = pd.read_csv("./Flood/202240527_Flood_Simulation_Results.csv") # read the data
31 print(data) # print the dataframe
32
33
34 # Get input names from the first row of the data DataFrame
35 input_names = list(data.columns [:7])
36 output_names = list(data.columns [8:12])
37
38 print(input_names)
39 print(output_names)
40
41 # Step 2: Extract input and output columns
42 inputs = data.iloc[:, :7] # Assuming the first five columns are inputs
43 outputs = data.iloc[:, 8:] # Assuming columns after the first five are outputs
44
45 print(outputs)
46
47 print(inputs.shape)
48 print(outputs.shape)

```

```

in:Facade_span(in_mt) in:Facade_height(in_mt) in:Facade_Thickness_glass(in_m) ... Total_force_on_facade(in_N) Distribyuted load_q(in_N/m) out:Max bending_moment(in_NM)
0 0.5 3.5 0.005 ... 613.75 1227.5 38.257083
1 0.7 3.5 0.005 ... 859.25 1227.5 38.257083
2 1.0 3.5 0.005 ... 1227.50 1227.5 38.257083
3 1.5 3.5 0.005 ... 1841.25 1227.5 38.257083
4 2.0 3.5 0.005 ... 2455.00 1227.5 38.257083
... ..
163835 1.5 4.5 0.024 ... 123247.80 82165.2 46065.097730
163836 2.0 4.5 0.024 ... 164330.40 82165.2 46065.097730
163837 2.4 4.5 0.024 ... 197196.48 82165.2 46065.097730
163838 2.7 4.5 0.024 ... 221846.04 82165.2 46065.097730
163839 3.0 4.5 0.024 ... 246495.60 82165.2 46065.097730

[163840 rows x 13 columns]
['in:Facade_span(in_mt)', 'in:Facade_height(in_mt)', 'in:Facade_Thickness_glass(in_m)', 'in:Bending_strength(in_N/m2)', 'in:Flood_depth(in_mt)', 'in:Flood_velocity(in_m/s)', 'in:Den
ity_of_different_type_of_flow(in_kg/m3)']
['out:allowable_bending_moment(in_NM)', 'out:Stagnation_pressure (in_N/m2)', 'Total_force_on_facade(in_N)', 'Distribyuted load_q(in_N/m)']
out:allowable_bending_moment(in_NM) out:Stagnation_pressure (in_N/m2) Total_force_on_facade(in_N) Distribyuted load_q(in_N/m) out:Max bending_moment(in_NM)
0 66.666667 4905.0 613.75 1227.5 38.257083
1 93.333333 4905.0 859.25 1227.5 38.257083
2 133.333333 4905.0 1227.50 1227.5 38.257083
3 200.000000 4905.0 1841.25 1227.5 38.257083
4 266.666667 4905.0 2455.00 1227.5 38.257083
... ..
163835 6480.000000 61283.5 123247.80 82165.2 46065.097730
163836 8640.000000 61283.5 164330.40 82165.2 46065.097730
163837 10368.000000 61283.5 197196.48 82165.2 46065.097730
163838 11664.000000 61283.5 221846.04 82165.2 46065.097730
163839 12960.000000 61283.5 246495.60 82165.2 46065.097730

[163840 rows x 5 columns]
(163840, 7)
(163840, 5)

```

Figure B.16: Graphical representation of input and output columns flood (Source: Author)

```

1 """
2 Compute the correlation between each input and output variable
3 """
4
5 # Step 3: Compute the correlation between each input and output variable
6 correlation_matrix = pd.DataFrame(index=inputs.columns, columns=outputs.columns)
7
8 for input_col in inputs.columns:
9     for output_col in outputs.columns:
10         correlation = np.corrcoef(inputs[input_col], outputs[output_col])[0, 1]
11         correlation_matrix.loc[input_col, output_col] = correlation
12
13 # Step 4: Create a custom colormap
14 # Define the greyish red and custom blue colors
15 greyish_red = (178/255, 34/255, 34/255) # Greyish red normalized to [0, 1] range
16 custom_blue = (70/255, 130/255, 160/255) # Custom blue normalized to [0, 1] range
17
18 # Create a colormap that transitions from greyish red (-1) to white (0) to custom blue (+1)
19 custom_cmap = LinearSegmentedColormap.from_list('custom_cmap', [greyish_red, 'white',
20     custom_blue], N=256)
21
22 # Step 5: Plot the correlation matrix
23 plt.figure(figsize=(10, 8)) # width, height
24 sns.heatmap(correlation_matrix.astype(float), cmap=custom_cmap, vmin=-1, vmax=1, annot=True,
25     fmt=".2f", square=True, cbar_kws={"shrink": 0.8})
26
27 # Set axis labels and title
28 plt.xlabel('Output Variables')
29 plt.ylabel('Input Variables')
30 plt.title('Correlation Matrix between Inputs and Outputs')
31
32 plt.show()

```

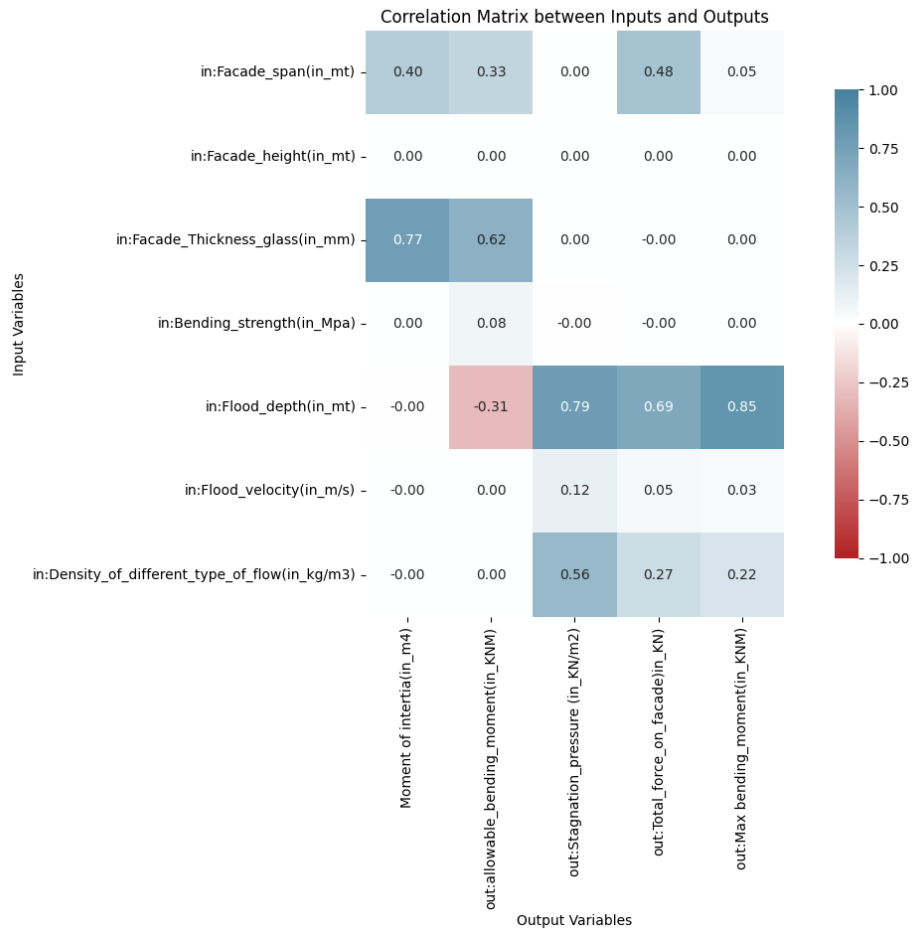


Figure B.17: Graphical representation of correlation matrix with 7 input variables (Source: Author)

```

1 """
2 Create a separate list of (min, max) tuples for each input variable
3 """
4 bounds = [(inputs.iloc[:, i].min(), inputs.iloc[:, i].max()) for i in range(inputs.shape[1])]
5 print(bounds)
6
7
8
9 Create an empty list to store the distribution curves
10 """
11 distribution_curves = []
12
13 """
14 Plot histograms with density in Y axis for each input variable
15 """
16 # Set the seaborn style with gridlines and blueish gray color
17
18 sns.set_style("whitegrid", {'axes.grid': True, 'grid.color': 'lightsteelblue', 'grid.
19     linewidth': 0.5})
20
21 # Create a grid of subplots with a fixed number of columns
22 num_cols = 2
23 num_rows = (len(input_names) + num_cols - 1) // num_cols
24 fig, axs = plt.subplots(nrows=num_rows, ncols=num_cols, figsize=(15, 15))
25 axs = axs.flatten()
26
27 for i, name in enumerate(input_names):
28     # Plot the histogram with density curve using the specified color code
29     sns.histplot(data=data, x=name, kde=True, stat='density', ax=axs[i], color='#5ca0ce',

```

```

29         line_kws={'color': '#5ca0ce'}) # Using the color code for both histogram
        and density curve
30     axs[i].set_ylabel('Density')
31     axs[i].set_xlabel(name)
32
33     # Add thin gridlines with blueish gray color inside the subplot
34     axs[i].grid(True, linewidth=0.5)
35
36 for j in range(len(input_names), len(axs)):
37     axs[j].axis('off')
38
39 plt.tight_layout()
40 plt.show()

```

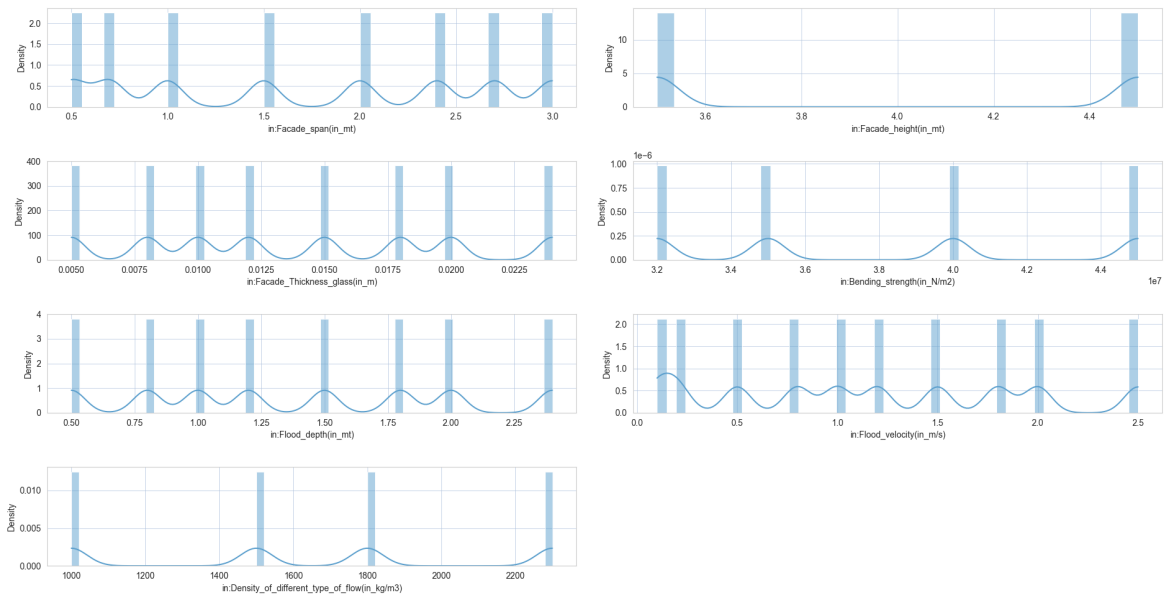


Figure B.18: Graphical representation of histograms with density in Y axis for each input variable for flood resilience quantification (Source: Author)

```

1  """
2  Preparing prediction data for machine learning models (Artificial regression model)
3  """
4  # Separate input and output values
5  X = data.iloc[:, :7].values
6  y = data.iloc[:, 7:8].values
7
8  # Split the data
9  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
10
11 # Standardize the data
12 scaler_X = StandardScaler()
13 scaler_y = StandardScaler()
14
15 X_train = scaler_X.fit_transform(X_train)
16 X_test = scaler_X.transform(X_test)
17
18 y_train = scaler_y.fit_transform(y_train)
19 y_test = scaler_y.transform(y_test)
20
21 # Build the model
22 model = Sequential()
23 model.add(Dense(64, input_dim=7, activation='relu'))
24 model.add(Dense(64, activation='relu'))
25 model.add(Dense(1, activation='linear')) # 1 outputs
26
27 model.compile(optimizer='adam', loss='mean_squared_error')

```



```

28
29 # Train the model
30 history = model.fit(X_train, y_train, epochs=10, batch_size=10, validation_split=0.2)
31
32 # Evaluate the model
33 y_pred = model.predict(X_test)
34 y_pred = scaler_y.inverse_transform(y_pred)
35 y_test = scaler_y.inverse_transform(y_test)
36
37 # Calculate R-squared
38 r2 = r2_score(y_test, y_pred)
39
40 # Plot the scatter plot
41 color = (70/255, 130/255, 160/255) # Set the RGB color
42 plt.figure(facecolor='white') # Set background color to white
43 plt.scatter(y_test, y_pred, color=color)
44 plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='black', linestyle
         = '--', linewidth=1) # Plotting the ideal line
45 plt.xlabel('Actual Values')
46 plt.ylabel('Predicted Values')
47 plt.title('Accuracy of ANN Regression Model')
48 plt.grid(color='lightgrey', linestyle='-', linewidth=0.5) # Set grid properties
49
50 # Convert R-squared to percentage accuracy
51 accuracy_percentage = r2 * 100
52
53 # Display accuracy percentage on the graph
54 plt.text(0.05, 0.9, f'Accuracy: {accuracy_percentage:.2f}%', transform=plt.gca().transAxes)
55
56 plt.show()
57
58 # Print accuracy percentage
59 print("Accuracy Percentage:", accuracy_percentage)
60
61
62 # Plot the loss graph
63 plt.figure(figsize=(10, 5))
64 plt.plot(history.history['loss'], label='Training Loss', color=(234/255, 78/255, 97/255))
65 plt.plot(history.history['val_loss'], label='Validation Loss', color=(70/255, 130/255,
        160/255))
66 plt.title('Model Loss')
67 plt.xlabel('Epoch')
68 plt.ylabel('Loss')
69 plt.legend()
70 plt.show()
71
72 # Calculate Mean Squared Error (MSE)
73 mse = mean_squared_error(y_test, y_pred)
74
75 # Calculate Root Mean Squared Error (RMSE)
76 rmse = np.sqrt(mse)
77
78 # Calculate R-squared (R2)
79 r_squared = r2_score(y_test, y_pred)
80
81 # Calculate Mean Absolute Error (MAE)
82 mae = mean_absolute_error(y_test, y_pred)
83
84 # Calculate Accuracy Percentage
85 accuracy_percentage = (1 - mae) * 100
86
87 print("Mean Squared Error (MSE) ANN:", mse)
88 print("Root Mean Squared Error (RMSE) ANN:", rmse)
89 print("R-squared (R2) ANN:", r_squared)
90 print("Accuracy Percentage ANN:", accuracy_percentage)

```

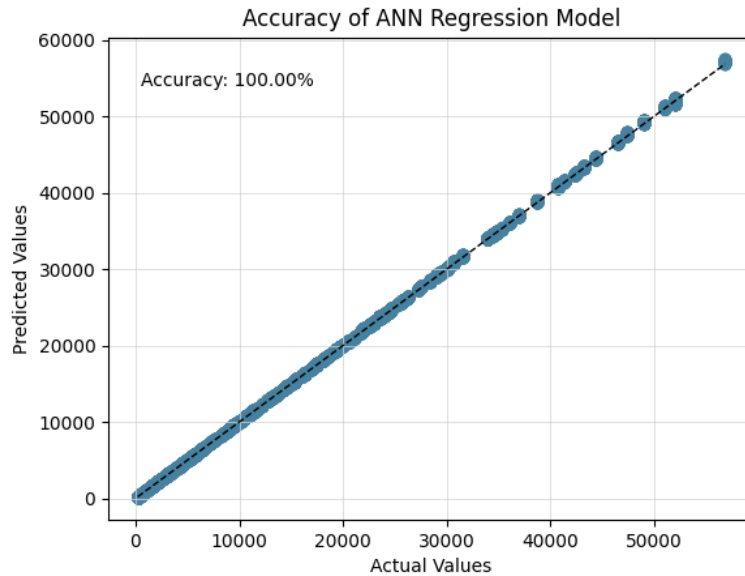


Figure B.19: Graphical representation of accuracy of ANN model (Source: Author)

```
Accuracy Percentage: 99.99916211403475
Mean Squared Error (MSE)_ANN: 5.0348297517423396e-18
Root Mean Squared Error (RMSE)_ANN: 2.243842630788162e-09
R-squared (R2)_ANN: 0.9999916211403475
Accuracy Percentage_ANN: 99.99999984180606
Training set shapes - Input: (131072, 7) Output: (131072, 6)
Testing set shapes - Input: (32768, 7) Output: (32768, 6)
```

Figure B.20: Graphical representation of evaluation metrics RFM for flood calculations (Source: Author)

```
1  """
2  Preparing prediction data for machine learning models (Randomforest regression model)
3  """
4  # Split input and output variables
5  X = data.iloc[:, :7] # Input variables
6  y = data.iloc[:, 7:] # Output variables
7
8  # Split data into training and testing sets (80% for training, 20% for testing)
9  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
10
11 # Check the shapes of training and testing sets
12 print("Training set shapes - Input:", X_train.shape, "Output:", y_train.shape)
13 print("Testing set shapes - Input:", X_test.shape, "Output:", y_test.shape)
14
15 # Train the model
16 regressor_Dataset = RandomForestRegressor()
17 regressor_Dataset.fit(X_train, y_train)
18
19 # Make predictions
20 y_pred = regressor_Dataset.predict(X_test)
21 print(y_pred)
22
23 # Convert Y to a pandas DataFrame
24 Y_df = pd.DataFrame(y_pred)
25
26 # Export Y to an Excel file
27 Y_df.to_excel('NEW6.xlsx', index=False)
28
29 # Calculate and print the accuracy
30 mae_Dataset = mean_absolute_error(y_test, y_pred)
31 Prediction_Model_Accuracy = round((1 - mae_Dataset) * 100, 1)
```

```

32 print(f"Prediction_Model_Accuracy:_{Prediction_Model_Accuracy:.2f}%")
33
34
35 # Load the trained model
36 trained_model = RandomForestRegressor()
37 trained_model.fit(X_train, y_train)
38
39 # Set the color
40 scatter_color = (70/255, 130/255, 160/255)
41
42 # Calculate and print the accuracy
43 mae_Dataset = mean_absolute_error(y_test, y_pred)
44 Prediction_Model_Accuracy = round((1 - mae_Dataset) * 100, 1)
45 print(f"Prediction_Model_Accuracy:_{Prediction_Model_Accuracy:.2f}%")
46
47 # Calculate Mean Squared Error (MSE)
48 mse = mean_squared_error(y_test, y_pred)
49
50 # Calculate Root Mean Squared Error (RMSE)
51 rmse = np.sqrt(mse)
52
53 # Calculate R-squared (R²)
54 r_squared = r2_score(y_test, y_pred)
55
56 print("Mean_Squared_Error_(MSE):", mse)
57 print("Root_Mean_Squared_Error_(RMSE):", rmse)
58 print("R-squared_(R²):", r_squared)
59
60 # Set the color
61 scatter_color = (70/255, 130/255, 160/255)
62
63 # Create a scatter plot of predicted vs. actual values
64 plt.figure(figsize=(8, 6), facecolor='white') # Set the figure size and background color
65 plt.scatter(y_test, y_pred, color=scatter_color, alpha=0.7) # Set the color and transparency
66 plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='black', linestyle
        = '--', linewidth=1) # Plotting the ideal line
67 plt.xlabel('Actual_Values')
68 plt.ylabel('Predicted_Values')
69 plt.title('Accuracy_of_RandomForest_Regression_Model\nAccuracy:_{:.2f}%'.format(
        Prediction_Model_Accuracy))
70 plt.grid(color='lightgrey', linestyle='-', linewidth=0.5) # Set grid properties
71
72 # Display accuracy percentage on the graph
73 plt.text(0.05, 0.9, f'Accuracy:_{Prediction_Model_Accuracy:.2f}%', transform=plt.gca().
        transAxes)
74
75 plt.show()

```

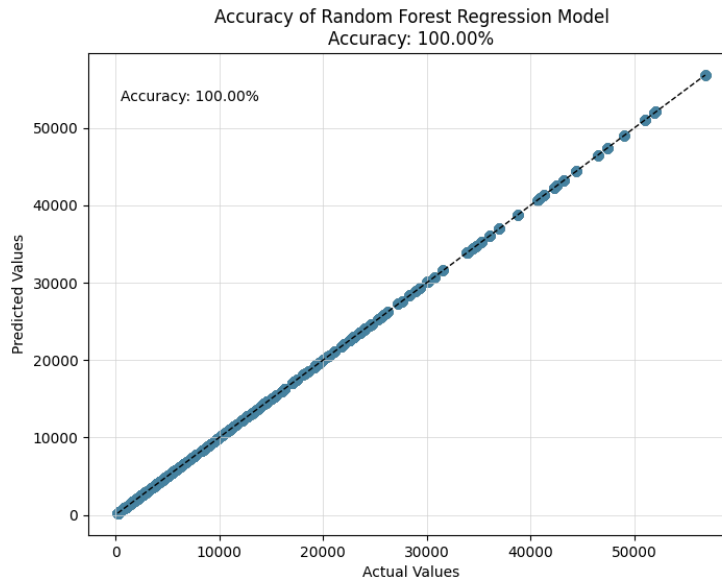


Figure B.21: Graphical representation of accuracy of Random forest regression model (Source: Author)

```

1  """
2  Sensitivity Analysis by using Sobol's indices
3  """
4  def calculate_outputs(rho, sigma, W, h, v, H, t):
5      # Constants
6      g = 9.81 # acceleration due to gravity (m/s^2)
7
8      # Calculate Total Pressure (F)
9      F = 0.5 * rho * W * g * h**2 + 0.5 * rho * W * v**2 * h
10
11     # Calculate q (load per unit width)
12     q = F / W
13
14     # Calculate y (distance from neutral axis to extreme fiber)
15     y = t / 2
16
17     # Calculate moment of inertia (I)
18     I = (W * t**3) / 12
19
20     # Calculate allowable Bending Moment (BM)
21     allowable_BM = sigma * I / y
22
23     # Calculate Maximum Bending Moment (Max BM)
24     max_BM = (q * h**2 / 6) * ((0.42 * h / H) - 0.808)
25
26     return F, allowable_BM, max_BM
27
28
29 # Define the problem definition for sensitivity analysis
30 problem = {
31     'num_vars':7, #X.shape[1] ,
32     'names':  ['in:Facade_span(in_mt)', 'in:Facade_height(in_mt)', 'in:Facade_Thickness_glass(
33               in_mm)', 'in:Bending_strength(in_Mpa)', 'in:Flood_depth(in_mt)', 'in:Flood_velocity(in_m
34               /s)', 'in:Density_of_different_type_of_flow(in_kg/m3)'],
35     'bounds': [(inputs.iloc[:, i].min(), inputs.iloc[:, i].max()) for i in range(inputs.shape
36               [1])],
37     'dists' : ['unif', 'unif', 'unif', 'unif', 'unif', 'unif', 'unif']
38 }
39
40 # Sampling Parameter Values Using Saltelli's Method
41 param_values = saltelli.sample(problem, 8192)

```

```

40 print("paramevalue", param_values)
41 print("paramevalue", param_values.shape)
42
43 # Evaluate the model with the adjusted sample size
44 g = 9.81 # Assuming a constant value for g (acceleration due to gravity)
45
46 # Evaluate the model with the adjusted sample size
47 Y = np.array([calculate_outputs(params[6], params[3], params[0], params[4], params[5], params
    [1], params[2]) for params in param_values])
48
49 # Check the shape of Y
50 print("Shape of Y:", Y.shape)
51
52 # Perform sensitivity analysis for each output separately using Sobol indices
53 output_titles = ["Total Hydraulic Force", "Allowable Bending Moment", "Maximum Bending Moment
    "]
54 for i in range(Y.shape[1]):
55     Si = sobol.analyze(problem, Y[:, i], print_to_console=False)
56
57     # Extract the first-order indices and total indices
58     first_order_indices = Si['S1']
59     total_order_indices = Si['ST']
60
61     print(output_titles[i])
62     print("First-Order Indices:", first_order_indices)
63     print("Total-Order Indices:", total_order_indices)
64
65     # Create figure and axis objects for first-order indices
66     fig, ax = plt.subplots(figsize=(8, 6))
67     indices = np.arange(len(problem['names']))
68     width = 0.35
69     ax.barh(indices, first_order_indices, width, label='First-Order Indices', color=(128/255,
    128/255, 128/255))
70     ax.barh(indices + width, total_order_indices, width, label='Total-Order Indices', alpha
    =0.5, color=(70/255, 130/255, 160/255))
71     ax.set_title(output_titles[i])
72     ax.set_ylabel("Parameters")
73     ax.set_xlabel("Indices")
74     ax.set_yticks(indices + width / 2)
75     ax.set_yticklabels(problem['names'])
76     ax.legend()
77     ax.grid(True, linestyle=':', linewidth='1', color='black', alpha=0.5)
78     plt.show()

```

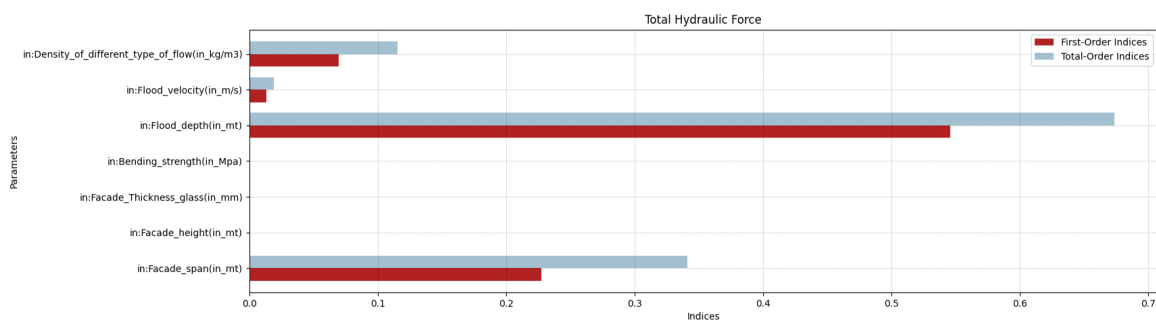


Figure B.22: Graphical representation of sensitivity analysis on total hydraulic pressure (Source: Author)

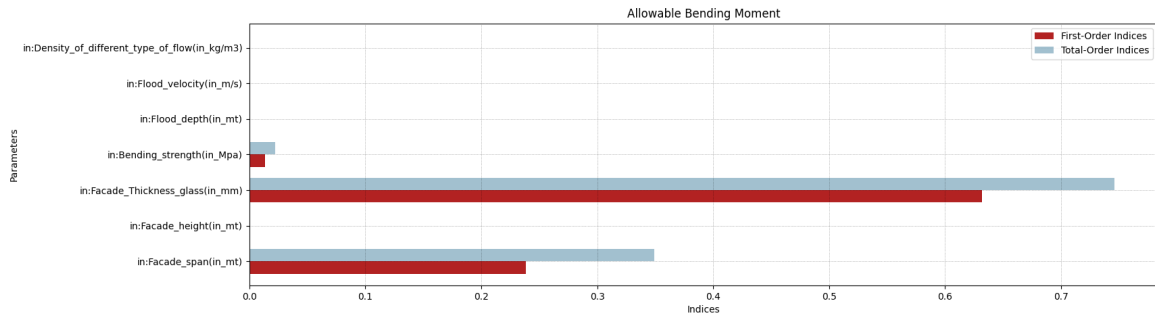


Figure B.23: Graphical representation of sensitivity analysis on allowable bending moment (Source: Author)

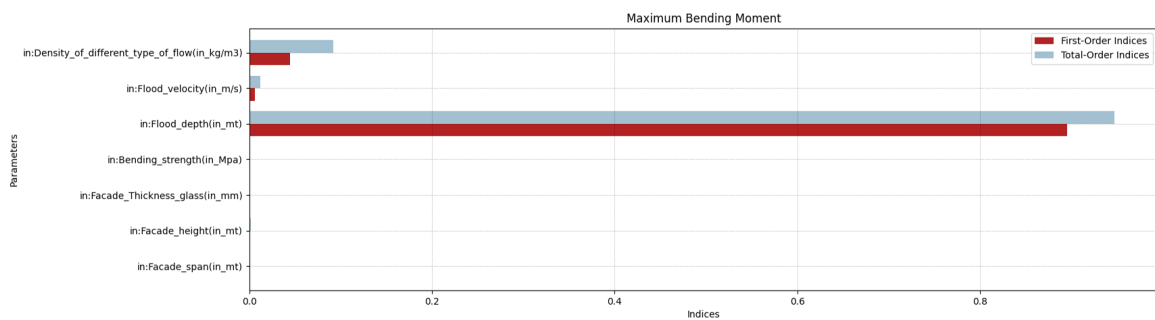


Figure B.24: Graphical representation of sensitivity analysis on maximum applied bending moment (Source: Author)

```

1  """
2  Resilience matrix flood
3  """
4  # Load the data from CSV file
5  data = pd.read_csv('./Flood/Resilience_matrix_dataset_floods.csv')
6  print("data",data)
7  Applied_bending_moment = data.iloc[:, 1]
8
9  # Extract columns
10 duration = data['Duration(in_hour)']
11 bending_moment = pd.to_numeric(data['Applied_bending_moment(in_Nm)'], errors='coerce') #
12   Convert to numeric
13 flood_height = data['Flood_height(in_m)']
14 bending_moment = 4266 - bending_moment
15 # Create figure and axis objects
16 fig, ax1 = plt.subplots()
17
18 # Plot bending moment on left y-axis
19 ax1.plot(duration, bending_moment, color=(70/255, 130/255, 160/255), label='Bending_Moment')
20 ax1.set_xlabel('Duration(in_hours)')
21 ax1.set_ylabel('Bending_Moment(in_Nm)', color=(70/255, 130/255, 160/255))
22 ax1.tick_params('y', colors=(70/255, 130/255, 160/255))
23
24 # Set y-axis limit for bending moment dynamically to cover the entire range of data
25 ax1.set_ylim(0, max(bending_moment.max(), 4500))
26
27 # Add another straight line at 4266 Nm bending moment for all durations
28 ax1.axhline(y=4266, color=(178/255, 34/255, 34/255), linestyle='--', label='Allowable_Bending_Moment(4266_Nm)')
29
30 # Create another y-axis for flood height
31 ax2 = ax1.twinx()
32 ax2.plot(duration, flood_height, color='grey', linestyle='--', label='Flood_Height')
33 ax2.set_ylabel('Flood_Height(in_meters)', color='grey')

```

```

33 ax2.tick_params('y', colors='grey')
34 ax2.set_ylim(0, 2) # Setting y-axis limit for flood height
35
36 # Set x-axis limit
37 ax1.set_xlim(0, 24)
38
39 # Show legend for both y-axes
40 lines1, labels1 = ax1.get_legend_handles_labels()
41 lines2, labels2 = ax2.get_legend_handles_labels()
42 lines = lines1 + lines2
43 labels = labels1 + labels2
44 # Place legend above the box, left-align it, and set padding between legend items
45 ax1.legend(lines, labels, loc='upper_left', bbox_to_anchor=(0, 1.2), frameon=False, fontsize=
    'small', labelspacing=1)
46
47 # Highlight the area difference between bending moment line and reference line from duration
    5 to 23
48 x_values = duration[(duration >= 5) & (duration <= 23)]
49 y_values_bending_moment = bending_moment[(duration >= 5) & (duration <= 23)]
50 y_values_reference = 4266 * pd.Series([1] * len(x_values)) # Creating a series with 4266 Nm
    for the same length
51 ax1.fill_between(x_values, y_values_bending_moment, y_values_reference, color=(192/255,
    192/255, 222/255), alpha=0.3)
52
53 # Calculate the area under Cooling Energy demand during Heatwaves and typical weather
    condition
54 # Calculate area of the trapezoid formed by the reference line and x-axis
55 F_typical = 0.5 * (4266 + 4266) * (23 - 5)
56 print("F_typical", F_typical)
57
58 print("bending", bending_moment)
59
60 # Define the x-axis range
61 x_start = 5
62 x_end = 23
63
64 # Calculate the indices for the range
65 start_index = x_start
66 end_index = x_end + 1 # +1 because slicing is exclusive of the end index
67
68 # Slice the bending_moment array to only include values from x_start to x_end
69 bending_moment_sliced = bending_moment[start_index:end_index]
70
71 # Calculate the area using np.trapz
72 F_flood = np.trapz(np.abs(bending_moment_sliced), dx=1)
73 print("F_flood", F_flood)
74
75 # Calculate the area between Cooling Energy demand during Heatwaves and typical weather
    condition
76 Resilience_loss = F_typical - F_flood
77 print("Resilience_loss", Resilience_loss)
78
79 plt.title('Bending_Moment_and_Flood_Height_over_Duration')
80 plt.grid(True) # Adding grid
81 plt.show()

```

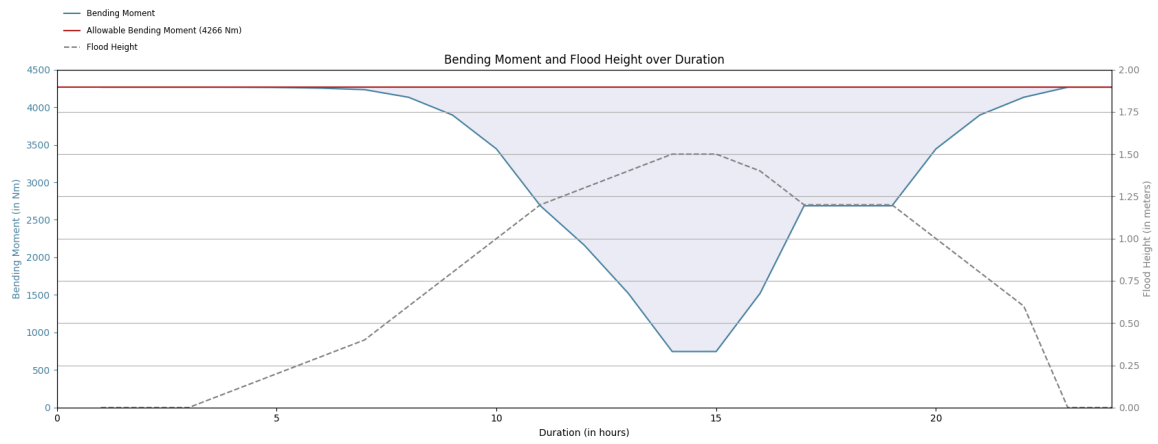


Figure B.25: Graphical representation of Resilience score floods

```
F_flood 53145.4
Resilience_loss 23642.6
```

Figure B.26: Graphical representation of Resilience loss floods calculation



Project timeline

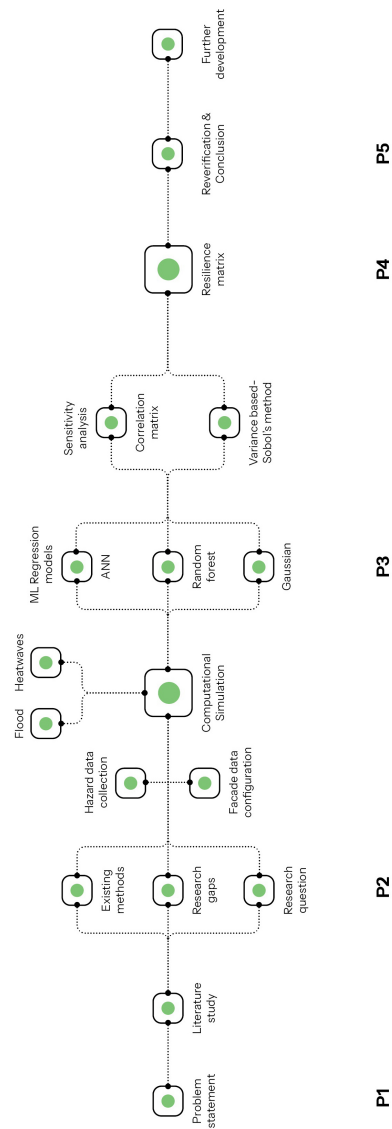


Figure C.1: Graphical representation of project timeline (Source: Author)