Enhancing Evacuation Planning in Public Buildings: Optimising Egress Location and Protection

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To Mum and Dad

Abstract

Effective evacuation strategies are crucial for ensuring the safety of individuals during emergencies and disasters. Despite significant progress in evacuation planning, the intricate dynamics of disaster scenarios and uncertainties inherent in such situations need to be better incorporated in planning egress locations to enhance safety in buildings. This work focuses on strategically locating egress points within public buildings, acknowledging their pivotal role in facilitating secure evacuations. Optimising egress points improves evacuation efficiency and minimises associated risks, significantly improving evacuation planning. This research introduces an innovative approach that integrates optimisation models, addresses decision-making complexities, explores practical applications, and considers potential attack scenarios. The study explores evacuation dynamics across diverse scenarios, elevating preparedness, and safety protocols to protect public assets and lives. Developing mixed-integer programming models establishes a foundation for optimising egress locations. Multi-criteria decision-making (MCDM) is then employed, leveraging the Fuzzy Analytic Hierarchy Process (F-AHP) to address uncertainties in egress selection. Practicality is realised through integrating Revit and AnyLogic software, facilitating assessment through Building Information Modelling (BIM) and Agent-Based Models (ABM). A stochastic Bi-level Programming (BP) model is formulated, addressing both Defender and Attacker perspectives for enhanced egress strategies. This model strategically allocates resources to fortify egresses, ensuring occupant safety during evacuations. Contributions further optimisation approaches, fortification strategies, and progressive enhancements in evacuation planning. These collectively address key challenges and gaps in existing literature, enhancing evacuation efficiency and public safety during emergencies. By addressing challenges and introducing innovative methodologies, adaptable strategies to respond effectively to diverse scenarios are provided. The research bridges gaps in existing approaches, providing a framework for future investigations into optimising evacuation strategies, enhanced disaster preparedness, and further advancements in the field.

Authorship attribution statements

Published	My Contributions	Relevant Chapters
Alac, R., Hammad, A. W., Hadigheh, A., & Opdyke, A. (2023). Optimising egress location in school buildings using mathematical modelling and Agent-Based simulation. *Safety Science*, *167*, 106265. https://doi.org/10.1016/j.ssci.2023.106265	Design, methodology, data curation, conceptualisation, analysis, visualisation, writing-original draft preparation.	Chapter 2 Chapter 3 Chapter 4

Attesting authorship attribution statements

In addition to the statements above, in cases where I am not the corresponding author of a published item, permission to include the published material has been granted by the corresponding author.

Ruken Alac, 2023

As the supervisor for the candidate upon which this thesis is based, I can confirm that the authorship attribution statements above are correct.

Ali Hadigheh, 2023

Statement of originality

This is to certify that to the best of my knowledge; the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

Signature,

Ruken Alac

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Just as the seasons shift in Vivaldi's masterpiece, my research has undergone its own metamorphosis, evolving through the cycles of conception, exploration, and realization. The delicate harmonies of Bach's Prelude or the profound resonance of Chaconne resonate with the ebb and flow of my academic journey—moments of clarity intertwined with periods of intricate contemplation. These compositions serve as a backdrop, infusing my work with the timeless spirit of creativity and emotion, much like the intellectual melody that has guided me through the labyrinth of research.

With heartfelt appreciation,

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Chapter 1

Introduction

1.1. Motivation and Significance

Evacuation planning is paramount in various critical scenarios, ranging from emergencies within structures to disaster management, recovery, and defence preparedness. Effective evacuation strategies play a pivotal role in identifying optimal routes and timings to ensure the safe movement of individuals during catastrophic events, disasters, and attacks (Alexander & Wells, 1991; Thywissen, 2006).

Evacuation, constituting the strategic withdrawal of individuals from specific areas when confronted by actual or anticipated threats or hazards (Vogt & Sorensen, 1992), is a proactive and affirmative disaster response measure. It remains one of the most efficient approaches to curbing further damage and preserving human lives. Successful execution of evacuation operations hinges on comprehensive planning and implementation, encompassing a spectrum of political, environmental, social, technological, legislative, and economic considerations. A pivotal element of effective evacuation planning is strategically identifying egress locations in buildings. Egress locations and pivotal exit points enable the swift and seamless evacuation of individuals to safety. Identifying and optimising these egress locations represent a critical step in augmenting evacuation efficiency and minimising potential human risks.

Each evacuation scenario has distinctive challenges and complexities, rendering a universally applicable approach impractical. Effective evacuation strategies must instead be finely tailored to the specific context, capable of adapting to dynamic variables, and quick to respond to ever-evolving circumstances. Over the past few decades, substantial headway has been achieved in dissecting evacuation planning through various methodologies, including mathematical and simulation models (Dixit & Wolshon, 2014; Santos & Aguirre, 2004). These techniques offer valuable insights into comprehending evacuation dynamics and evaluating potential courses of action. However, there remains gaps in refining existing evacuation models to more comprehensively address the complex dynamics of disaster scenarios and the uncertainties that reality presents. Thus, the call to enhance existing models and extend their purview to a broader spectrum of scenarios becomes increasingly pronounced, allowing more comprehensive analysis and application.

This thesis focuses on egress locations within public buildings, acknowledging their pivotal role in facilitating effective and secure evacuations. By strategically pinpointing optimal exit points, this approach enhances evacuation efficiency and minimises risks to human lives. It contributes significantly to the practical evacuation planning for public buildings. In addition, the research introduces a unique dimension by considering the perspectives of both defenders and potential attackers. This model strategically allocates resources to fortify egresses, ensuring occupant safety during evacuations while accounting for potential attacker strategies. Consequently, this holistic approach strengthens public facilities' security and enhances evacuation plans' overall effectiveness.

Furthermore, this research addresses the need for more comprehensive and adaptable evacuation strategies. It proposes an innovative approach integrating various relevant components to ensure a well-prepared strategy and incorporating disaster dynamics into the modelling process. The thesis aims to advance the development of more effective and efficient evacuation strategies by examining the comprehension of evacuation dynamics. This research strives to promote enhanced preparedness and safety protocols during evacuations by exploring diverse scenarios and perspectives. Its ultimate goal is to protect human lives and reduce the economic impacts in the face of natural hazards and potential threats.

1.2. Research Objectives

The thesis is dedicated to tackling the critical challenges associated with evacuation planning and optimising egress locations within buildings, addressing a broad spectrum of natural hazards and potential threats. Furthermore, it seeks to reinforce egress strategies for public buildings, contributing to their enhanced resilience and safety. This research aims to introduce an innovative approach that combines multi-objective optimisation (MOO) with advanced computer simulation. This approach also incorporates applying a fuzzy analytic hierarchy process (F-AHP) to address decisions involving multiple criteria. Moreover, it manages uncertainties while integrating the hierarchical relationship between the upper and lower levels within the bi-level programming (BP) framework. As a result, the research endeavours to significantly enhance the selection of optimal egress locations within buildings, fostering improved overall evacuation efficiency and safety during emergencies. To achieve the above goals, the objectives of this study are summarised as follows:

I. To establish a solid foundation by designing and implementing a mixed-integer programming (MIP) model for optimising egress locations. Factors considered include evacuation time, total cost, and optimal distribution during evacuations set the stage for effective decision-making, ensuring well-planned egresses.

II. To acknowledge the inherent complexity of decision-making, this research embraces the multi-criteria decision-making (MCDM) method, explicitly harnessing the power of F-AHP. This strategic approach empowers decision-makers to navigate the uncertainties that come with selecting egress locations. Gaining a nuanced understanding of trade-offs and implications facilitates more informed choices, ultimately enhancing the identification of optimal egress points.

III. To utilise a combination of Building Information Modelling (BIM) and Agent-Based Models (ABM). This collaborative strategy contributes to assessing egress performance by leveraging the visualisation capabilities of BIM-Revit and the evaluation provided by ABM-AnyLogic. This combination results in a dynamic representation of evacuation dynamics and challenges, forming the basis for deeper insights and strategic foresight to enhance the evacuation process.

IV. To delve deeper into this exploration, the journey progresses with developing a stochastic BP model that uniquely incorporates both the Defender and Attacker perspectives. Within this comprehensive viewpoint, innovative strategies for enhancing egresses, particularly in scenarios of potential attacks, come to the forefront. By optimising secure links, the Defender strategically prioritises critical pathways, culminating in establishing a comprehensive defence mechanism. This mechanism not only safeguards public facilities but also ensures the security of occupants by reinforcing egress routes.

V. To present these explorations practically, a real-case scenario featuring a one-storey school building layout serves as a guiding example. Through the optimisation of egress locations and the fortifying egresses, it provides crucial insights that contribute to enhancing emergency readiness in educational institutions and similar environments.

1.3. Contributions

This research offers a series of major contributions to enhance evacuation planning and safety management within public buildings. Critical challenges are addressed through these contributions, and specific methodology gaps in the existing literature are addressed. In addition, practical solutions are provided to enhance evacuation efficiency and public safety during emergencies. The contributions of this thesis address the research objectives outlined in the previous Section 1.2 and can be divided into the following areas.

I. Enhancing evacuation efficiency and public safety during emergencies in various public buildings, including schools.

II. A comprehensive strategy to consider mathematical modelling, simulation techniques, and decision-making frameworks for optimising egress locations.

III. Framework for optimising egress locations in school buildings through a novel mathematical model integrating MOO:
   - Developing a novel mathematical model within the framework to optimise egress locations in school buildings, simultaneously minimising egress costs, maximising coverage, and minimising travel time.
   - Incorporation of optimisation and simulation techniques to improve evacuation planning and time.
   - Incorporation of BIM and ABM for scenario-based evacuations, facilitating egress performance assessment and enhancement of evacuation plans.
   - This capability enables planners to evaluate the effectiveness of egress strategies, pinpoint potential congestion points, and make informed improvements to evacuation plans.

IV. Addressing gaps in egress location selection methodologies by introducing a MCDM framework with F-AHP:
   - F-AHP accommodates uncertainties and nuances in real-world scenarios for adaptable preferences.

- A harmonious integration of social, economic, and technical aspects for context-sensitive evacuation plans in real-world scenarios results in more robust and context-sensitive evacuation plans.
- Enhancement of egress strategy evaluation from social and economic perspectives.

V. Protecting public facilities from potential attacks reinforcing egress locations:
   - Identification of egresses within secure links as potential targets for fortification.
   - Proposal of a stochastic BP model addressing the Defenders-Attackers (DA) problem.
   - Balancing the probability of damage versus maximisation provides a dynamic strategy for protection buildings.
   - Numerical illustration demonstrating the model's potential for real-world application in fortifying egress points and refining evacuation planning.

VI. Progressive contributions build upon each other towards enhancing evacuation planning, safety management, and public safety during emergencies in diverse building scenarios.

1.4. Thesis Structure

This thesis is structured into seven chapters, collectively contributing to understanding and enhancing evacuation planning strategies in various public buildings. Chapter 1 serves as an introduction, providing a comprehensive overview of the research context, objectives, and key contributions. In Chapter 2, an extensive literature review is presented, focusing on a detailed analysis of methodologies, strategies, and approaches relevant to the research. This review distinguishes and delves into specific topics, including the significance of egress in buildings, mathematical models, MOO, and BP. A literature review on the MCDM tools, specifically F-AHP, BIM, and ABM, is presented, along with their applications. The insights gathered from this review plays a crucial role in guiding the selection of research methodologies and models, ensuring a purposeful and informed trajectory for the study. Chapter 3 outlines the methodology employed for studying evacuation planning in public buildings. It introduces three frameworks. The Framework-I combines multi-objective programming with BIM-ABM simulation for comprehensive evacuation optimisation. Framework-II employs multi-criteria decision-making for efficient strategy selection. Framework-III uses stochastic BP for robust strategies. Solution methods development refines proposed approaches. The chapter outlines procedures for model solving, integrating computational methods to enhance evacuation strategies. This overview lays the groundwork for tailored evacuation plans, elevating public safety during emergencies.

Chapter 4 introduces a comprehensive approach for optimising egress locations in densely occupied buildings, focusing on schools. This mathematical optimisation model minimises egress costs, maximises coverage, and reduces travel time. Incorporating BIM and ABM enhances evacuation planning, offering insights into human behaviour and emergency dynamics. Chapter 5 presents a multi-criteria decision-making framework utilising F-AHP to select optimal egress locations. Considering social, economic, and technical criteria, this approach empowers decision-makers to prioritise safety amidst uncertainties. Chapter 6 introduces a stochastic BP model for enhancing building protection against potential threats. Considering Defenders and Attackers, the model strategically allocates resources for defence and attack scenarios, ensuring occupant safety during evacuations. Numerical illustrations showcase the model's effectiveness in real-world situations. Finally, Chapter 7 concludes the thesis by summarising key findings, contributions, and research implications. It discusses the impact of proposed approaches on evacuation planning and safety management in public buildings, emphasising their potential to enhance preparedness and response and outlining potential areas for future research and development. It is important to mention that an effort has been made to standardise the symbols used across the proposed models. However, the notation described is specific to the formulations presented in each relevant chapter. Consequently, the notation will be separately defined for Chapters 4 – 6.

Chapter 2

Literature Review

2.1. Overview

This chapter embarks on a comprehensive review of the existing knowledge encompassing evacuation planning and egress optimisation. This exploration critically assesses diverse methodologies, strategies, and approaches that grapple with the intricate challenges of ensuring secure evacuations in a broad spectrum of public buildings. By delving into specific subjects such as MOO, BP, BIM, ABM and MCDM, this review aspires to uncover pivotal insights, recurring patterns, and research gaps within the landscape. Further, this chapter introduces F-AHP and provides insight into the DA situation, thus illuminating these concepts. Through a systematic analysis of relevant studies, the literature review informs the ongoing research and shapes the subsequent methodology and model selection. By identifying best practices and areas that require further exploration, this chapter lays a foundation for advancing the understanding of effective evacuation strategies and safety management in the face of emergencies. Figure 2.1 visually captures the interlinkages between the various elements scrutinised throughout this chapter.

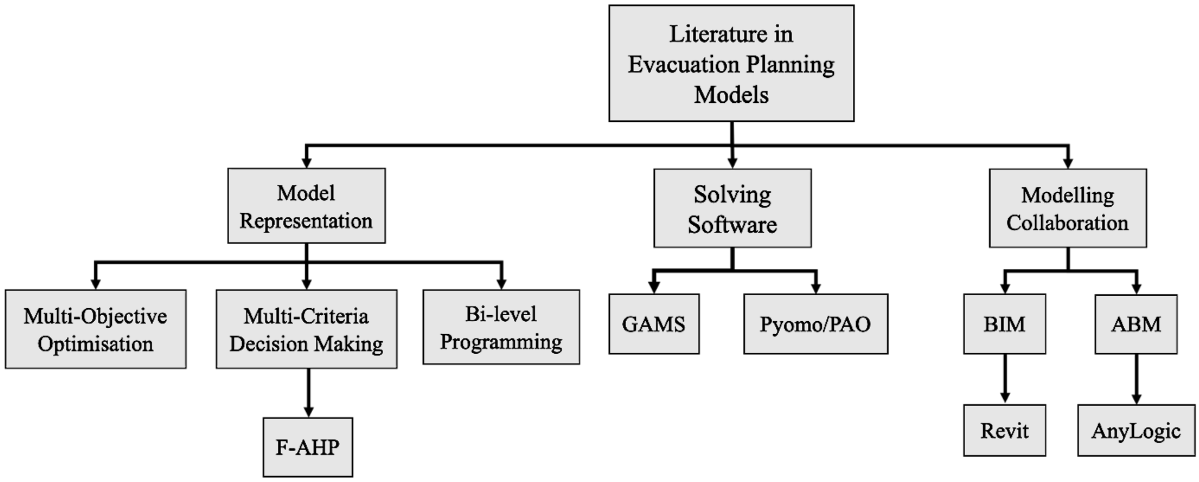


Figure 2.1: General outline of literature review within thesis.

2.2. Evacuation Planning

Evacuation processes and emergency evacuation planning are critical strategies in disaster risk management. The phases of evacuation processes and the significant steps involved in evacuation planning are discussed in this section. According to Emergency Management Australia (EMA) (EMA, 2005), evacuation is considered a risk management strategy used to mitigate the impact of emergencies or disasters on a community by relocating people to safer locations. However, for evacuation to be efficient, it must be thoroughly planned and implemented (EMA, 2005).

The concept of evacuation encompasses various aspects, including relocation from high-risk areas to safer locations (Southworth, 1991), rescue processes employed to safeguard communities or infrastructure from potential disasters (Perry & Lindell, 2003), and diverse strategies varying in scale and control by emergency services agencies (Sorensen, 2000). In essence, evacuation is the process that unfolds when people are confronted with hazards, such as bushfires, floods, and hurricanes (Dash & Gladwin, 2007).

Emergency evacuation procedures represent an everyday practical approach to managing disaster situations (Muckett & Furness, 2007). An emergency evacuation plan aims to ensure the safe and timely evacuation of all affected individuals within a town or area facing imminent risk. Such plans outline vital actions and strategies for responding to events that pose a significant risk of injury or loss of life. An emergency evacuation plan provides instructions detailing, where, when, who and how people should securely leave high-risk areas during an emergency. The proper design and implementation of an emergency evacuation plan are crucial for safeguarding lives and minimizing the impact of disasters.

Furthermore, evacuation planning is a highly intricate and multi-phase process (Stepanov & Smith, 2009), leading to the development of numerous evacuation models documented in the literature. Notably, these models address various scenarios, such as building evacuations (Friedman, 1992; Park et al., 2004; Ren et al., 2019; Ren et al., 2021; Roan, 2014), evacuations from ships (Arteaga & Park, 2020) and aircraft (McLean, 2001; Trainor et al., 2013), and simulations of evacuations during hurricanes (Brown et al., 2009; Maghelal et al., 2017; Sherali et al., 1991; Trainor et al., 2013), nuclear accidents (Cova & Church, 1997), volcanic fields (Tomsen et al., 2014), wildfires (Beloglazov et al., 2016; Cova et al., 2005; León & March, 2016), and tsunamis (Clerveaux et al., 2008; Fraser et al., 2014; Lämmel et al., 2010; León & March, 2017). These diverse case studies and their varying study areas (Naser & Birst, 2010; Trainor et al., 2013) contribute significantly to understanding the current state of evacuation planning across different disaster scenarios. They also highlight the trend of implementing microscopic and individual-based simulations to comprehend complex events more effectively.

2.2.1. Evacuation Planning in Buildings

Evacuation planning in buildings has been studied from various perspectives. For instance, Luh et al. (2012) employed a novel stochastic dynamic programming approach based on network flow to optimise the evacuation process in buildings, maximising the flow of individuals through exits while considering multiple constraints. Mirahadi and McCabe (2021) focused on building evacuations during fire emergencies, proposing a real-time approach using Dijkstra's shortest path algorithm to identify the safest path. Abusalama et al. (2020) studied routing and evacuation planning, specifically addressing capacity constraints. In addition, Murray-Tuite and Mahmassani (2003) integrated individual behaviours during evacuation into their modelling. Christensen and Sasaki (2008) introduced the BUMMPEE (Bottom-up Modelling of Mass Pedestrian flows implications for the Effective Egress of individuals with disabilities) model, which focused on hospital evacuation and incorporated considerations for the diverse range and prevalence of disabilities among evacuees. Cao et al. (2018) introduced a model to simulate pedestrian evacuation in a room during fire emergencies. Their model considers the effects of smoke and fire, providing a more comprehensive representation of the evacuation process.

2.2.2. Importance of Egress Location in Buildings

The ability of occupants to safely evacuate a building during emergencies can be a matter of life and death (Kinateder & Warren, 2021). Selecting egress locations is paramount when minimizing the loss of life and property (FEM Agency, 2018). In buildings with multiple rooms, the evacuation route forms a complex network of interconnected doors, where each egress point plays a vital role in facilitating the evacuation process (Hosseini et al., 2021). Therefore, it is crucial to carefully consider the location of each egress to ensure an efficient and effective evacuation (Gao et al., 2020). Furthermore, selecting egress locations is a complex problem (Gwynne et al., 2020) that requires considering various technical, social, and economic criteria.

Egress locations should be easily identifiable and unobstructed to minimise the time required for occupants to reach them (Lovreglio et al., 2019). The capacity of the egress routes must be sufficient to accommodate the expected occupant load, and the routes themselves must be designed to minimise the potential for congestion and delays (Ronchi et al., 2019). By carefully considering egress location during the design process, building owners and designers can help ensure the safety of occupants in the event of an emergency. Furthermore, human behaviour during evacuation is highly influenced by the visibility and accessibility of egress locations (Haghani & Sarvi, 2016). Studies have shown that occupants use the most visible and accessible egress locations, even if they are not optimal (Larsson et al., 2021). Therefore, the design and placement of egress locations should consider human behaviour patterns to ensure occupants can quickly locate and use them during an emergency (Kuligowski et al., 2017). Consequently, properly considering egress location during building design is paramount in effective evacuation planning.

2.2.3. Importance of Egress Protection in Buildings

Egresses play a critical role in the safe and efficient evacuation of buildings during emergencies. In a fire, earthquake, or other crisis, the availability of accessible and safe egresses can determine the success or failure of evacuation efforts (Gwynne et al., 2019). Therefore, ensuring buildings have well-planned egress systems is crucial in the design and construction (Gorte et al., 2019). However, the significance of egress protection cannot be overstated, as it directly impacts the ability of occupants to exit a building fast and safely, potentially saving lives.

One of the primary reasons for prioritizing egress protection is to mitigate the potential risks and hazards associated with emergencies. By providing well-designed and adequately maintained egress routes, including marked exit signs, unobstructed pathways, and sufficient exit capacity, the chances of panic, confusion, and injuries can be significantly reduced (Bukowski & Bukowski, 2009; Cassol et al., 2017). Investing in egress protection measures is essential to responsible building management and contributes to safeguarding lives (Bukowski & Tubbs, 2016). Timely evacuation is crucial for minimizing the exposure of individuals to life-threatening conditions, such as smoke inhalation, structural collapses, or the spread of fire (FEM Agency, 2018).

Furthermore, egress protection contributes to buildings and communities' overall resilience and emergency preparedness (Hong & Lee, 2018). It enables emergency responders to access affected areas swiftly and efficiently, facilitating their life-saving efforts (Mossberg et al., 2021). By promoting a culture of safety and preparedness, egress protection advances a proactive approach to emergency management, including regular drills and training programs (Kong et al., 2013). These measures help to ensure that occupants are familiar with evacuation procedures, enabling them to respond effectively in high-stress situations (Andrée et al., 2016). Consequently, egress protection is essential to building safety and emergency preparedness during attacks. It is vital that building owners, architects, and emergency response personnel prioritise egress planning and continually assess and improve egress systems to ensure that they are effective in protecting building occupants during emergencies (FEM Agency, 2018).

2.2.4. Evacuees' Behaviour

Evacuation planning hinges on the decisions made by individuals and households during crises (Ding et al., 2021). Predicting their behaviour is vital for understanding potential obstacles that could impede evacuations (Shahparvari et al., 2019). However, modelling these behaviours is intricate due to the complex human psychology and cognition (Pel et al., 2012). Age, physical abilities, mobility, family responsibilities, perception of risk, and preparedness levels impact evacuation choices (Lindell et al., 2018). Murray-Tuite and Mahmassani (2003) highlighted key factors like family composition, gender, disabilities, and fear of looting driving evacuation choices (Hsu & Hsu, 2008). Indeed, understanding the intricate nuances of human psychology remains the challenge in evacuation models (Dash & Gladwin, 2007). Researchers have investigated diverse factors influencing evacuation behaviour (Bowser & Cutter, 2015; Dash & Gladwin, 2007). Evacuation planning is influenced by disaster characteristics and behavioural factors to estimate the total evacuating population for more in-depth insights into evacuation modelling (Pel et al., 2012; Yazici & Ozbay, 2008).

2.2.5. Evacuation Phases

The evacuation process consists of several phases (Lindell, 1995), each with specific objectives and actions. The first phase involves the detection of an incident or emergency. In the second phase, decision-makers assess specific areas' risks and potential threats. Moving to Phase III, a warning alert is issued to inform the affected population about the emergency. In Phase IV, the affected population must decide whether to stay or evacuate. This phase aims to prepare the community or population for evacuation. Phase V entails moving the populace through the transportation network to predefined safe zones or shelters. During this phase, efforts are made to clear affected people from hazardous zones to ensure their safety. Phase VI involves the transfer of affected individuals to safe areas located outside of hazardous points. Finally, verification measures are undertaken in the last phase to ensure the community's safety. The average evacuation time, encompassing Phases III to VI, may vary significantly, ranging from hours to weeks, depending on factors such as the size of the population, the hazard scale, road conditions, and availability of resources (Ruggiero, 2018). Figure 2.2 illustrates the phases of evacuation.

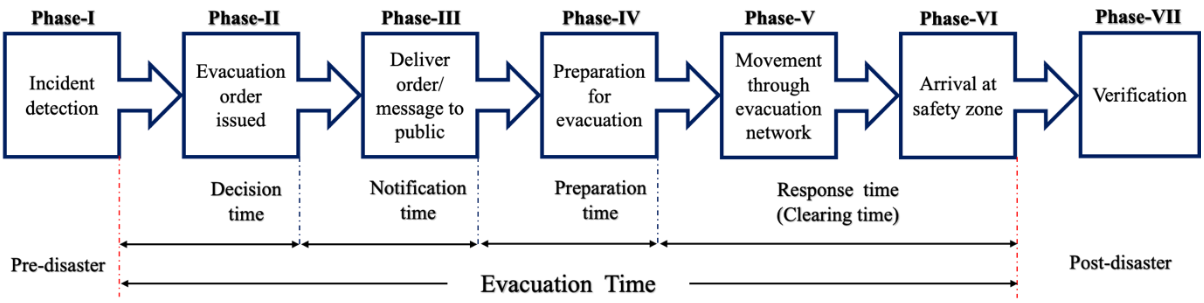


Figure 2.2: Evacuation phases (adapted from Lindell (1995)).

2.3. Mathematical Optimisation Modelling

Mathematical programming, also known as optimisation, involves the process of minimizing or maximising one or more objective functions under a set of constraints (Fourer et al., 2003). In the context of pedestrian dynamics and evacuation planning, mathematical optimisation has been widely employed to devise optimal evacuation plans (Vermuyten et al., 2016). It has proven to be a popular and effective method for tackling evacuation challenges (Flores et al., 2020; Hammad, 2019; Nath et al., 2021). The application of optimisation models not only yields efficient results for evacuation and design purposes but also enables realistic representation of crowd dynamics based on adjusted practical data (Kang et al., 2015). These models offer an effective approach to tackle evacuation optimisation and devise efficient solutions when planning building evacuations (Haghpanah & Foroughi, 2018). The following sections will address some optimisation problems and some optimisation methodologies.

2.3.1. Types of Optimisation Models

The following section provides an overview of various mathematical models commonly used to solve MOO problems in the field. This comprehensive review sets the foundation for understanding the modelling approaches applied throughout this thesis. However, it is important to note that the choice of models discussed here is directly relevant to the scope of this thesis and its specific applications. This approach allows for a thorough exploration of the modelling landscape within the context of this research and the associated scenarios, emphasising selecting problems that align with the study's objectives and goals.

The application methods for each model are described in the related chapters where they are employed in this thesis. It explains examples of the models used in the thesis, showcasing their versatility and relevance in addressing real-world problems. Chapter 4 focuses on practical applications of mathematical models, particularly highlighting the Set Covering Problem (SCP), Maximum Coverage Problem (MCP), and Network Design Problem (NDP). Meanwhile, Chapter 6 emphasises the application of Defender-Attacker scenarios and Stochastic optimisation.

2.3.1.1. Set Covering Problem

The SCP model is classified as a combinatorial optimisation problem (Hofmanninger et al., 2020) and is known to be strongly NP (Non-deterministic Polynomial)-hard (Caprara et al., 1999; Chvatal, 1979). In the context of SCP, the problem involves using a collection of sets as input to find the smallest number of sets needed to cover all elements within a universal set (Cai et al., 2020). A key factor in this process is minimizing the total cost associated with the chosen subsets. The formal definition of the SCP is as follows. Consider a binary $m \times n$ matrix $A = (a_{ij})$ and an integer vector $c = (c_j)$ in n dimensions. The terms rows and columns refer to the rows and columns of matrix A, respectively. Let $M = \{1, \dots, m\}$ and $N = \{1, \dots, n\}$. The value c_j ($j \in N$) denotes the cost associated with column j, and it is assumed, without loss of generality, that $c_j > 0$ for $j \in N$. A column $j \in N$ is assumed to cover a row $i \in M$ if $a_{ij} = 1$. The SCP seeks a subset $S \subseteq N$ of columns (Owen & Daskin, 1998) with the minimum total cost, such that each row $i \in M$ is covered by at least one column $j \in S$. For additional information on SCP, the reader is referred to Beasley & Chu, 1996; Eiselt & Marianov, 2009; Owen & Daskin, 1998.

2.3.1.2. Maximum Coverage Problem

The (MCP) is a well-known NP-Hard challenge that finds applications across diverse contexts (Church et al., 1996). In the maximum coverage problem, the objective is to choose a limited number of sets to maximise the total weight of the covered elements within these selected sets (Hochbaum & Pathria, 1998; Murawski & Church, 2009). In the conventional unweighted version of the MCP, the problem involves a universe of elements, $U = \{e_1, e_2, \ldots, e_n\}$, and a collection of sets denoted as $S = \{S_1, S_2, \ldots, S_m\}$, where each set S_i encompasses specific elements from U $(i.e., S_i \subseteq U)$. An integer k is also provided. The primary objective is to identify a subset $S' \subseteq S$ with $|S'| \leq k$, aiming to maximise the count of covered elements, $| SS_i \in S' \; S_i|$. Various techniques have been employed to tackle this problem, encompassing heuristic and exact methods. The approach choice depends on the context (Chung, 1986; Pirkul & Schilling, 1991). For additional information on MCP, the reader is referred to the following studies: Berman & Krass, 2002; Church & ReVelle, 1974; Nemhauser et al., 1978.

2.3.1.3. Network Design Problem

The NDP is NP-hard and complicated to solve (Shu et al., 2005). The significance of the NDP is well recognised in the academic and practical literature. This problem domain has garnered significant attention due to the imperative of effective transportation planning (Johnson et al., 1978). Indeed, addressing NDP intensifies as the convergence of growing populations and economic expansion generates a travel demand surpassing the existing transportation infrastructure's capacity (Bagloee et al., 2017). The demand for road travel has surged beyond the capacity of urban infrastructure to accommodate it, while resources available for expansion remain limited (Farahani et al., 2013). Over time, this problem has manifested in two primary variations: a discrete version involving the addition of new links or road segments to an existing network, known as the discrete network design problem (DNDP), and a continuous version focusing on the optimal enhancement of capacity for existing links, termed the continuous network design problem (CNDP) (Gao et al., 2005). Moreover, from an optimisation perspective, the NDP can be perceived as a hierarchical decision-making challenge, presenting complexities in the solution (Gao et al., 2005). It frequently addresses the optimal expansion of road systems to meet escalating travel demands (Farvaresh & Sepehri, 2011).

2.3.1.4. Defender-Attacker Problem

One prominent area of focus revolves around the strategic interaction between defenders and attackers. This subject has garnered significant attention, leading researchers to employ game theory as a powerful mathematical modelling tool to analyse and understand these interactions (Madani et al., 2015). Using game theory has gained valuable operational insights, contributing to a deeper understanding of the dynamics in DA scenarios (Shan & Zhuang, 2013). It is a fundamental problem in security and emergency management (Aslanyan et al., 2016). The complex nature of security and defence challenges is increased by adversaries' varying intentions, motivations, and strategic behaviours, as well as their adaptive nature and variable attack capacities (Hunt & Zhuang, 2023).

The manner in which a DA game unfolds is determined by the sequence of moves, which can be categorised as either sequential or simultaneous, depending on the timing and order of the moves made by the involved parties. One common DA problem is where the defender aims to minimise the attacker's objective function by interdicting or eliminating some aspects of the attacker's plan. This expression is used in various applications such as logistics, transportation, and public facilities protection (i.e., Bricha & Nourelfath, 2013; Pawlicki et al., 2020; Rodríguez et al., 2015). Another widespread problem is where the defender moves first, and the attacker responds. This expression is used in military operations and cyber security applications, i.e., Duddu (2018) and Fielder et al. (2016). Therefore, game-theoretic approaches in modelling are typically categorised into different classes based on various factors, allowing for a comprehensive understanding of the underlying dynamics.

The choice of modelling and the specific application of DA games often necessitate various solution approaches (Bell et al., 2008). For instance, linear and nonlinear programming has been widely used to solve the problem, while game theory provides a theoretical framework for investigating the problem (Sandberg et al., 2015). Heuristics and meta-heuristics are also applied to resolve the problem in cases where the problem is computationally intractable (Chakraborty et al., 2018). In addition, the roles of risk preferences (Zhang et al., 2020), players (Hunt et al., 2022), budget constraints (Guan et al., 2017), and contest success functions (Xu & Zhuang, 2016) are considered essential in DA game models. Diverse intentions and motivations among adversaries often lead to varying impacts on affected populations and economies, as evidenced by the significant harm caused by successful attacks worldwide (Estrada & Koutronas, 2016; Garcia & von Winterfeldt, 2016). Consequently, the DA problem is a crucial problem in security and emergency management, with a wide range of formulations, solution methods, and applications (Chakraborty et al., 2018).

2.3.1.5. Stochastic Optimisation

Numerous optimisation models are inherently deterministic, implying that they do not incorporate uncertainty within the model (Birge & Louveaux, 2011). However, methodologies exist to tackle this by establishing the deterministic equivalent of stochastic problems. Assuming total determinism might be unrealistic in specific optimisation contexts, mainly when certain aspects of the model are prone to uncertainty (Beale, 1961; Powell et al., 1995; Dantzig & Thapa, 2003). In a pioneering effort, Dantzig (1955) highlighted the motivation behind crafting the stochastic programming modelling framework, aiming to encompass scenarios involving uncertain demands. This was exemplified in the optimal allocation of a carrier fleet to airline routes to meet anticipated demand distributions. Another early work on stochastic programming can be found in Beale (1955), where he proposed methods to solve stochastic programs using the conjugate directional approach.

Stochastic optimisation represents a toolbox of techniques that target the optimisation of objective functions amidst random influences (Yang & Barton, 2016). Over the recent decades, these methods have achieved prominence in many domains, spanning science, engineering, business, computer science, and statistics (Li & Grossmann, 2021). Over time, stochastic programming has evolved into a research foundation within mathematical programming and operations research communities. Notable advancements in theory and algorithms are extensively chronicled in Birge and Louveaux (2011) and Shapiro et al. (2021). As algorithmic and computational techniques have matured, stochastic programming has found applications in various domains (Wallace & Ziemba, 2005), including financial planning, electricity generation, supply chain management, climate change mitigation, and pollution control. Furthermore, the influence of randomness on the problem typically emanates from either the cost function or constraint sets (Li et al., 2020). Like deterministic optimisation, a universal solution applicable to all scenarios still needs to be discovered (Lara et al., 2020).

2.3.2. Model Complexity

This section provides a grasp of the terminology employed to categorize the optimisation models examined in this thesis. It delves into the fundamental terms that outline the complexities inherent in these models. For further in-depth insights, please refer to the following studies: Arora & Barak, 2009; Hämäläinen, 2006; Plaisted, 1984.

The primary problem classes, denoted as P and NP (Wigderson, 2006), are defined based on their solvability through deterministic polynomial algorithms. This revolves around the existence of a polynomial with a degree of m that dictates the problem's resolution time. A problem belongs to the P (Polynomial) class if it can be accurately solved by a deterministic algorithm within polynomial time. The widely recognised Linear Search problem is an illustrative example. Consequently, solutions for problems falling under the P class can be verified within polynomial time, establishing P as a subset of the NP problem class ($P \subset NP$). The NP (Non-deterministic Polynomial) class encompasses problems soluble through non-deterministic polynomial algorithms with verifiable candidate solutions within polynomial time. Within the NP class, intricate problems arise, including NP-Complete (NPC) and NP-Hard. The literature offers varying definitions for NP-Hard problems, yet the most pertinent and precise one for this thesis is outlined by (Valadi & Siarry, 2014).

Regarding the NPC problem class, both NP and NP-Hard classifications are applicable. This comprehension facilitates understanding optimisation problems' complexities, mainly when classified as NP-Hard, regardless of whether they are mono-objective or multi-objective. The problems explored in Chapters 4 and 6 fall within the NP-hard class. An NP-Hard problem is defined as one to which each problem in NP can be diminished in polynomial time. In simpler terms, problems classified as NP-hard within this thesis tend to become more challenging as the instance size increases.

2.3.3. Model Classes

This section introduces prevalent class distinctions for optimisation models, encompassing Linear Programming (LP), Non-linear Programming (NLP), Mixed-Integer Linear Programming (MILP), and Mixed Integer Non-linear Programming (MINLP).

2.3.3.1. LP

LP is a mathematical method that optimises a linear function while adhering to specific linear constraints (Dantzig, 2002). Despite the complexity, LP manages to stay computationally manageable even when dealing with numerous variables (Vanderbei, 2020). In principle, LP focuses on finding the best outcome of a linear function within the confines of a convex polyhedron (Gass, 2003). The intersection of linear constraints and non-negativity requirements forms this polyhedron. The goal is to strike the optimal balance between the function and constraints, and all are expressed using linear mathematical relationships (Dantzig & Thapa, 2003). In addition, it tackles a specific set of programming challenges where the objective function and the relationships between variables (often denoting significant resources) follow linear patterns (Bazaraa et al., 2011). LP's practicality is widely recognised in business and industry sectors (Dorfman, 2022). This practicality is supported by the thorough theoretical development that LP has undergone in a relatively short timeframe. One interesting aspect of LP is the idea of convexity, which ensures that a solution that seems locally optimal is the globally best one within the defined constraints. For further in-depth insights, please refer to Bertsimas and Tsitsiklis (1997) and Dantzig and Thapa (2003). Further, various solvers are available to challenge LP problems, spanning both commercial and academic offerings. Prominent among these are CPLEX (IBM CPLEX, 2022), Gurobi (Gurobi, 2022) and GLPK (GLPK, 2012).

2.3.3.2. NLP

NLP addresses a system of constraints, which includes equalities and inequalities, over a set of unknown actual variables. This programming becomes non-linear when the objective function or certain constraints exhibit nonlinearity (Avriel, 2020). NLP models can be distinctly categorized into convex and non-convex, as outlined by Boyd and Vandenberghe (2004). The concept of convexity plays a crucial part in establishing the concept of global optimum. The global optimum of a function is the point within its domain where it achieves the lowest or greatest value throughout the whole function. In other words, it is the overall optimum answer to the optimisation issue. A local optimum is a position inside a function's domain where the function achieves the lowest (or greatest) value in its local neighbourhood. Please refer to Floudas and Pardalos (2013) and Fedorov and Leonov (2013) for further in-depth insights.

Moreover, it provides a foundational grasp of NLP's key elements, integral for comprehending subsequent sections that delve into convex MINLP. Within the context of convex NLP, the Karush-Kuhn-Tucker (KKT) conditions assume a crucial role by offering essential and adequate criteria to achieve an optimal result. Specifically, in cases involving certain types of problems, the KKT system can be directly addressed, leading to an optimal solution. However, it is important to note that in the domain of non-convex NLP. At the same time, the KKT conditions remain necessary for optimising solutions; they no longer guarantee global optimality. For those seeking a more comprehensive exploration of NLP, please refer to

Forsgren et al. (2002). A variety of efficient solvers have been devised to tackle convex NLP problems, including CONOPT (CONOPT, 2021), IPOPT (IPOPT, 2017) and KNITRO (KNITRO, 2023).

2.3.3.3. MIP

During the late 1950s algorithms were introduced to tackle MILP problems in response to the requirement of incorporating integer variables into optimisation problems (Dantzig & Thapa, 2003). Incorporating integer variables enables the representation of discrete quantities and distinct decisions. The MIP category encompasses two distinct model types: MILP, where both objective and constraint functions are integer linear (Jünger et al., 2009), and MINLP, where the objective and constraint functions defining the feasible area include non-linear terms (except for integer constraints) (Belotti et al., 2016). While MIP in its general form is NP-hard (Pochet & Wolsey, 2006), specific variants, notably LP, can be solved in polynomial time (Bixby, 2012).

Solving MIP models often poses more significant challenges than LP due to their inherent combinatorial nature, which opens the door to numerous potential solution combinations (Pochet & Wolsey, 2006). MINLP further complicate matters by merging the combinatorial aspects of MILP with the non-linear characteristics of NLP (Costa & Oliveira, 2001). While MILP remains applicable to cases transformable into separable programming, it is essential to note that most MINLP models lack convexity (Floudas & Pardalos, 1990). However, this non-convexity can be rectified by employing a procedure proven as convexification (Tawarmalani & Sahinidis, 2013), which includes approximating non-convex functions with convex counterparts. The widely used cutting plane algorithm is a versatile technique for resolving MIP (Pochet & Wolsey, 2006). This approach commences by relaxing integrity and solving the resulting LP formulation. Linear constraints in the form of cuts are introduced if the solution is a non-integer, progressively narrowing the feasible region until an integer solution is achieved, or infeasibility is determined. These cuts aim to eliminate non-integer solutions from the relaxed model, effectively aligning it with the convex hull of the feasible region. The optimal solution is only reached after accumulating sufficient cuts, risking unresolved outcomes due to time or space constraints. These approaches' popularity has diminished compared to alternative algorithms (Beale, 1961).

Lagrangian relaxation, introduced by Geoffrion (Geoffrion, 1974), represents another avenue of IP algorithm advancement. This method employs Lagrangian multipliers to incorporate certain constraints into the objective function. Complex constraints are relaxed to enhance the solvability of integer programs (Chansombat et al., 2019). By using LP to address IP with specific configurations as the transportation problem, the focus lies in selecting the appropriate constraints for relaxation and deriving Lagrangian multiplier principles that guide the desired solution. This technique is frequently integrated into branch and bound (B&B) algorithms to establish upper bounds, aiding the assessment of whether further branching is justified (Beresnev, 2013).

Another viable strategy for addressing MIPs is the B&B, which follows an enumerative path. The initial stage employs the simplex algorithm (Dantzig & Thapa, 2003), followed by tree search (Dakin, 1965), where LP relaxation aids in establishing an upper bound on the optimal objective function. The branching strategy in B&B is governed by rules that select a variable sufficient for the solved LP relaxation, still partial (Marchand & Wolsey, 2001). This division creates two nodes for examination, with pruning decisions based on factors such as infeasibility, bound discrepancies, or optimality. In problems of minimisation or maximization, the lower and the upper bound are determined through the relaxation of the problem's integrity requirement within a linear context. Unlike cutting plane, B&B constraints set upper and lower bounds on variables (Beresnev, 2013). The B&B approach generate two problems (branches) for each LP solution, refining the LP problem by eliminating non-integer solutions. Decisions are made, such as which variable to branch and which problem to solve. While a specific problem might yield an integer solution, the optimal integer result remains uncertain until each problems are resolved, either implicitly or explicitly (Marchand & Wolsey, 2001).

The algorithm, widely employed in various commercial software implementations, stands as the highest utilised approach for solving IP problems (Brusco & Stahl, 2005). Several solvers are available for MILP problems, including CBC (Lougee-Heimer, 2005), CPLEX (IBM CPLEX, 2022), Gurobi (Gurobi, 2022), and SCIP (Gamrath et al., 2020). Besides, notable MINLP solvers include ANTIGONE (Misener, 2022), BARON (BARON, 2023), KNITRO (KNITRO, 2023) and SCIP (Gamrath et al., 2020).

2.4. Optimisation Solution Methods

Over time, optimisation techniques have gained increasing prominence in addressing emergency evacuation problems. The central emphasis here centres on three specific categories: exact methods, heuristics, and meta-heuristics.

2.4.1. Exact Methods

The earliest and conventional techniques are exact methods, encompassing goal programming, linear programming, weighting, and constraint methods. These methodologies convert a MOO problem into a scalar problem, subsequently resolving it as a singular optimisation challenge (Coutinho-Rodrigues et al., 2012). The most competent algorithms used in commercial optimisation software involve the revised simplex algorithm (Dantzig & Thapa, 2003) for LP models. This algorithm iteratively navigates the extreme vertices of the polytope delineated by the LP constraints. In addition, a separable extension of the revised simplex algorithm is tailored for separate representations (Dantzig & Thapa, 2003; Alloin, 1970). Furthermore, for integer programming problems, the B&B algorithm is a widely practical choice (Beresnev, 2013). The exact optimisation approaches might require substantial computational time for large-size problems. Global optimality can be reached with the exact optimisation solvers, such as CPLEX, BARON, CONOPT, and others. For comprehensive insights into evacuation planning solved through exact methods, relevant studies include those conducted by Anjos et al., 2018; Dulebenets et al., 2019; Hammad et al., 2017; Shahparvari et al., 2017; Thywissen, 2006.

2.4.2. Heuristic Methods

Heuristic methods are tailored for specific optimisation problems, particularly challenging combinatorial optimisations. Conventional methods rooted in linear and nonlinear programming models often demand significant computational resources due to difficulties in achieving optimality. Despite this, heuristics provide a pragmatic alternative, producing solutions that closely approximate the optimum, albeit not guaranteeing absolute optimality (Valadi & Siarry, 2014; Sorensen, 2000). Several studies used various heuristic-based algorithms for evacuation planning; relevant studies include those conducted by Bish et al., 2014; Bretschneider & Kimms, 2012; Kimms & Maassen, 2012; Li & Ozbay, 2015.

2.4.3. Meta-heuristic Methods

Metaheuristic algorithms have gained recognition for their efficiency in tackling complex problems, offering optimal solutions within reasonable time frames (Hopper & Turton, 2001). Despite not ensuring global optimal solutions, these algorithms enhance feasible solutions iteratively using various heuristic techniques. Unlike heuristics, meta-heuristics do not necessitate tailored adjustments for the problem's specific structure upon application (Chen et al., 2011). These methods are popular due to their capacity to optimise multiple and conflicting objectives while furnishing non-dominated solutions (Desale et al., 2015). Notable techniques encompass Genetic Algorithm (GA) (Bozorg-Haddad et al., 2017; Ganesan et al., 2021; Reca et al., 2008), Particle Swarm Optimisation (PSO) (Pozna et al., 2022; Chen et al., 2021), Tabu Search (TS) (Cheikh-Graiet et al., 2020; Mathlouthi et al., 2021), Ant Colony Optimisation (ACO) (Ning et al., 2018; Wong et al., 2019) and Artificial Bee Colony (ABC) (Mann & Singh, 2019; Chandar, 2021). Not all these algorithms exhibit equal efficiency, with only a subset demonstrating proficiency in solving real-world problems (Agrawal et al., 2021) and each algorithm having inherent limitations. Numerous studies have employed metaheuristics, including those conducted by Garrett, 2009; Xu et al., 2020; Saeidian et al., 2018.

2.5. Mathematical Model Representation

This section provides an overview of the two prevalent approaches utilised for representing the mathematical optimisation models proposed in this thesis: single-level MOO and BP.

2.5.1. Multi-Objective Optimisation

Numerous real-world issues cannot be effectively represented using a single objective function (Alothaimeen & Arditi, 2019). Unlike single-objective optimisation, MOO is to find a set of solutions where one solution is not dominating another solution in all objective function values (Deb & Jain, 2013). There are several parameters for determining the solution's performance and many potentially conflicting objectives to be optimised simultaneously (Abraham & Jain, 2005). This statement can be formally defined as minimise or maximise as follows:

$$Z(x) = \{z_1(x), z_2(x), \ldots, z_n(x)\} \tag{2.1}$$

subject to

$$x \in S \tag{2.2.}$$

where $Z(x)$ is the n-dimension objective function, $z_k(x)$ is an objective function ($k = 1, 2, \ldots, n$), S is the set of feasible alternatives, and $x = (x_1, x_1, \ldots, x_m)$ is a vector of decision variable, $x_i \geq 0$, for $i = 1, 2, \ldots, m$ (Coello, 2007).

Several fundamental terminologies are incorporated into MOO. Decision variables are adjustable parameters that decision-makers have the power to manipulate, and they exert an influence on the system's operations. These independent variables can be represented as x_j, $j = \{1, 2, \ldots, n\}$. Subsequently, a decision vector X encompassing n decision variables can be expressed as $X = \{x_1, x_2, \ldots, x_n\}^T$. A feasible solution is characterized by the vector (a collection of decision variable values) that fulfils all imposed constraints. On the other hand, an optimal solution is achieved when a balance between conflicting objectives is maximised or minimised among all feasible solutions. The objective function embodies the fundamental aim of the problem, while the fitness function measures the quality or fitness of the solution to the objective function.

In MOO, the objective is to identify favourable compromises or trade-offs among various objectives, a departure from the single solution focus of single objective optimisation. The solution of different models has offered many approaches to model the trade-off between multiple objective functions from the decision maker's perspective (Coello, 2007). Besides, the MOO problems generally have conflicting objectives, preventing the optimisation of each objective simultaneously (Konak et al., 2006). Ascione et al. (2016) stated that multi-objective solutions are complex and complicated but more realistic since real-life optimisation problems have multi-objective structures. Within this set of solutions, one of the objectives is to improve other objectives that may be negatively affected (Von Lücken et al., 2014). Thus, the decision-maker can select the solution according to the properties of the proposed problem.

Furthermore, the concept of Pareto optimality facilitates the assessment of trade-offs across optimal combinations of multiple criteria or objectives. A solution denoted is labelled Pareto optimal when it stands uncontested by any other element within the set of solutions. Within a collection of multi-objective solutions, the subset that remains unmatched in dominance across all feasible solutions is referred to as the Pareto-optimal set. The boundary defined by the set of all points mapped from the Pareto optimal set is called the Pareto-optimal front (Deb et al., 2002). The following section studies common methods used to solve MOO problems. For each of these methods, detailed implementation techniques are provided in the corresponding chapters where they are applied within this thesis. For a comprehensive survey of various methods, the reader is referred to Coello (1999) and Marler & Arora (2004)

2.5.1.1. ε -constraint Method

The ε -constraint method is a well-known scalarization in MOO (Chankong & Haimes, 1983). It aims at optimising one objective function while considering all other objective functions as constraints. The traditional ε-constraint, employed in solving the MOO problem outlined in Eq. (2.1) to Eq. (2.2), is formulated as depicted in Eq. (2.3) to Eq. (2.5):

$$min\ or \max \ \{z_1(x)\} \tag{2.3}$$

subject to

$$z_2(x) \geq k_2 \tag{2.4}$$

$$z_3(x) \geq k_3$$

$$\ldots$$

$$z_p(x) \geq k_p$$

$$x \in S \tag{2.5}$$

Through the changing of the constrained objective functions' right-hand side k_i, the approach yields effective solutions. The resolution of the problem takes place incrementally on an $N_2 \times N_3 \times \ldots \times N_p$ grid, where N_i represents the integer range of the objective function f_i.

One of the primary advantages of this method is its capacity for the controlled generation of efficient solutions. This is achieved by strategically tuning the number of grid points utilised for each optimisation operation across the spectrum of each objective function. However, it is essential to calculate this range accurately, and there is no guarantee that the solutions obtained will be robust rather than suboptimal. Besides, addressing problems with more than two objective functions tends to be a time-consuming process. To ensure the absence of weakly efficient solutions among the outcomes, this thesis employs the augmented ε-constraint method (AUGMECON) when addressing the MOO problems (Mavrotas, 2009). The novelty of AUGMECON is to modify the original ε-constraint method to secure the acquisition of effective Pareto solutions by (i) converting all constraints associated with the p − 1 objective functions into strict inequalities; and (ii) introducing slack (or surplus) variables to both the primary objective function and the constrained ones. It also accelerates the model's solution process, especially when dealing with scenarios where the problem is infeasible (Mavrotas & Florios, 2013). The AUGMECON employs lexicographic optimisation (Zykina, 2004)To determine the range of objective values, defining the right-hand side of the constraints objective functions. The optimisation starts with the highest-priority objective function, followed by the second-priority function with an added constraint to fix the first function's value at its optimum. This process iterates for all objective functions, yielding a trade-off table. This task is complex due to the challenge of deriving values that are Pareto efficient. Nonetheless, this approach ensures that the solutions generated are derived with careful consideration of multiple priorities and trade-offs.

2.5.1.2. Lexicographic Optimisation

The lexicographic optimisation problem is another significant formulation connected to multi-objective optimisation. It establishes a structured hierarchy among the optimisation objectives. In the presence of such a priority, a unique solution can be achieved by organizing the objective functions in a lexicographic order (Wang et al., 2020), starting with the most crucial Z_1 to the least critical Z_{n_j}. A particular vector $\vec{f}^* \in F$ is a lexicographic minimiser if there is no $\vec{f}^* \in F$ and a value j such that $Z_j\ (\vec{f}) < Z_j\ (\vec{f}^*)$and $Z_j\ (\vec{f}) = Z_j\ (\vec{f}^*)$ for all $i = 1, \ldots, j - 1$. This definition implies that a solution achieves a lexicographic minimum only when an objective Z_i can be decreased solely by increasing at least one of the higher-priority objectives $\{Z_1, \ldots, Z_{(i-1)}\}$. Consequently, a lexicographic solution is a distinctive Pareto-optimal solution incorporating the objective order. This hierarchical structure defines an objective function sequence, asserting that a more crucial objective carries infinitely more weight than a comparatively less important one. While the fundamental aspect of efficiency involves achieving a trade-off between objectives, lexicographic optimisation employs lexicographic order to compare objective vectors within the objective space (Khosravani et al., 2018).

A conventional approach for obtaining a lexicographic solution involves addressing a sequence of single-objective constrained optimisation problems in order (Toro et al., 2011). The process begins by minimizing the most critical objective function while adhering to the initial constraints. As a result, this problem yields a unique solution; it serves as the resolution for the entire MOO challenge. However, the next most crucial objective function is minimised if the solution is not unique. Here, a new constraint is introduced alongside the original constraints to preserve the optimal value of the most significant objective function. If this subsequent problem offers a singular solution, it becomes the solution for the original problem. In the event of further non-uniqueness, the process continues iteratively. In a more structured framework, the lexicographic minimiser denoted as $lex\ min_{\vec{f} \epsilon F}\ \vec{Z} \in F$, can be ascertained using Algorithm 2.1.

Algorithm 2.1 Lexicographic Optimisation

$Z_1^* = \ min_{\vec{f} \epsilon F} \left[Z_1(\vec{f})\right]$

$\boldsymbol{for}\ i = 2\ to\ n_j\ \boldsymbol{do}$

$Z_i^* = \ min_{\vec{f} \epsilon F} \left[Z_1(\vec{f}) \middle| Z_j(\vec{f}) \leq \ Z_j^*\right.$, j=1…, i-1]

$\boldsymbol{end\ for}$

Determine the lexicographic minimiser set as:

$\vec{f}^* =$ arg $(Z_{n_j}^*)$

Lexicographic optimisation requires a pre-defined arrangement of the various optimisation criteria based on their significance. However, this pre-requisite may pose challenges in situations where determining an absolute order of importance among the objective functions proves intricate. Another limitation arises from situations where, in some cases, the relatively less crucial objective functions might need to be adequately considered. This occurs when there are insufficient degrees of freedom in the subsequent optimisation problems following the initial iteration.

2.5.2. Bi-level Programming

A BP model is characterised by a hierarchical arrangement consisting of two levels, each hosting its optimisation problem: the upper-level and the lower-level problem (Talbi et al., 2012). The structure of this model draws parallels to a Stackelberg game in game theory (Stackelberg & Peacock, 1952) where a leader makes a decision that subsequently influences the follower's choice. A BP model embodies this game's static, non-cooperative variant (Bard, 1991). Consequently, these problems are often called leader and follower problems, mirroring the game theory context. In bi-level models, each decision-maker optimises its objective function independently of the other players' objectives. However, their achieved objective value and decision space are contingent upon the decisions made by the other players (Talbi et al., 2012)

The problem can be formally described using the following notation: the upper-level decision-maker is associated with their own objective function $Z(x, y(x))$, while the lower-level decision-maker has their distinct objective function $z(x, y(x))$. Here, the variables $x \ \in \ X \ \subseteq$

R^{n1} and $y(x) \in Y \subseteq R^{n2}$ represent the decision variables for the upper-level and lower-level problems, respectively. Notably, $y(x)$ signifies that the lower-level decision hinges on the decision variables of the upper-level problem. Notable generalized bi-level model formulations are presented in studies like Colson et al. (2005) and Bard (1991). These formulations culminate in the subsequent general representation of a bi-level model:

$$min_{x \epsilon X} \quad Z\big(x, y(x)\big) \tag{2.6}$$

subject to

$$G(x, y(x) \leq 0 \tag{2.7}$$

$$min_{y(x) \epsilon Y} \quad z\big(x, y(x)\big) \tag{2.8}$$

subject to

$$g(x, y(x) \leq 0 \tag{2.9}$$

The upper-level problem is focused on optimising the decision variables x and, indirectly, on $y(x)$. Conversely, in the lower-level problem, decisions are exclusively managed through the $y(x)$ variables. The upper-level and lower-level problems are subject to constraint sets $G(x, y(x))$ and $g(x, y(x))$, respectively. In the context of a bi-level optimisation model, each participant has a single move. The upper-level model is initially solved, considering its objective function and constraint set. Subsequently, the lower-level problem is addressed, taking into account the solution obtained from the upper-level problem. Thus, in BP models, the upper-level decision can influence the behaviour of the lower-level decision but does not possess complete control over them.

The classification of general bi-level optimisation problems as NP-hard is well-known (Jeroslow, 1985). As a result, developing efficient algorithms for solving these generic problems is a challenging endeavour. However, the process of modelling bilevel problems is theoretically more straightforward. This modelling step can determine whether a tractable model with a feasible solution approach can be established for realistic cases. Given the inherent complexity and diversity of BP models within mathematical programming, many modelling languages need more functionality to address these intricate problems effectively (Colson et al., 2005). Comprehensive introductions to bi-level optimisation are available in various research studies that contains theoretical background, solution algorithms, analysis for specific classes, and functions (Dempe, 2003; Bard, 2013). Furthermore, numerous reviews on BP have been published over the last decades, shedding light on different aspects (Dempe et al., 2015; Kalashnikov et al., 2015; Vicente & Calamai, 1994; Beck et al., 2023). For an extensive compilation of publications related to BP, interested readers can refer to Dempe (2018).

Numerous strategies have been proposed to address the linear BP problem. Several prominent techniques are built upon classical algorithms, including the simplex method, the B&B method, and the interior-point methods. Given the combinatorial nature characteristic in many BP, some initial approaches are inherently combinatorial. The K^{th}-best algorithm stands out within a wide array of enumeration algorithms, often considered adaptations of the simplex method for LP (Bialas & Karwan, 1984).

The primary technique explored in this study involves the transformation of the BP into a single-level problem by incorporating the lower-level KKT conditions into the upper-level problem. This modified optimisation problem is termed Mathematical Programming with Equilibrium Constraints (MPEC) (Kim et al., 2020). These approaches are sometimes called enumeration-based due to their focus on managing complementarity constraints. Consequently, a traditional solution method involves a customized B&B approach (Bard, 1991). Rather than constructing a B&B method from scratch, an alternative approach involves reformulating the single-level problem to align with pre-existing off-the-shelf algorithms such as MIP solvers. This strategy was initially introduced using big-M formulations by Fortuny-Amat and McCarl (1981). More recently, specialised formulations known as the Special Ordered Set of type 1 (SOS1) were devised by Siddiqui and Gabriel (2013).

In the context of non-linear BP, two predominant algorithms are commonly employed. One such approach is the trust region algorithm, which approximates the original BP during each iteration (Colson et al., 2007). This algorithm approximates the upper-level objective function within a trust region, defined as a ball with a predetermined radius. Another solution technique for non-linear BP involves replacing the lower-level problem with a penalised version, often referred to as a penalty function method (Chen & Florian, 1995). This approach provides the option to transform the BP into a single-level formulation if the lower level is substituted with its stationary condition.

In addition, strategies for solving bilevel problems encompass a variety of techniques: bundle-type algorithms (Falk & Liu, 1995), semi-definite relaxations (Fampa et al., 2008), methods based on penalty functions (Kleinert & Schmidt, 2020), benders decomposition (Byeon & Van Hentenryck, 2022), and cutting-plane (Tahernejad et al., 2020), which have gained recent attention due to their ability to manage lower-level with integer variables solvers were devised by Ralphs et al. (2019). Descent methods, introduced by Vicente and Calamai (1994), offer quick local solutions. Evolutionary approaches are also covered by Sinha et al. (2017).

2.5.2.1. Stochastic BP

A stochastic BP model introduces uncertainty through probabilistic elements or random variables (Kalashnikov et al., 2015). This uncertainty impacts both the leader's and follower's decision-making processes, making the model more realistic and applicable to situations with uncertain parameters or outcomes (Talari et al., 2017). Therefore, the stochastic BP is a subset of the broader BP modelling framework, explicitly accounting for stochasticity in decision-making (Dempe et al., 2015)

Applications of stochastic BP can be found in various fields, such as supply chain management, energy systems, transportation, logistics, and construction (Carrión et al., 2009). In supply chain management, models have been used to optimise the coordination between the leader and the follower in a supply chain (Setak et al., 2019). In contrast, in energy systems, models have been used to optimise the operation of power systems under uncertainty (Beraldi & Khodaparasti, 2023; Do Prado & Qiao, 2020). In transportation and logistics, these models have been used to optimise the scheduling and routing of vehicles (Kovacevic & Pflug, 2014), (Alizadeh et al., 2013). In construction, there are two critical strategies for mitigating the impact of intentional disruption risks: facility location and protection (Kleindorfer & Saad, 2005). Facility location strategy is primarily employed during the design phase of supply networks to determine optimal locations for facilities (Scaparra & Church, 2019). On the other hand, the concept of protection strategy involves allocating resources across different targets to fortify them against threats (Starita & Paola Scaparra, 2022; Liberatore et al., 2011). These strategies play vital roles in minimising vulnerabilities and enhancing the resilience of buildings. Overall, stochastic BP provides insights into decision-making under uncertainty and enables decision-makers to make more informed decisions by considering other decision-makers' responses.

2.5.3. Optimisation Solvers

Two primary solvers have been utilised for the optimisation models introduced in this study. While each solver's mechanism is outside this thesis's scope, a concise summary of each solver follows. Readers are encouraged to refer to the provided references for more comprehensive insights into each solver.

2.5.3.1. CPLEX

The CPLEX optimiser offers robust and high-performance mathematical programming solvers suitable for LP, MIP, quadratic programming, and quadratically constrained programming problems (IBM CPLEX, 2022). Notably, these solvers encompass a distributed parallel algorithm for mixed integer programming, enabling the utilisation of multiple computers to address challenging problem scenarios. CPLEX employs the simplex algorithm as its primary algorithmic foundation for solving LP models (Koch et al., 2022). While for MIP models, CPLEX utilises a combination of B&B algorithms, along with cutting plane algorithms to locate integer solutions efficiently. Note that cutting plane algorithms entail multiple cuts to attain an integer solution. In addition, CPLEX is under active development by IBM (International Business Machines) and is equipped with diverse interfaces that enable integration with various programming languages and applications and standalone executable versions. The optimiser's accessibility is further enhanced through compatibility with various modelling systems (Anand et al., 2017).

2.5.3.2. SCIP

SCIP is a robust solver able to handle diverse optimisation challenges, gaining significant recognition across both academic and industrial domains (Gamrath et al., 2020). It is a software framework for constraint integer programming (SCIP, 2023). This novel paradigm incorporates constraint programming (CP), CPLEX, MIP, and satisfiability (SAT) modelling and solving techniques (Yilmaz & Yorke-Smith, 2021). It tackles both MILP and MINLP using numerous unique tools, such as constraint handler (Achterberg et al., 2008). SCIP employs a unified B&B approach across all three domains: MIP, CP, and SAT. This approach is enriched by LP relaxations, cutting plane separators akin to those in MIP, and domain-specific constraint propagation algorithms akin to CP and SAT. Besides, SCIP includes conflict analysis similar to modern SAT solvers. The solver's source code is readily accessible and accompanied by tutorials and extensive documentation on its official website. This accessibility empowers researchers and practitioners to enhance their capabilities and design custom plug-ins. For a comprehensive overview and recognition of the contributors to SCIP's development, please refer to SCIP (2023).

2.6. AML for Optimisation

Traditionally, optimisation solvers were developed at a low level to achieve maximum performance (Jusevičius et al., 2021). However, manually formatting the input for these solvers proves to be a difficult and error-prone task that does not adapt well to the increasing complexity of problems. This has prompted the emergence of Algebraic Modelling Language (AML), software designed to bridge the gap by offering a high-level interface between optimisation models and solvers. Just as higher-level programming languages were created atop assembly languages, AML provide domain experts with the means to express optimisation problems in algebraic structures resembling their original mathematical expressions. Creating an AML involves translating user algebraic models, performing necessary transformations, and delivering the required input to optimisation solvers, as illustrated in Figure 2.3. The following section introduces AML utilisation, which exhibits a wide range of functionalities and is applicable in both industrial and academic settings.

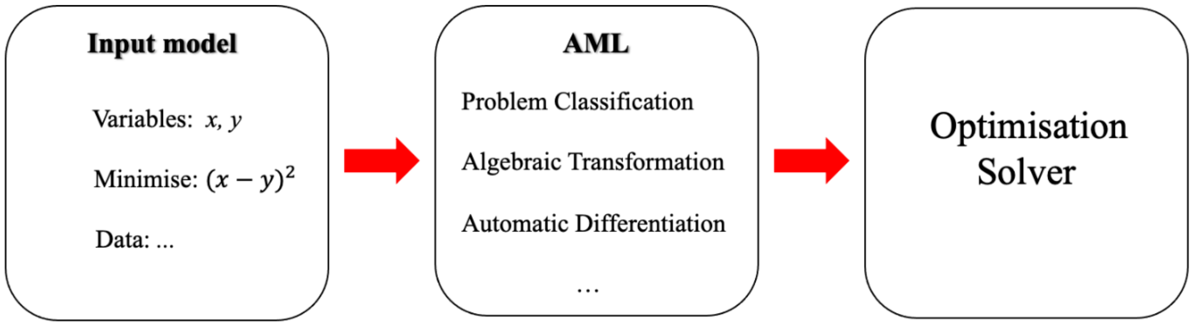


Figure 2.3: AML allows user-provided models and produces the necessary input for mathematical optimisation solvers.

2.6.1. GAMS

The General Algebraic Modelling System (GAMS) is a powerful modelling tool designed for mathematical programming problems (GAMS, 2021). It consists of a language compiler and an array of integrated high-performance solvers. GAMS provides users with the advantage of focusing on model formulation rather than grappling with intricate solution algorithms. Users can construct their models using the GAMS language and leverage built-in solvers to solve problems effectively.

Specifically tailored for linear, nonlinear, and mixed-integer optimisation problems, GAMS excels in managing complex scenarios where extensive refinement is needed. This adaptability makes it particularly valuable for addressing intricate issues. GAMS facilitates the concurrent development, solution, and documentation of models within a single GAMS model file. The core structure of a GAMS-coded mathematical model involves components like sets, data, variables, equations, models, and outputs (Robichaud, 2010).

Although GAMS offers robust support for mathematical optimisation and enjoys wide use in academia and industry, it lacks seamless integration with modern application pipelines that connect software components and reuses problem instances (Andrei & Andrei, 2013). Using monolithic modelling systems like AMPL (A Mathematical Programming Language) and GAMS are often more challenging than using embedded AML built within familiar host languages. This is precisely why numerous contemporary AML, such as Pyomo, have been embedded within Python (Hart et al., 2011). This integration significantly simplifies the usage process and allows users to harness the power of AML more seamlessly. Figure 2.4 indicates GAMS solution procedure.

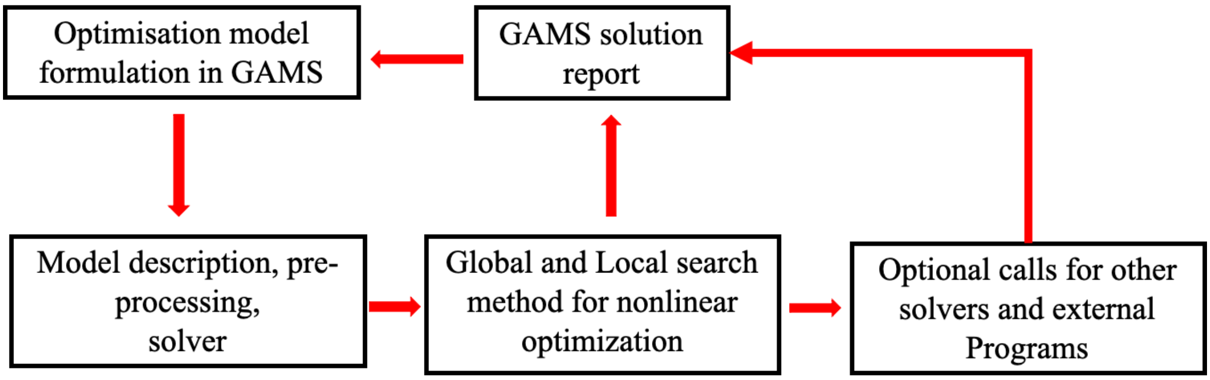


Figure 2.4: GAMS modelling and solution procedure.

2.6.2. Pyomo and PAO

Pyomo, a Python-based tool, streamlines the development of optimisation models through its object-oriented design (Hart, 2009). At its core is the Pyomo model object, which encompasses various modelling components essential for defining optimisation problems. These components include fundamental elements such as variables, objectives, constraints, index sets, and parameters commonly supported by modern AMLs.

The principle of Pyomo is to encapsulate key concepts from contemporary AMLs within a framework that embodies flexibility, extensibility, portability, openness, and maintainability (Hart et al., 2017). As an extension of Python, Pyomo introduces dedicated objects for optimisation modelling, allowing users to articulate optimisation models and convert them into formats that external solvers can process (Bynum et al., 2021).

Pyomo stands out as a flexible and extensible modelling framework that channels core concepts in modern algebraic modelling languages, all while leveraging a widely used programming language. Pyomo can seamlessly handle a diverse range of optimisation models. From LP and MILP to NLP and MINLP, stochastic programs, BP, mathematical programs with equilibrium constraints, and more, Pyomo offers extensive coverage (Andersson et al., 2019). Furthermore, Pyomo seamlessly interfaces with various prominent optimisation software and optimisers, enhancing its effectiveness and applicability.

The capacity to handle BP is also present within the Pyomo Adversarial Optimisation (PAO), a Python package that extends the capabilities of Pyomo (Hart et al., 2017). In PAO, the mechanism involves creating a (lower) sub-model as an adjunct to the main (upper) model. Variables and constraints are then incorporated into their respective parent models, allowing variables to be shared in objectives and constraints. Similar to the AMLs mentioned earlier, Pyomo automatically transforms the problem, offering reformulation. Subsequently, the reformulated problem can be directed towards either an NLP solver (Ralph & Wright, 2004) or a MIP solver (Fortuny-Amat & McCarl, 1981) in Pyomo's context. Table 2.1 displays the modelling interfaces for bilevel optimisation, including Pyomo/PAO and GAMS.

Table 2.1: Modelling interfaces for bilevel optimisation.

Name	***Pyomo/PAO***	***GAMS***
Language	Python	GAMS
License	BSD	Commercial
MIP solvers	Yes	No
NLP solvers	Yes	Yes
MPEC solvers	No	Yes
Dual-Var	No	Yes
Upper-Level	QP/Int	QP/NLP/Int
Lower-Level	QP/Int	QP/NLP/VI

2.7. MCDM Methods

MCDM is a systematic approach used to solve problems with varying degrees of structure, making it particularly valuable in addressing uncertainties in construction engineering (Aruldoss et al., 2013; Wątróbski et al., 2019; Khosravi et al., 2019). This technique involves generating alternative scenarios, establishing criteria, assessing and ranking alternatives, and weighing the criteria (Zavadskas et al., 2014). Weighing techniques can be subjective or objective, with subjective methods relying on the decision-makers' preferences and objective methods utilizing mathematical models (Deng et al., 2000). MCDM encompasses various approaches, including single methods like the analytic hierarchy process and fuzzy sets and hybrid approaches that combine multiple methods (Jato-Espino et al., 2014).

Moreover, decision-making is a systematic process where a single alternative is chosen from a set of options. This process includes defining the problem, understanding its causes, and identifying criteria based on goals. A comprehensive set of non-redundant criteria helps in selecting better alternatives. After identifying alternatives and comparing them against criteria, pairwise comparisons assign importance weights to each criterion. Criteria for each alternative are then scored, forming a matrix used in decision rules that consider weights and scores. Evaluating alternatives against criteria enables ranking or selecting a more favourable option. The final phase determines the best alternative, aligning with the desired goal. The process involves problem definition, criteria establishment, alternative identification, weight assignment, criterion scoring, decision rule application, alternative evaluation, and ultimate selection. Figure 2.5 illustrates the main steps in solving MCDM problems, providing a systematic framework for effective decision-making in various domains.

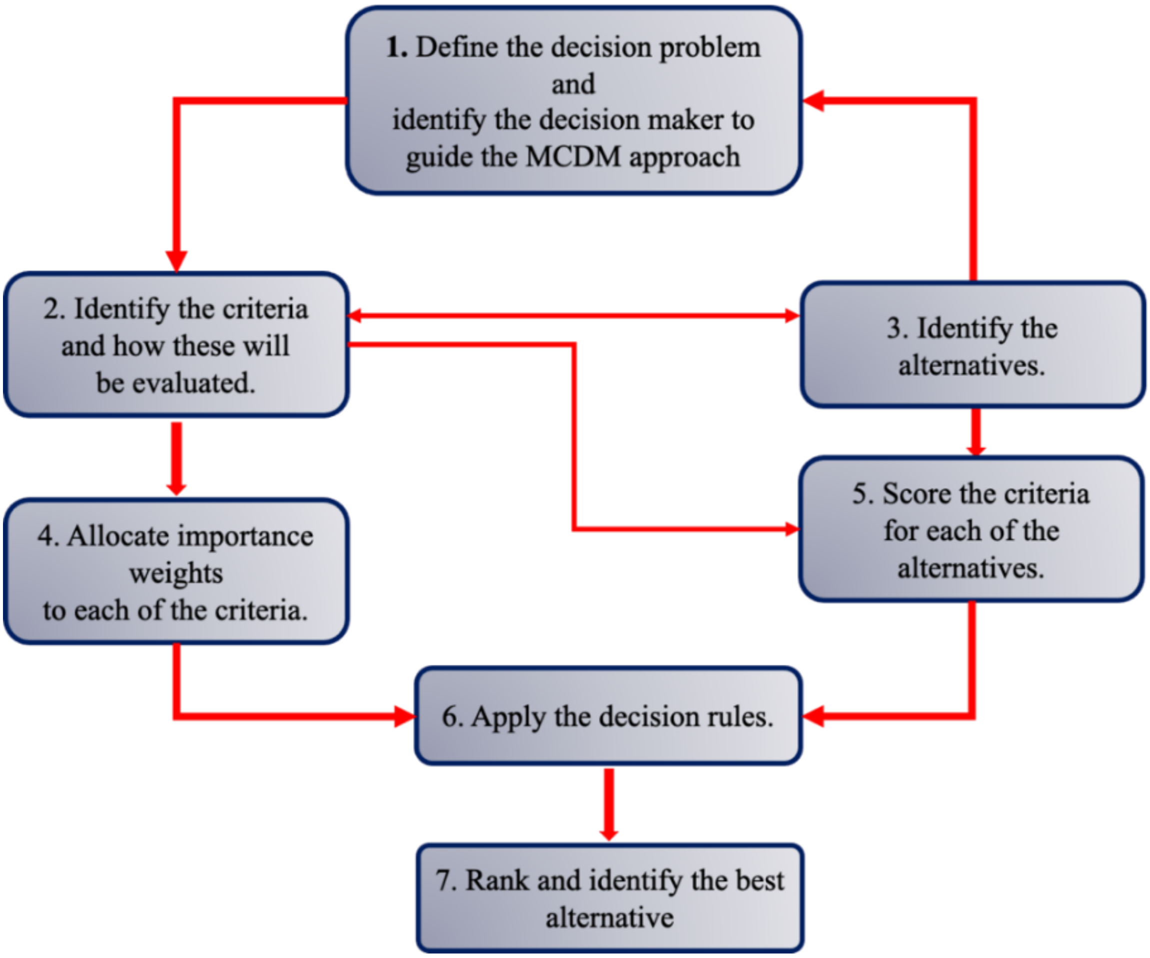


Figure 2.5: A generalized scheme of the mains steps of a MCDM approach.

Individuals often navigate situations with undefined boundaries in decision-making by relying on their experience and expertise. To address the complexities of uncertain or unavailability of information, Fuzzy MCDM emerges as a valuable technique, drawing upon experts' linguistic input to model intricate and ambiguous systems (Liang, 1999). Fuzzy MCDM, including its integration with methodologies like AHP has demonstrated its efficacy across various decision-making levels and functions (Singh & Nachtnebel, 2016). Leveraging real-time data and information, MCDM proves especially advantageous for short-term decisions, enhancing the decision process and mitigating uncertainties (Chen et al., 2011). Traditional evaluation systems encompass structured frameworks utilizing both quantifiable and non-quantifiable metrics for assessment. Quantifying performance dimensions, such as the elusive concept of responsiveness, can prove challenging. Fuzzy logic offers a viable approach in contexts characterized by uncertainty and imprecision. Problems involving subjectivity, fuzziness, and imprecise information are effectively addressed through performance evaluation techniques harnessing fuzzy logic (Nguyen et al., 2022).

MCDM has been deployed across various fields, including personnel selection and ranking (Afshari et al., 2010), robot manufacturing (Omoniwa, 2014), maintenance contractor selection (Brauers et al., 2008), and project feasibility studies to avoid wrong choices by investors (Marzouk & Mohamed, 2019). In evacuation planning, researchers have applied MCDM techniques for different purposes. For instance, one study developed an adaptive and configurable model for risk event scenarios (Chan & Armenakis, 2014), while another focused on designing an appropriate evacuation strategy for a metro station (Mei & Xie, 2019). Besides, MCDM has been employed to minimise injuries and losses during the evacuation of construction sites (El Meouche et al., 2018) and to evaluate and prioritise alternative structural and architectural designs of buildings (Vaidogas & Šakėnaitė, 2015). In the following sections, specific MCDM approaches adopted in relevant studies will be discussed in detail and organised chronologically.

2.7.1. AHP

The Analytic Hierarchy Process (AHP), initially developed by Saaty (1980), provides a systematic framework for incorporating various factors, including logic, experience or knowledge, emotions, and optimisation considerations, into the decision-making process. AHP consists of two main components: establishing a hierarchy and assigning priorities to the elements within each level. Expert opinions are converted into numerical values to determine these priorities. Moreover, this method simplifies complex multi-criteria problems by organizing them into a hierarchical structure (Darko et al., 2019). According to Saaty and Vargas (1980), the hierarchy represents a multi-level structure where the top level represents the objective, criteria and sub-criteria, and the lowest level of alternatives. By breaking down a complex problem into manageable sections and arranging them hierarchically, the problem becomes more structured and systematic (Saaty, 1990). The AHP has found widespread application in various fields, including energy efficiency (Salvia et al., 2019), sustainable management (Ahmed et al., 2016), location selection (Alosta et al., 2021), supply chain management (Radivojević & Gajović, 2014) and emergency plan (Basirat et al., 2018) where MCDM problems arise.

2.7.2. F-AHP

The Fuzzy Analytic Hierarchy Process (F-AHP) is an advanced technique extending traditional AHP by incorporating fuzzy numbers. Integrating fuzzy numbers in F-AHP provides a robust framework for dealing with uncertainties when assigning scores to human preferences in multi-criteria decision-making (Vilasan & Kapse, 2022). Applying F-AHP can assist decision-makers in making more effective and practical decisions by flexibly considering the available criteria and alternatives (Ghosh & Maiti, 2021). Previous studies have provided significant evidence supporting the applicability and effectiveness of F-AHP in addressing various real-life problems. Numerous studies have consistently demonstrated the utility of F-AHP in practical applications, such as risk assessment (Ghosh & Maiti, 2021), weapon alternatives selection (Dağdeviren et al., 2009), energy alternatives selection (Seddiki & Bennadji, 2019), performance evaluation systems (Lee et al., 2013) and evacuation planning (Jamrussri & Toda, 2018). The calculation steps for F-AHP are explained in Chapter 5.

2.7.3. ELECTRE Family

The Elimination Et Choix Traduisant la Realitè (ELECTRE) method originated in the 1960s as a response to the limitations of existing decision-making approaches for addressing choice problems (Figueira et al., 2013). ELECTRE introduces the concept of the outranking relation (Jun et al., 2014) to overcome these limitations. In ELECTRE, the outranking relation represents a complete ordering of alternatives established through pairwise comparisons among alternatives for each criterion (Roy, 1991). This approach enables a comprehensive assessment of alternatives based on various criteria, leading to a more robust and nuanced decision-making process (Figueira et al., 2013). The ELECTRE methods have been utilised in diverse fields, including renewable energy (Mousavi-Taghiabadi et al., 2020), site selection (Kumar et al., 2016), evacuation strategy (Mei & Xie, 2018), finance (Angilella & Mazzù, 2015), and decision analysis (Komsiyah et al., 2019). Extensive literature is available for more details and derivative methods based on ELECTRE (Govindan & Jepsen, 2016).

2.7.4. PROMETHEE Family

The Preference Ranking Organisation Method for Enrichment Evaluation (PROMETHEE) initially introduced by Brans (Behzadian et al., 2010) and further expanded upon, is an outranking approach used for ranking and selecting a finite set of alternatives (Oubahman & Duleba, 2021). In PROMETHEE, a predefined set of alternatives is evaluated based on multiple criteria, with each criterion assigned a weight and a suitable preference function employed (Behzadian et al., 2010). The preference function quantifies the difference in evaluations between two alternatives, resulting in a preference degree (Brans, 2015). By incorporating weighted criteria and preference functions, PROMETHEE allows for a comprehensive assessment of alternatives, facilitating decision-making. Extensive literature is available on the methodologies and applications of PROMETHEE (Behzadian et al., 2010). Numerous studies have delved into the intricacies and derivatives of the PROMETHEE method, including its applications in facility location selection (Athawale et al., 2012), urban evacuation planning (Asadi & Karami, 2019), waste management (Stanković et al., 2021), and sustainable energy (Oberschmidt et al., 2010), contributing to its well-documented status in the literature.

2.7.5. SWARA

The Stepwise Weight Assessment Ratio Analysis (SWARA) method, introduced by Keršuliene (Keršuliene et al., 2010), is a recent approach used in multi-criteria decision-making problems to determine subjective criteria weights based on their importance ratios (Keshavarz-Ghorabaee et al., 2018). SWARA follows a stepwise process where pairwise comparisons are conducted to establish the relative importance of criteria (Keshavarz-Ghorabaee et al., 2018). The weights are calculated by considering the ratio of the number of comparisons in favour of a criterion to the total number of comparisons made for that criterion (Stanujkic et al., 2015). SWARA is particularly useful when there is uncertainty or subjectivity in assigning precise numerical values to criteria weights (Mardani et al., 2017). The SWARA method has been applied in various MCDM problems, including waste management (Ghoushchi et al., 2021), supply selection (Alimardani et al., 2013), site selection (Ghoushchi et al., 2021; Yücenur & Ipekçi, 2021), emergency evacuation planning (Rahman et al., 2021) and renewable energy (Ghenai et al., 2020).

2.7.6. TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) proposed by Hwang and Yoon (Hwang et al., 1981), is a widely recognised MCDM method used to evaluate alternative performances by measuring their proximity to the ideal solution (Shih et al., 2007). In TOPSIS, the preferred alternative is determined based on two key factors: the shortest distance to the positive ideal solution and the longest distance from the negative ideal solution (Behzadian et al., 2010). This approach aims to identify alternatives that possess favourable attributes while being distinct from the unfavourable ones (Yoon & Kim, 2017). The TOPSIS method has been extensively explored and applied in various fields, including energy (Afsordegan et al., 2016), evacuation strategy (Mei & Xie, 2019), medicine (Hsu & Hsu, 2008), chemical engineering (Hasanzadeh et al., 2022), and logistics (Sirisawat & Kiatcharoenpol, 2018).

2.7.7. VIKOR

The VIekriterijumsko KOmpromisno Rangiranje (VIKOR) method is a decision-making approach primarily focused on finding the optimal compromise solution among a set of feasible alternatives by evaluating their proximity to the ideal solution while considering conflicting criteria (Mardani et al., 2017; Opricovic & Tzeng, 2004). The compromise solution is determined based on its closest distance to the ideal solution (Yazdani & Graeml, 2014). The VIKOR technique has been applied in various fields, including construction management (Liu & Yan, 2007), material selection (Jahan et al., 2011), emergency shelter location and evacuation (Geng et al., 2021), supply chain (Rostamzadeh et al., 2015), and renewable energy (Kaya & Kahraman, 2010).

2.7.8. WASPAS

The Weighted Aggregated Sum Product Assessment (WASPAS) method is a decision-making approach to address ranking and choice problems involving conflicting multicriteria (Zavadskas et al., 2012). This method combines the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) to improve the accuracy of rankings (Badalpur & Nurbakhsh, 2021). In addition to its simplicity, WASPAS is more accurate than WSM and WPM (Ali et al., 2021). The WASPAS method has been applied in various fields, such as renewable energy systems (Masoomi et al., 2022), site selection (Turskis et al., 2015), emergency evacuation path selection (Chandrawati et al., 2020), supplier selection (Stojić et al., 2018), and manufacturing decision-making (Chakraborty et al., 2021).

2.8. Methods Adopted to Augment Optimisation Models

This section provides a concise overview of two concepts that enhance evacuation planning within this thesis. The initial segment of the section delves into Agent-Based Models (ABM), while the subsequent part focuses on reviewing Building Information Modelling (BIM).

2.8.1. BIM

BIM is emerging as a transformative working methodology, offering enhanced process efficiency and product quality compared to traditional 2D or 3D CAD in construction, thus creating a competitive edge in the industry (Smith & Tardif, 2009). This approach leads to fragmented work, data loss, rework, miscommunication, and limited visualisation. It emerges as a transformative technology for the design phase, facilitating cooperation and efficient information sharing among diverse stakeholders (Alizadehsalehi et al., 2020). BIM creates a virtual representation of a building, encompassing both graphical and non-graphical data (Nielsen & Madsen, 2010), resulting in a data-rich, intelligent, and parametric digital model (Sampaio, 2017). BIM involves collaboration among stakeholders to enhance design and construction efficiency. Integrating BIM into a project leads to streamlined design and construction, improved building quality, reduced costs, and shorter project timelines (Eastman et al., 2011). BIM offers benefits like early clash detection, enhanced collaboration, visualisation, time efficiency, well-documented design processes, improved work quality, and simplified material quantity estimation (Bartley, 2017; Chen & Tang, 2019; Mehrbod et al., 2019).

Contrary to common misconceptions, BIM's scope extends beyond buildings to include diverse infrastructure projects (Davies et al., 2017). BIM offers more than just a 3D model, providing a versatile suite of applications throughout project life cycles. These applications, named dimensions, enhance the 3D model by integrating functionalities like parametric design, coordination, communication, and visualisation (Eastman et al., 2011). As a shared knowledge resource, BIM provides digital representations of a facility's physical and functional attributes. Central to BIM is stakeholder collaboration across various lifecycle phases, enabling information insertion, extraction, and updates for each role (Tang et al., 2019). Despite facilitating collaboration, information sharing, and supply chain integration, current BIM implementation primarily focuses on modelling and automated documentation at the company level (Arayici et al., 2009; Coates et al., 2010). Many software applications under the BIM, such as Revit, lead to an effective space design. Revit is the most popular BIM software package in the AEC industry. It is architectural software designed for creating 2D and 3D building models enriched with diverse structural and engineering details, catering to the requirements of BIM (Banfi, 2019). Revit enables the incorporation of furnishing elements, architectural features, indoor space definition, staircases, and more, facilitating comprehensive modelling of the building interiors (Yori et al., 2019).

Moreover, BIM plays a vital role in supplying real-time and accurate building information in an emergency due to its extensive standardised data format (Wang et al., 2014). In addition, BIM is an effective risk management tool, particularly in disasters and emergencies (Wehbe & Shahrour, 2021). It can generate indoor and outdoor navigation models for the evacuation safety performance of a building design (Hamieh et al., 2020). BIM also offers a straightforward collection of information and data that can be used as a platform for conducting simulation design (Montiel-Santiago et al., 2020). Consequently, BIM is interoperable with other software and analysis tools to apply various applications, such as building energy modelling with IES-VE (Rinne et al., 2022), comprehensive urban planning and management with GIS (D'Amico et al., 2020), evacuation simulation with AnyLogic, etc. (Shams et al., 2021).

Several studies proposed a BIM-based model to support emergency management, including evacuation assessment for escape route planning (Boguslawski et al., 2016). In their study, Lotfi et al. (2021) proposed a framework using BIM that can be used for the evacuation assessment of occupants in high-rise buildings. Likewise, Sun and Turkan (2020) optimise building design and investigate factors affecting the evacuation efficiency of people applying the BIM-based simulation framework. While Ma et al. (2017) offers a framework using BIM to guide the three-dimensional building within the evacuation path. A case study by Chen and Chu (2016) seeks to respond to emergencies in buildings by combining network analysis and BIM models. Wang et al. (2014) and Rüppel and Schatz (2011) have also demonstrated the path finding for evacuation using BIM in the area of evacuation analyses. Figure 2.6 indicates the general development of the BIM model.

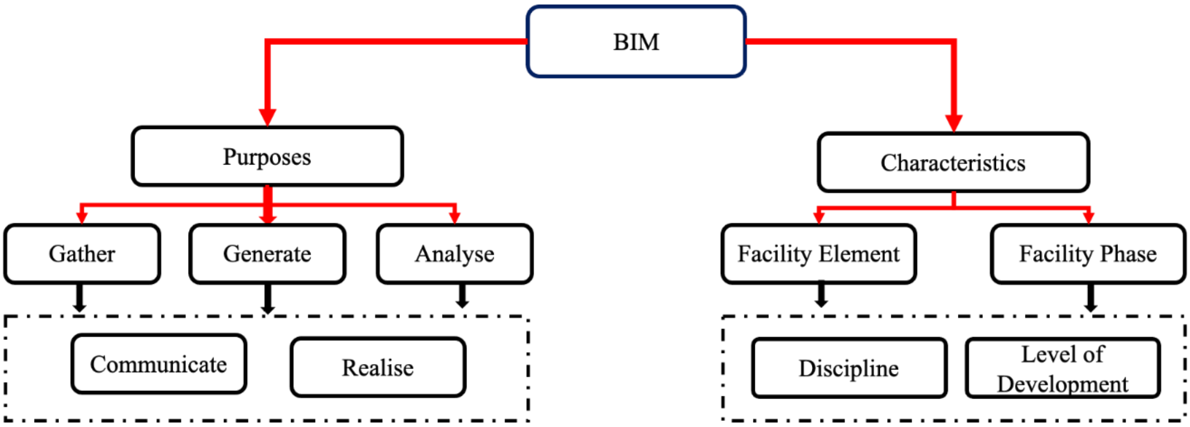


Figure 2.6: The components of a BIM application (adopted from Kreider and Messner (2013)).

2.8.2. ABM

ABM represents a dynamic and versatile approach to understanding complex systems by simulating the behaviours and interactions of individual agents within the system (Heckbert et al., 2010). These agents, representing individuals, groups, organisations, or even companies, collectively form the autonomous components that constitute the system under study (Bina & Moghadas, 2021). One of the key advantages of ABM is its ability to capture emergent phenomena (Ghorbani et al., 2014). Emergent properties are system-level outcomes that emerge from the interactions and behaviours of individual agents rather than being explicitly programmed into the model. This allows ABM to represent complex and often unpredictable behaviours that may arise from simple rules followed by individual agents (Secchi & Neumann, 2016). As a result, ABM is particularly suitable for modelling systems where the interactions between agents lead to outcomes that cannot be easily deduced from the individual agents' properties. These models allow for incorporating diverse and heterogeneous agents with varying behaviours, attributes, and decision-making processes (Lake, 2015). This flexibility makes ABM suitable for studying systems where agents' behaviour can vary widely, such as human behaviour in different contexts.

ABM is often used to describe evacuation behaviour. It is an approach for investigating complicated interactions between humans and their surroundings (Gutierrez-Milla et al., 2015). Within ABM, agents can represent individuals, groups, and companies (Cimellaro et al., 2017). They are flexible and learn based on their experience, which comprises autonomous decision-making entities (Macal & North, 2014). Since the realisation of the emergency evacuation plan for a building is often limited, ABM is promising as a tool for planning support (Johnson & Sieber, 2009) and carrying out the evacuation plan realistically (Wu et al., 2020; Tah, 2005). These significant challenges, such as linking building configuration with human behaviour during an evacuation, emphasise the importance of ABM systems, which can provide information about real-world system dynamics implemented in an evacuation plan (Bonabeau, 2002). Due to its low cost and ability to simulate emergency situations, ABM is frequently employed to model and evaluate evacuation plans (Macal & North, 2014). Indeed, ABM is ideal since they permit relatively complex individual cognition, leading to more effective results (DeAngelis & Diaz, 2019; Manzo, 2014).

Several applications of ABM to simulate evacuation at different spatial scales are presented. Arteaga and Park (2020) analyse the structural parameters associated with determining their potential effects on reducing casualties and evacuation efficiency. Another study conducted by Cimellaro et al. (2019) applied ABM with a human behaviour analytical model to define emergency evacuation and affect the evacuation process. Likewise, Kim et al. (2022) presents an approach to include human behaviour in an agent-based model, which takes into account the consequences of behaviours such as overcrowding, congestion, individuals rushing or in a disorganised manner, decision-making under stress, information dissemination challenges, delays in evacuation scenarios induced by a crowd. Mas et al. (2015) introduce a practical application of agent-based tsunami evacuation models and show that agent-based modelling has contributed to tsunami evacuation simulation and mitigation efforts. Ha and Lykotrafitis (2012) also, implement ABM to analyse the effect of building architecture's complexity on the behaviour of agents' collective during an emergency evacuation.

Among various options designed for agent-based evacuation simulations, the selected software for this study is AnyLogic (Anylogic, 2021), chosen following a comprehensive evaluation process. Its unique and robust features guided this choice, including compatibility with BIM models through DXF file import for seamless integration and ease of model construction without requiring advanced Java skills or complex mesh setups (Borshchev, 2014). It can represent pedestrians as individual agents with customisable parameters and behaviours, realistic 3D visualisation of pedestrian interactions and reactions within predefined scenarios, and the addition of a pedestrian density map to observe dynamic movement flow (Ivanov, 2016). Table 2.2 provides a comparison between AnyLogic and alternative choices.

The AnyLogic Pedestrian Library (APL) is a crowd analysis tool for modelling, visualising, and analysing pedestrian movements during emergency evacuations (Li et al., 2014). It uses space markup and essential block elements to simulate pedestrian agents' movements within a specified environment. The simulation process entails creating a physical environment using space markup elements and importing a building layout from Revit (Alac et al., 2023). Within this environment, pedestrians interact with objects, avoid collisions, and independently determine their movements (Siyam et al., 2019).

Table 2.2: Assessment of ABM Software.

Characteristics	AnyLogic	Netlogo	Pathfinder
BIM Revit model interoperability	Yes	No	Yes
Does not require high-level Java skills	Yes	No	Yes
Does not require the establishment of model meshes	Yes	Yes	No
Allows for agent behaviour personalization	Yes	Yes	Yes
3D visualisation	Yes	No	Yes
Contains an observable pedestrian density map	Yes	No	No

Pedestrian movements are defined through a flowchart system that employs block elements to describe pedestrian behaviours, preferences, and states. Simulation outputs provide insights into pedestrian flow and movement time statistics (Ni et al., 2021). By default, pedestrians follow the shortest route towards exits. Enhancing simulation design involves adjusting the predefined movement logic and considering critical factors that impact evacuation performance, leading to more accurate and applicable evacuation planning. Consequently, AnyLogic emerges as a user-friendly and feature-rich solution for conducting agent-based evacuation simulations. It effectively bridges the gap between complex information systems development practices (Ren et al., 2021) and the realm of simulation modelling. AnyLogic's flexibility extends to incorporating arbitrary Java code within models, offering the potential to enhance parallelism and customization within the simulations. This makes it a powerful tool for researchers and practitioners in the field.

2.9. Concluding Remarks

This comprehensive literature review extensively explores critical aspects of enhancing emergency evacuation plans, particularly within the context of public buildings. It examines how the research community has addressed this issue and emphasizes the need to investigate paramount factors influencing evacuation decisions, such as uncertainty and operational complication.

The existing research literature highlights the significance of egress location decisions in enhancing evacuation efficiency and the vital role of egress protections in ensuring safe evacuations. Furthermore, the chapter assesses various methodologies, theories, and approaches for addressing the challenges of building evacuation, including complexity, conflicting objectives, and uncertainty. It reveals that:

- Developing an effective emergency evacuation plan faces challenges from complexity, uncertainty, and multiple conflicting or non-conflicting objectives, criteria, and constraints.
- A notable gap exists between the decision support demands of emergency evacuation and the currently available decision support tools.
- Complex systems' dynamics can be effectively modelled through simulation and optimisation-related approaches like mathematical programming. This allows for insightful analysis of problem configurations and potential management decisions through "what-if" scenarios.
- BP formulations are introduced to highlight the DA situation, adding depth to this research.
- A focus is placed on MCDM techniques, recognizing the complexity of decision-making in emergency evacuation planning, including F-AHP as a valuable tool for addressing uncertainties.
- The methodologies explored encompass mathematical programming modelling, BIM, and ABM.
- Existing research predominantly focuses on minimizing total evacuation time while neglecting other critical objectives, such as cost, supply consumption, and area coverage.

Consequently, the literature lays the foundation for this thesis, which aims to bridge identified gaps by integrating these methodologies to create effective and comprehensive evacuation strategies. It underscores the importance of enhancing emergency evacuation plans within public buildings. The subsequent chapter introduces the related research methodology and outlines the approaches for formulating egress location and protection.

Chapter 3

Research Methodology

3.1. Overview

The methodology in this thesis focuses on enhancing evacuation planning and efficiency within public buildings, particularly in facilities like schools, with a primary prominence on prioritising safety against natural and man-made disasters to human lives, assets, and the environment. It significantly emphasises optimising egress strategies and protective measures, particularly in security-related incidents. The chapter evaluates various quantitative methodological approaches, assessing their suitability in addressing egress location and protection challenges. In addition, the chapter outlines the procedures used to solve the proposed approaches, integrating computational methods and techniques to analyse and optimise evacuation strategies. It establishes the groundwork for developing context-specific evacuation plans, ultimately elevating public safety and preparedness during emergencies.

The methodology of frameworks introduces three distinct approaches. Framework-I combines MOO with BIM and ABM simulation, optimising evacuation planning by considering multiple objectives and simulating the evacuation process. Framework-II utilises one MCDM tool, F-AHP, to select suitable evacuation strategies based on multiple criteria and alternatives, enhancing decision-making efficiency. Framework-III adopts a stochastic BP approach, optimising strategic and tactical decisions to formulate more robust and adaptive evacuation strategies. The solution method development stage further refines and enhances the proposed methodologies, devising computational algorithms to solve complex optimisation and decision-making problems associated with evacuation planning. In addition, the methodology includes three case studies to improve evacuation planning and safety in public buildings. The first two cases focus on identifying optimal egress locations for efficient evacuations. These locations are then fortified in the third study to ensure security during emergencies. The approach is validated through a pilot test in a controlled environment and a comprehensive numerical case study simulating school building evacuations, representing an average Australian school. Chapters 4-6 assess the effectiveness of each case in terms of location selection and protection strategies within a school building context. A visual representation of the methodology applied in this thesis is depicted in Figure 3.1.

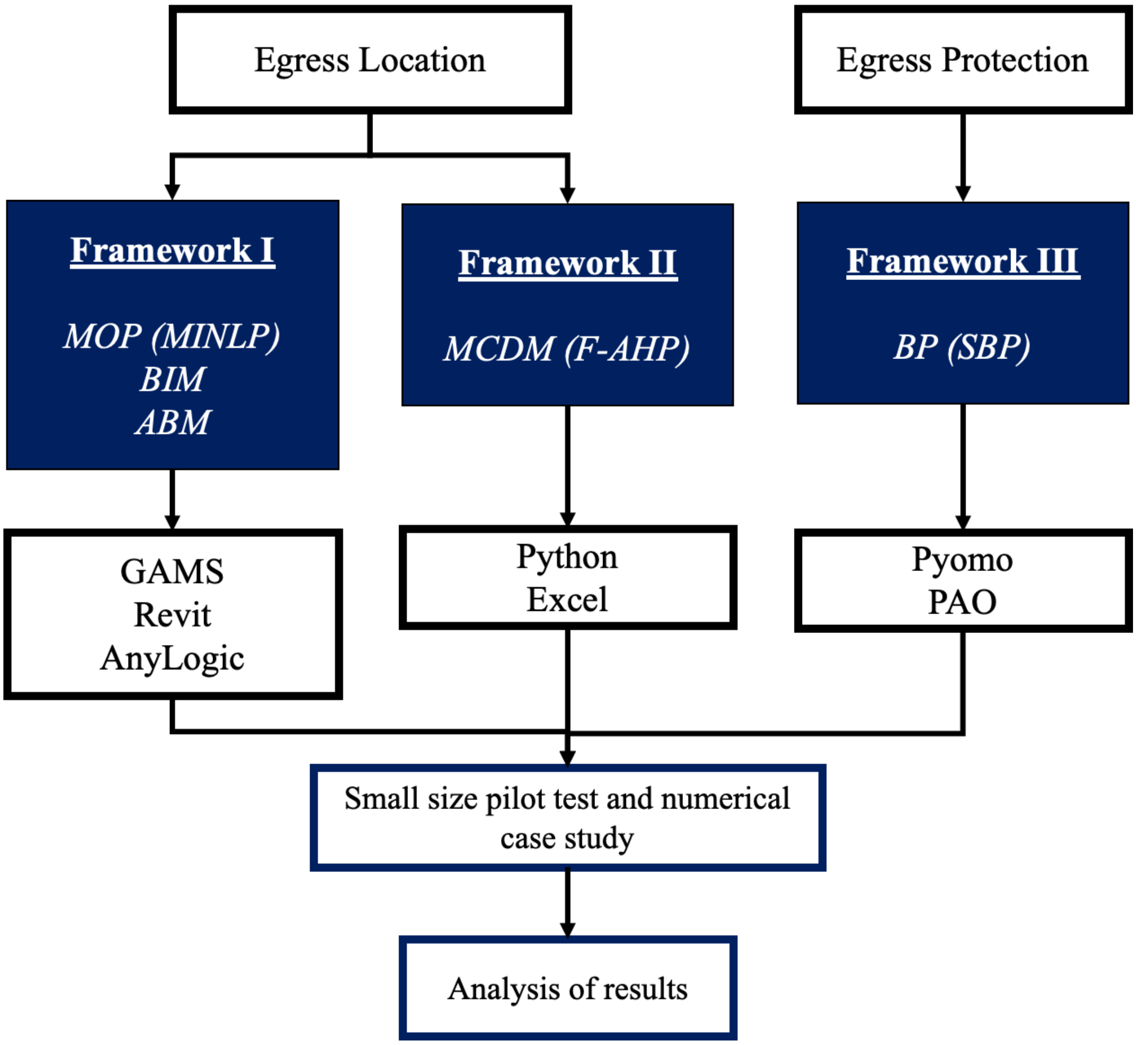


Figure 3.1: Research methodology of the study.

3.2. Developing the Frameworks

As discussed in Chapter 2, the optimisation approach is a prominent method within the field of operational research. It focuses on selecting the most favourable element, decision, or option from many alternatives. This research employs diverse optimisation techniques to enhance public building evacuation planning and safety management. The first framework utilises

MOO to identify optimal locations for three egresses out of six options, achieving efficient and effective evacuation strategies, as in Chapter 4. The F-AHP method is applied as an MCDM approach in the second framework to prioritise egress locations based on technical, economic, and social factors, as in Chapter 5. Lastly, the third framework employs BP to protect identified egresses, fortifying them against potential threats, as in Chapter 6. These methodological approaches enable comprehensive and context-specific evacuation planning, enhancing public safety in emergencies.

3.2.1. Framework-I: MOO Programming with BIM-ABM Simulation

The proposed framework is a valuable resource for decision-makers in building evacuation planning. Comprising three main components, namely the mathematical optimisation model, BIM, and ABM, this framework is specifically designed to enhance the efficiency of evacuation planning by assessing egress location and its performance. The mathematical model is dedicated to identifying the optimal egress location by incorporating advanced metrics, including evacuation time prediction, route assessment, bottleneck identification, coverage analysis, and cost considerations, all while ensuring its adaptability to various building systems and structural components. To this end, a MIP model is formulated to find optimal locations for a set of egresses that meet design requirements. BIM incorporates building geometry, properties, and quantities of building elements, while ABM simulates agents' behaviours during evacuations, accurately capturing their movements and decision-making processes. Figure 3.2 provides a schematic diagram of the proposed framework and its components. In addition, the optimisation model adopts a multi-objective approach to explore the egress location problem, drawing upon three distinct problems: the set covering problem (Sundstrom et al., 1996), the maximum coverage problem (Church & ReVelle, 1974), and the network design problem (Ng et al., 2010). The model presented here takes advantage of the efficiency of multi-objective problems to make decisions in finding optimum solutions for problems with more than one objective function. It addresses the evacuation process and omits social attributes to streamline complexity and computation time. Furthermore, it conducted a comprehensive evaluation through a numerical case study, analysing various evacuation scenarios within a mid-size school building. The building layout included standard room sizes, the number of students, and hallway dimensions, with multiple rooms on a single floor connected by a corridor. Further details on the proposed framework can be found in Chapter 4.

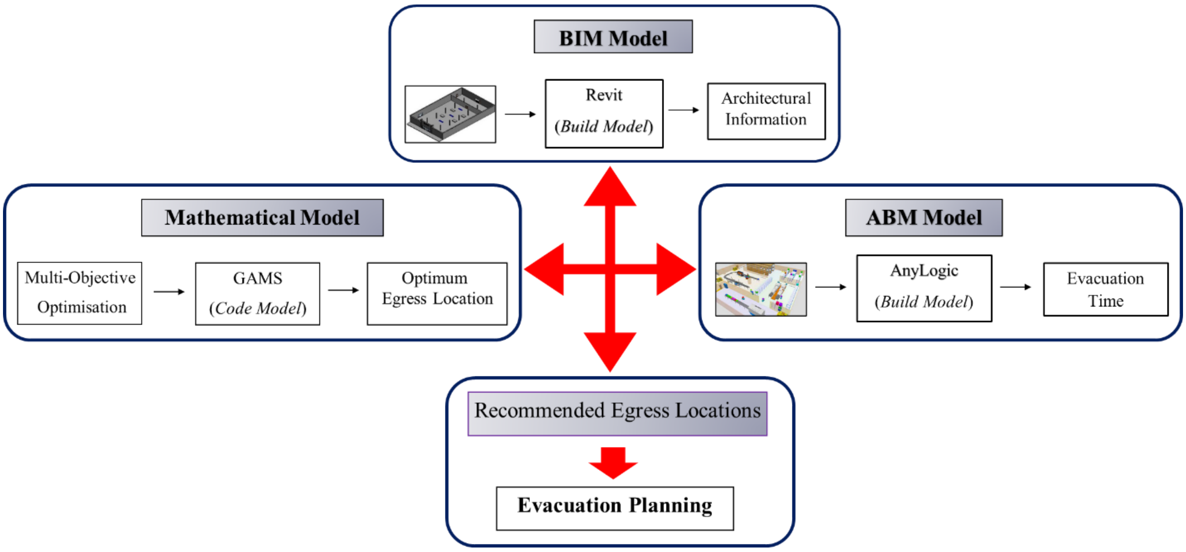


Figure 3.2: Proposed framework indicating model development stages for evacuation planning.

3.2.2. Framework II: MCDM Approach with F-AHP

This framework includes three stages: input, process, and output. Data analysis considers various criteria and alternatives during the input stage, focusing on technical, economic, and social aspects as reference points for decision-making. Building upon the previous chapter, the alternatives represent strategic choices for locations with implemented egresses; six such locations are considered. The significance of this limited set of alternatives lies in the details and optimisation achieved through computational analysis, ensuring the selection of the most effective egress locations. Moving to the process stage, the framework employs the F-AHP methodology, a systematic approach to comparing and managing criteria and alternatives. In the output stage, the framework generates egress location suitability results based on the dominant value obtained from the F-AHP calculations. Indeed, individuals often navigate situations with undefined boundaries in decision-making by relying on their experience and expertise. To address the complexities arising from uncertain or unavailable information, F-AHP emerges as a valuable technique and has demonstrated its efficacy across various decision-making contexts and levels. It offers a viable approach in contexts characterized by uncertainty and imprecision. It effectively addresses problems involving subjectivity, fuzziness, and imprecise information in performance evaluation techniques. Following a similar approach to Framework-I, Framework-II includes a numerical case study involving various evacuation scenarios within a standard school building. Figure 3.3 provides a schematic diagram of the proposed framework and its components. Further details on the proposed framework can be found in Chapter 5.

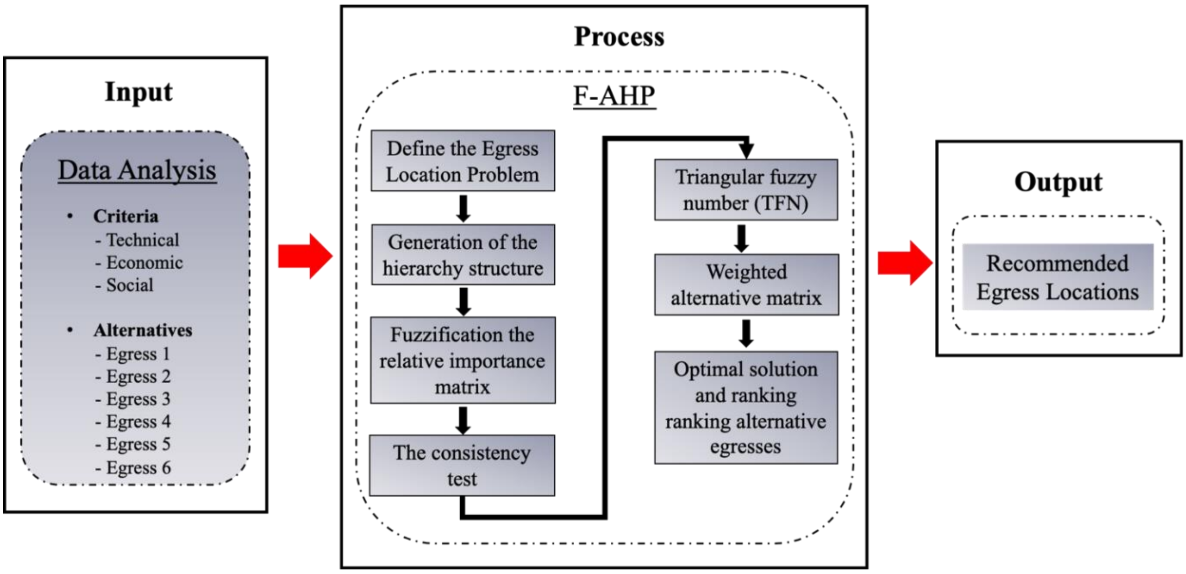


Figure 3.3: An overview of the framework for egress location selection.

3.2.3. Framework III: Stochastic BP

In this framework, a comprehensive approach is undertaken, encompassing four stages to address the security planning problem in buildings. The first stage involves formulating the critical problem statement, where the practical problem revolves around security planning in buildings and the theoretical problem is characterized as a BP. Moving to the second stage, the modelling process is initiated with upper-level programming aiming to minimise the objective, while lower-level programming focuses on maximising the objective. The third stage introduces the solution methodology, featuring a DA model designed as a stochastic BP. The progression of a DA game is shaped by the sequence of moves, which can be classified as either sequential or simultaneous, contingent upon the timing and order of actions taken by the involved parties. One prevalent challenge in DA scenarios involves the defender seeking to minimise the attacker's objective function by disrupting or eliminating specific aspects of the attacker's plan. Finally, the fourth stage revolves around a case study centred on a single-level school building. This case study includes considerations of the building layout and the implementation of egress fortification strategies, which are critical for enhancing security measures during emergencies. Using secure links offers a strategic approach to determining which egresses require fortification, ensuring that efforts are focused on the most critical pathways for potential attackers. Through these four stages, the research aims to contribute to more robust and effective security planning in buildings, ultimately ensuring the safety and protection of occupants. The structure of the framework is depicted in Figure 3.4.

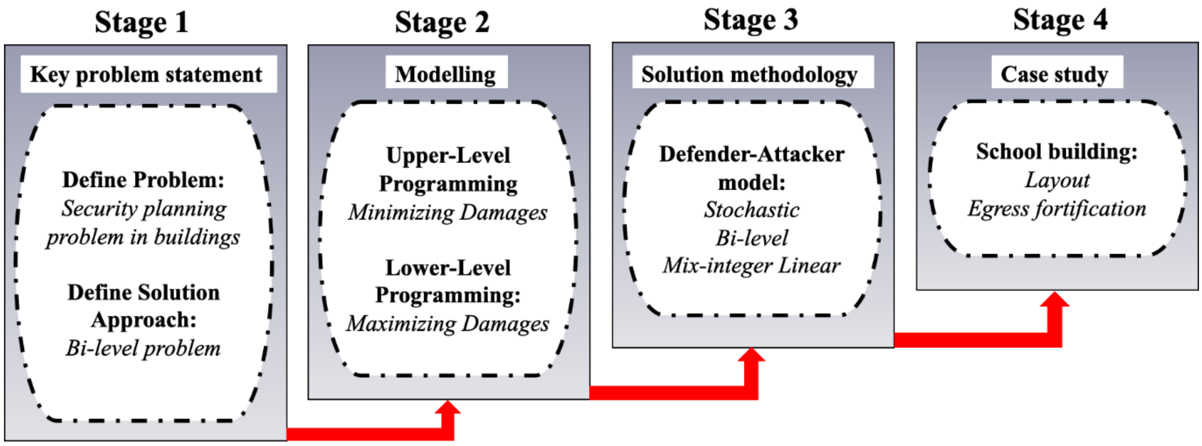


Figure 3.4: The stages of the egress fortification process.

3.3. Solution Approach

As previously discussed, this thesis employs a combination of modelling techniques to address the complexities of evacuation planning in public buildings comprehensively. The critical methodologies utilised include MOO, BP, and MCDM. In addition to these modelling techniques, BIM and ABM methodologies are integrated into the approach. This integration enhances the simulation and analysis process's granularity, focusing on optimising egress strategies within public buildings. Indeed, the primary goal of this thesis is to address the specific challenges posed by evacuation planning in various building scenarios. Bridging existing gaps and leveraging these techniques contribute to optimising public safety and enhancing emergency preparedness in public buildings.

3.3.1. Mathematical Modelling

As referred to in Chapter 1, this thesis develops two distinct mathematical models to address the research problem. Chapter 4 employs MOO to optimise egress locations, while Chapter 6 focuses on BP to enhance decision-making in protecting the egresses. The following sub-section will provide a detailed explanation of the models and solution approaches.

In Chapter 4, the main focus is on MOO programming, which involves solving multiple conflicting objectives. In such cases, enhancing one objective may reduce the value of other objectives, creating a trade-off between different solutions. The chapter explores various methodologies and techniques to address these complex multi-objective scenarios, aiming to find Pareto-optimal solutions that effectively balance the trade-offs and support decision-making processes. Since the emergency evacuation considered in this analysis involves a range of objective functions and stringent constraints, it is essential to find solutions that help decision-makers strike a balance between minimising cost, maximising egress coverage, and minimising time, ultimately leading to a more effective and efficient evacuation plan.

Moreover, the inclusion of the set covering, maximum coverage, and network design problems in the investigation of the egress location problem are highly relevant due to their inherent connections with the challenges posed by evacuation planning in public buildings. The set covering problem, well-known for its NP-completeness, aligns with the cost minimisation objective. Similarly, the maximum coverage problem is in harmony to ensure the maximum coverage of building occupants, much like maximising people covered during an evacuation. Lastly, the network design problem is crucial in crafting optimal evacuation routes by selecting nodes and links within the building's layout. This directly contributes to minimising evacuation time and enhancing public safety. By employing these well-established problem types, the thesis strives to tackle the intricacies of egress locations' effectiveness and evacuation planning for emergencies within public buildings. Figure 3.5 illustrates the generation of the MOO model presented in Chapter 4.

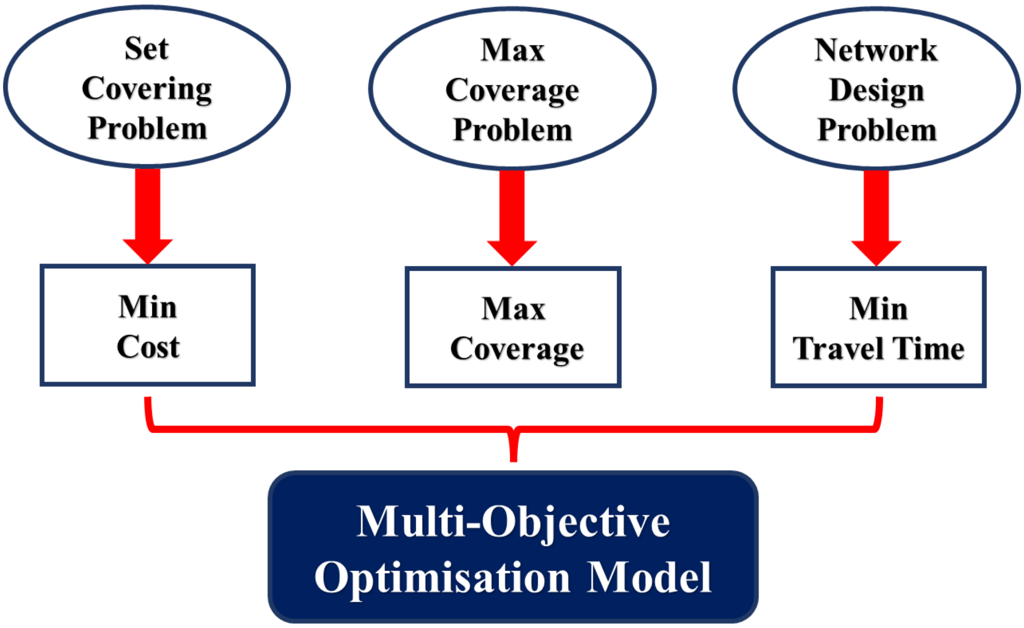


Figure 3.5: Flowchart of multi-objective model.

Multi-objective problems can be categorised into LP, NLP, IP, and MIP forms, each with distinct characteristics - continuous, discrete, or a combination of both. The nature of multi-objective mixed-integer programming (MOMIP) results in a diverse range of problem types. Chapter 4 primarily emphasises multi-objective mixed-integer non-linear programming problems, explicitly focusing on generating significantly supported non-dominated solutions for general MIP cases.

Several solution approaches have been developed for solving MOO programming. These include Pareto front optimisation methods (Zitzler & Thiele, 1998), such as the lexicographic min-max method (Bazaraa & Goode, 1982) and the ε-constraint method (Chankong & Haimes, 1983). However, in the domain of MOO, finding solutions for multi-objective integer problems is often challenging. Typically, achieving an absolute optimal solution that optimises all objective functions concurrently is not feasible (Ehrgott, 2006). To address this issue, much attention has been given to Pareto-optimal solutions, also known as posterior or non-dominated solution generation (Deb et al., 2002). Pareto-optimal solutions aim to optimise the primary objective while compromising at least one of the other objectives. Among adequate solutions, the lexicographic method stands out as an extensively used approach for ordering the weighted average aggregation of objectives. This method is appropriate when all objective functions are equally crucial for decision-makers. However, a drawback of this method is that some results may not be Pareto-optimal, as the solution is typically not unique (Chinchuluun & Pardalos, 2007). Likewise, the ε-constraint is another prevalent and versatile general-purpose approach for solving multi-objective integer problems (Eichfelder, 2009). Decision-makers find this method valuable as it allows them to adjust the lower or upper bounds to achieve different Pareto optima (Blank & Deb, 2020). Figure 3.6 illustrates the ε-constraint method in generating the Pareto frontier.

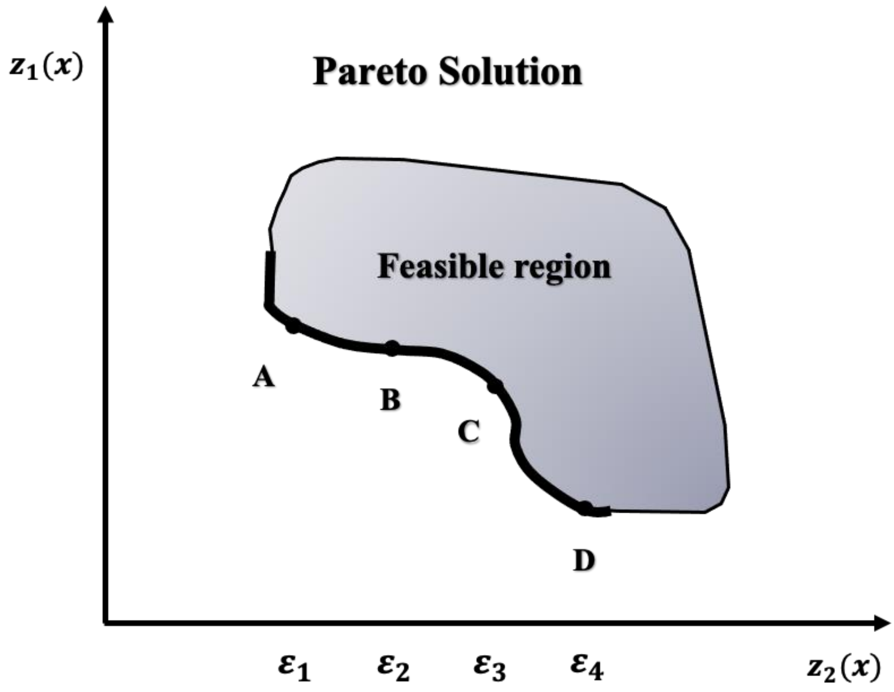


Figure 3.6: The Pareto frontier of a simplified example calculated by the ε-constraint method.

After determining the optimal locations for three out of the six egress points in Chapters 4 and 5, Chapter 6 investigates the stochastic BP model in the context of evacuation planning and egress locations. The fundamental motivation behind developing a stochastic BP decision-making approach is effectively handling parameter uncertainty within a scenario-based framework, ensuring robust adaptation to various uncertainties and scenarios. These optimisation challenges involve constraints that necessitate certain variables to be optimal solutions to another optimisation problem. Unlike traditional optimisation problems with analytically defined goal functions and predefined constraints, BP formalisation introduces a more flexible definition of the feasible area. This expanded flexibility allows for a comprehensive exploration of evacuation planning scenarios, accommodating intricate layers of constraints and complexities. The BP involves two optimisation levels, as depicted in Figure 3.7, which illustrates a general BP-solving structure involving interlinked optimisation and decision-making tasks at both levels.

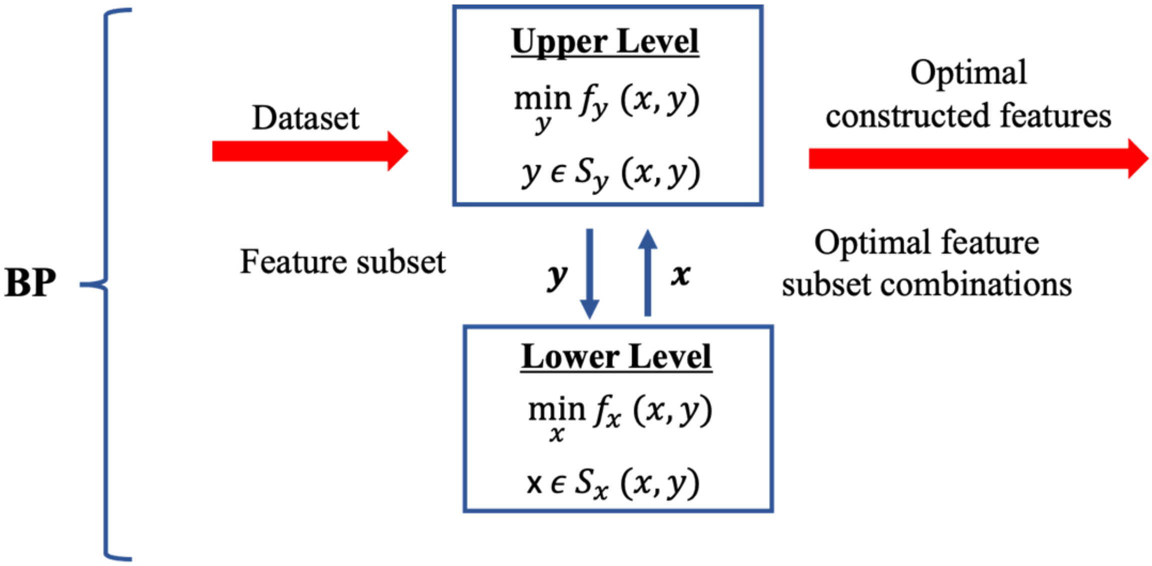


Figure 3.7: A bi-level hierarchical optimisation problem.

Furthermore, the proposed approach enhances the model's practicality in emergency evacuation scenarios, where the defender represents the upper-level, and the attacker forms the lower-level, as seen in Figure 3.8. Considering the inherent uncertainty in real-world systems, the developed model strives to minimise damages such as cost, loss of human lives, and financial risk at the upper-level while maximising damages at the lower-level. Specifically, the upper level focuses on minimising objectives related to safety and cost, aiming to protect building occupants and assets during evacuations. On the other hand, the lower level is concerned with maximising objectives related to potential threats and damages, enabling the identification of vulnerable points and potential weaknesses in the evacuation plan. The strategic fortification of egresses is guided by the concept of secure links, enabling the defender to prioritise protection efforts based on the potential impact of compromised egresses on these critical pathways. This approach allows for a more robust and adaptive evacuation strategy that accounts for uncertainties and potential threats, ensuring the development of efficient and effective emergency evacuation plans.

Adopting a purely deterministic approach in specific optimisation scenarios may not be practical, especially when specific model elements are susceptible to uncertainty (Powell, 2019). Recognising this, a stochastic bilevel model introduces uncertainty by incorporating probabilistic elements or random variables (Do Prado & Qiao, 2020). This uncertainty influences the decision-making processes of both the leader and the follower, enhancing the model's realism and suitability for situations characterised by uncertain parameters or outcomes

(Christiansen et al., 2001). Consequently, stochastic BP represents a specialised subset of the broader bilevel modelling framework, specifically designed to account for stochastic elements within the decision-making process (Pan et al., 2003).

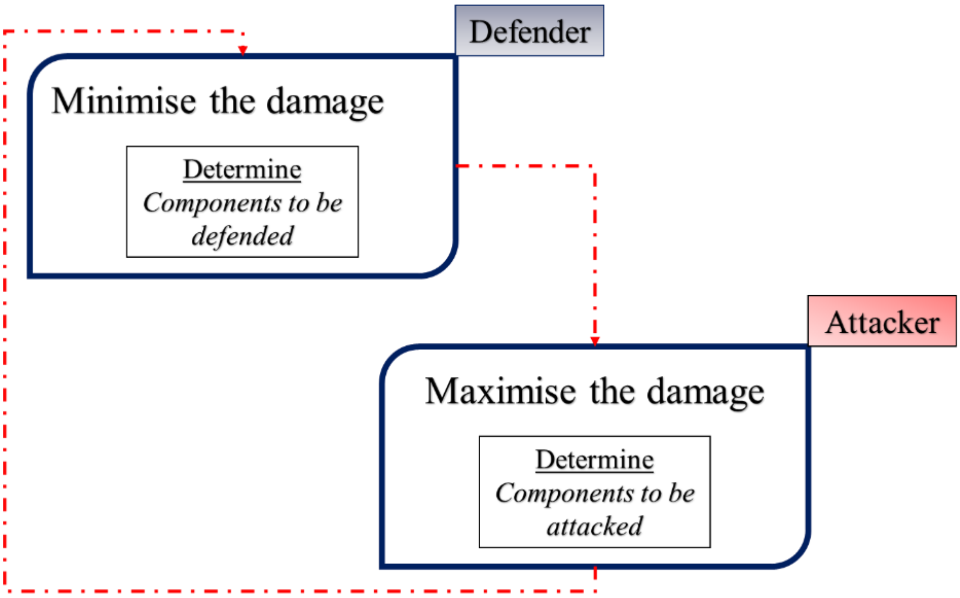


Figure 3.8: Conventional bi-level DA model.

Moreover, in Chapter 6, the proposed stochastic BP defender-attacker model is formulated as a MILP model. The application of game theory has proven instrumental in gaining operational insights and enhancing our comprehension of the dynamics inherent in DA scenarios (Wu et al., 2020). This forms a foundational issue within security and emergency management (Dibaei et al., 2020). Indeed, the intricate landscape of security and defence challenges is further complicated by adversaries' diverse intentions, motivations, strategic behaviours, adaptive traits, and fluctuating attack capabilities (De Dreu et al., 2021). However, it is essential to note that solving BP poses significant challenges due to the non-convex nature of their feasible regions in most cases. As a result, the solution techniques for BP are computationally intensive, and the problem is proven to be NP-hard (Bard, 1991). A comprehensive review of various solution approaches for BP can be found in Dempe, 2003; Colson et al., 2005; Pinar et al., 2021.

From a practical standpoint, methods for solving linear BP can be categorized into two main groups. The first category comprises dedicated solution algorithms specifically designed for solving BP, such as those proposed by Sinha et al. (2020), Calvete et al. (2014) and Labbé et al. (1998). While these methods are typically efficient and ensure global optimality, they require substantial additional coding for implementation in commercially available optimisation software like CPLEX (IBM CPLEX, 2022). On the other hand, the second category includes methods that can be implemented directly or in conjunction with general-purpose optimisation software without significant modifications, as demonstrated in the following studies: Fortuny-Amat & McCarl, 1981; Ralphs et al., 2019; Siddiqui & Gabriel, 2013; White & Anandalingam, 1993. Although these methods may be preferred for their straightforward implementation, they can sometimes impose a high computational burden or only guarantee local optimality. The method proposed in this paper falls within the second category. It has shown superior performance compared to existing methods regarding computational efficiency and global optimality.

3.3.2. BIM-ABM Simulation

BIM is a versatile and essential tool that enhances the precision and effectiveness of evacuation planning within public buildings. It provides an architectural information model for building projects (Samuel et al., 2017). In times of emergency, BIM's extensive standardised data format becomes valuable as it offers accurate building information (Wang et al., 2014). BIM's interoperability with various software and analysis tools allows for various applications, including evacuation simulations using tools like AnyLogic (Shams et al., 2021). Numerous studies have employed BIM to support emergency management, focusing on evacuation assessment and escape route planning (Boguslawski et al., 2016; Sun & Turkan, 2020; Ma et al., 2017). While these studies have substantially contributed to the field, this thesis extends these advancements by incorporating BIM with mathematical optimisation and ABM techniques.

Furthermore, ABM proves promising as a tool for supporting emergency planning and realistically executing evacuation plans, especially when the practical realization of an emergency evacuation for a building faces limitations (Johnson & Sieber, 2009). Notably, ABM addresses the significant challenges posed by the connection between building configuration and human behaviour during evacuations, shedding light on the dynamics that manifest in real-world evacuation plans (Bonabeau, 2002). ABM's appeal is further bolstered by its cost-effectiveness and capability to simulate emergency scenarios, making it a frequently employed technique for modelling and assessing evacuation plans (Macal & North, 2014). The literature abounds with diverse applications of ABM across various spatial scales to simulate evacuations (Arteaga & Park, 2020; Cimellaro et al., 2019; Kim et al., 2022). These applications underscore the significance of ABM as a versatile and powerful tool for understanding and improving evacuation behaviour, potentially enhancing emergency planning and preparedness.

Overall, planners and decision-makers can assess egress performance, identify potential bottlenecks, and enhance the evacuation plan by incorporating BIM, and ABM. It incorporates detailed building information, including spatial layouts, occupant characteristics, and environmental conditions, employing mathematical optimisation modelling to optimise egress locations. This approach empowers designers and planners to create more efficient and effective evacuation plans while capturing the dynamics and complexities of evacuation scenarios. It surpasses previous models solely relying on BIM, providing valuable insights for enhancing safety and efficiency.

3.3.3. MCDM

Chapter 5 delves into MCDM for selecting the most suitable egress location, a crucial aspect of evaluating evacuation planning during emergencies. Decision-making is a fundamental process involving problem identification, preference elicitation, alternative evaluation, and selecting the best option (Sitorus et al., 2019). Making decisions for practical problems is inherently complex, and this complexity intensifies when uncertainties, time constraints, and risks are present (Ishizaka & Labib, 2014). Various methods have been developed and refined to address diverse situations and applications (Velasquez & Hester, 2013), including techniques for handling problems with both quantitative and qualitative factors (Mardani, Jusoh, & Zavadskas, 2015). In the face of uncertainty, many of these methods incorporate fuzzy set theory into their algorithms (Zadeh, 1965) due to the ambiguity of human decision-makers judgments, which can make precise decisions difficult (Tsaur et al., 2002). Figure 3.9 demonstrates a general overview of the MCDM process for egress location selection.

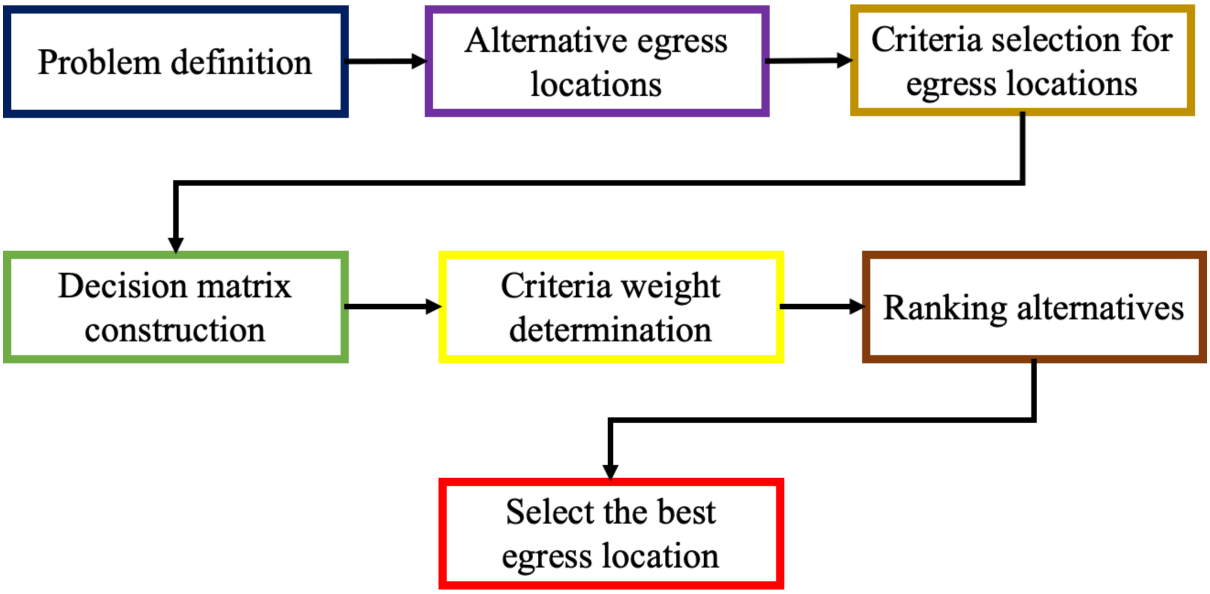


Figure 3.9: The MCDM process for best egress location.

Selecting an appropriate MCDM method for implementation is challenging, as a one-size-fits-all solution only exists to address some problems (Mardani et al., 2015). Different problems or scenarios may necessitate distinct computations, and the landscape of available MCDM methods is diverse, making identifying the optimal approach challenging (Aruldoss et al., 2013).

Among the MCDM methods, the AHP stands out as a powerful tool for handling conflicting and multiple criteria. AHP offers benefits such as its ability to easily manage multiple criteria, comprehensibility, and capacity to accommodate qualitative and quantitative data (de FSM Russo & Camanho, 2015). However, it does face criticism due to its limitations in dealing with the uncertainties and imprecision inherent in decision-making (Büyüközkan et al., 2011). Numerous researchers advocate adopting the F-AHP to address this inherent challenge to resolve MCDM issues, particularly selection problems (Mardani et al., 2015). F-AHP introduces the concept of fuzzy sets or fuzzy numbers to capture the vagueness inherent in human judgment, facilitating the expression of criteria importance in the face of uncertainty (Vilasan & Kapse, 2022).

Conventional planning methodologies often overlook the intricacies and uncertainties inherent in real-world scenarios, relying heavily on simplistic criteria. F-AHP bridges this gap by assimilating the nuances of fuzziness and uncertainties into the decision-making process, allowing for adaptable preferences that align with the intricacies of egress assessments. It harmoniously integrates considerations spanning social, economic, and technical dimensions, thereby empowering decision-makers to make choices that are attuned to the unique context of each building. The thesis encompasses a decision-making process that rigorously evaluates and prioritises diverse criteria and sub-criteria. The visualisation of the egress location selection process utilizing is illustrated in Figure 3.10. Chapter 5 implements this framework using the F-AHP approach, incorporating different linguistic scales to pinpoint the optimal egress location.

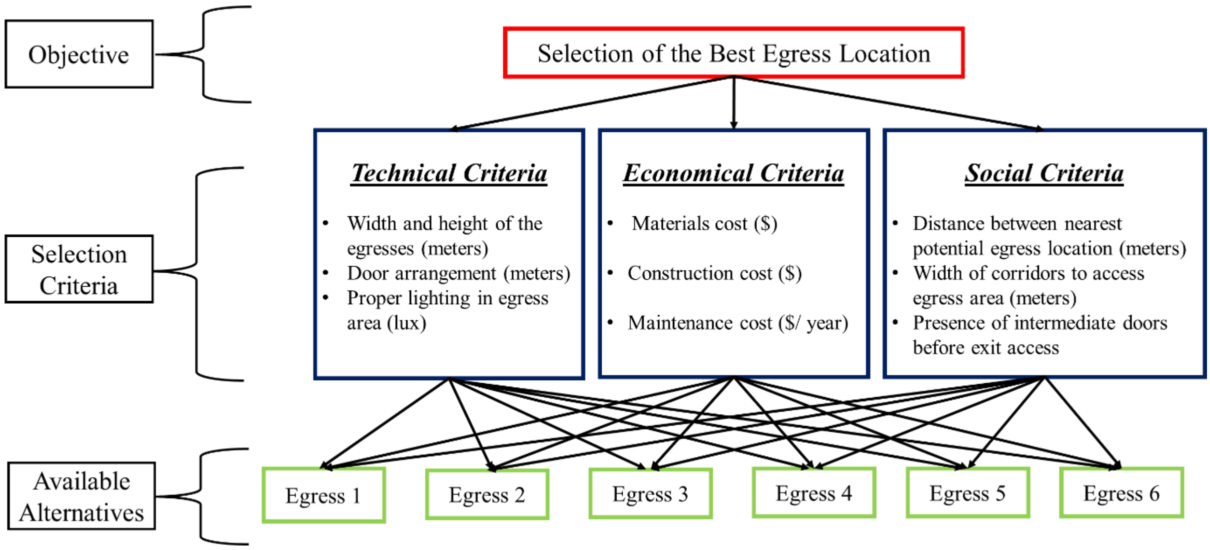


Figure 3.10: The process of selecting egress locations.

Chapter 4

Optimising Egress Location in School Buildings Using Mathematical Modelling and Agent-Based Simulation

4.1. Overview

This chapter, previously published in the Journal of Safety Science, offers comprehensive insights into evacuation planning, delving into integrating a mathematical programming framework for optimising egress locations within buildings (Alac et al, 2023). It explores practical aspects of evacuation modelling in public buildings like schools, examining the impact of technological advancements, evacuation management techniques, and operational strategies. This is achieved by applying mathematical methods and simulations to devise effective crisis responses (Gruler et al., 2019). Research has consistently highlighted the connection between delayed evacuation and casualties, indicating the importance of timely egress from buildings (Fahy & Proulx, 2001). Public facilities, susceptible to service disruptions, pose substantial social risks (Kuligowski et al., 2005). Addressing this requires reliable service systems to safeguard critical facilities against disruptions like operational failures, disasters, and criminal activities (Bernardini et al., 2014).

Within the context of facility evacuation, this chapter explores fundamental elements of building evacuation management, including emergency planning and its practical implementation (Vilar et al., 2018; Raikes et al., 2019; Lee, 2009). Notably, the Federal Emergency Management Agency (FEMA) emphasises building design's role in minimising damage and facilitating safe evacuations (FEMA Agency, 2002). Hence, preparing efficient evacuation plans becomes crucial to directing occupants away from hazards during emergencies in public structures (Lamont, 2017). Key to these plans is the prediction of evacuation time, a fundamental objective highlighted by EMA (Lamont, 2017). In addition, tailoring evacuation plans to align with evacuee objectives is essential for successful outcomes (Renne, 2018). These objectives encompass factors like subjective priorities, timing, communication, and spatial coverage, influencing evacuees' decision-making and behaviours during crises (Oxendine et al., 2012; Orui et al., 2017).

This chapter also addresses using advanced methodologies and tools for managing and planning evacuations in public buildings. The intersection of non-linear interactions and analytical tools within an architectural design is pivotal in addressing evacuation complexities (Usman et al., 2018; Cassol et al., 2017). Architectural design, which considers aesthetic qualities and spatial usability, intersects with the practicality of evacuation planning (Michalek et al., 2002). Mathematical models play a central role in this process, aiding in synthesising technical, practical, and aesthetic objectives (Rabbani et al., 2018). In addition to assessing evacuation time and casualties, mathematical programming is a practical tool for emergency planners and decision-makers (Haghpanah & Foroughi, 2018). Mathematical models and simulations offer insights into evacuation time and crowd management, aiding in formulating effective evacuation strategies (Wong, 2017; Lindell et al., 2018). Research also delves into solutions for intricate buildings with multiple rooms and floors to minimise fatalities and damages during evacuations (Khamis et al., 2019).

The primary contribution of this chapter is integrating a mathematical programming framework based on MOO and a computational simulation approach, to optimise egress locations within buildings for enhanced evacuation. The developed formulation is a mixed-integer programming model to determine optimal egress locations meeting specific design criteria. This model leverages multi-objective techniques to navigate scenarios with multiple objectives. A simulation method supplements this approach, evaluating the proposed egress locations and projecting evacuation outcomes within a building. Visualisation employs BIM, while evacuation simulations are conducted using ABM. A case study centred around a school illustrates the application of this framework, offering insights into optimising egress locations, particularly in educational institutions with emergency safety concerns.

4.2. Problem Definition

The framework is designed and implemented to help decision-makers in planning evacuation for buildings. It consists of three main components: the mathematical optimisation model, the BIM model, and the ABM model, as seen in Figure 4.1. Hither, the mathematical model seeks to find the optimum egress location. Since there are many types of buildings, the presented formulations are dimensionless in the model to be applicable in any building system to study the structural components. In addition, BIM encompasses building geometry, properties, and quantities of building elements. ABM incorporates agents' behaviour in evacuation situations, offering a natural description of agents' movements, decision-making processes, and interactions demonstrated in previous studies (Berger & Mahdavi, 2020; Cimellaro & Ozzello, et al., 2017) to satisfactorily represent human behaviour during evacuations. It is important to note that since this study examines an evacuation problem, the model is only associated with the evacuation process, with no inclusion of social attributes (e.g., cultures) and social factors (e.g., gender). While social attributes can play an essential role in evacuation planning, their inclusion would significantly increase the complexity of the model and the computational time required for simulation, which was beyond this study's resources and time constraints. Therefore, the proposed framework reduces the complexity of the model. Figure 4.1 describes a schematic diagram of the proposed framework and its components. The following sections describe in more detail the proposed framework.

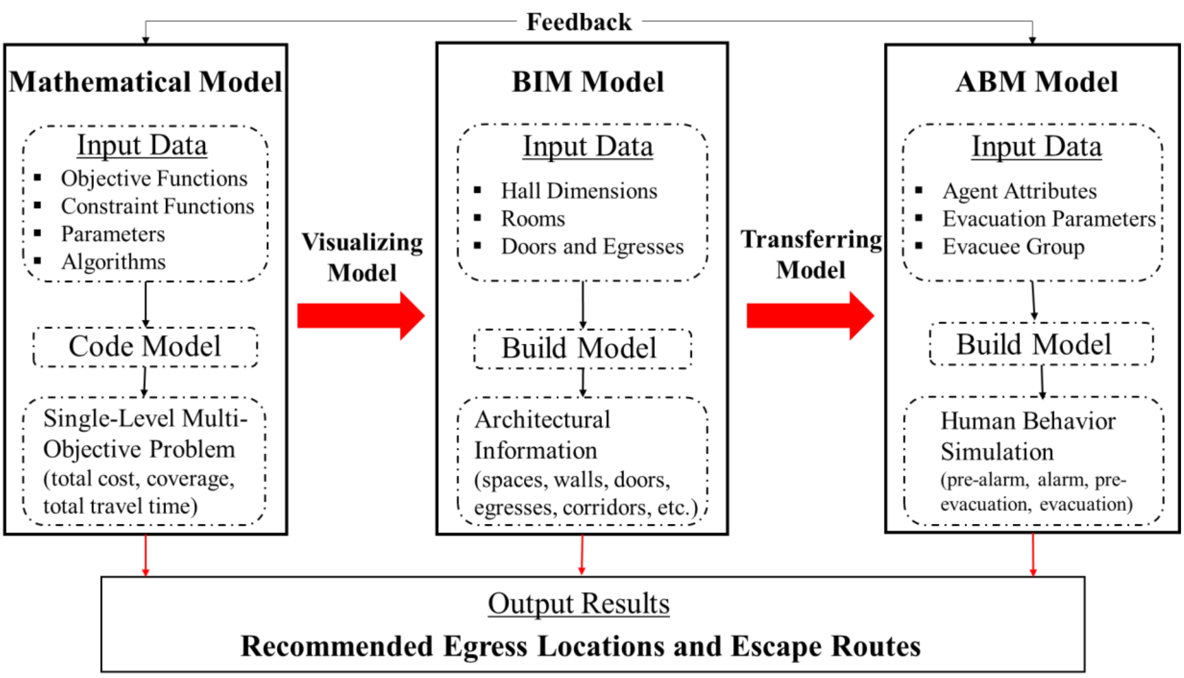


Figure 4.1: Proposed framework indicating model development stages for the evacuation planning.

4.2.1. Mathematical Model Formulation

The optimisation model is formulated in order to enhance the efficiency of building evacuation by optimising the egress location. To this end, the model comprises three objective functions: minimising cost, maximising coverage, and minimising times. Figure 4.2 represents an overview of the mathematical model development stage. The process starts with obtaining the collective constraints and objective functions, and the parameters of the problem are estimated in order to provide appropriate data for the optimisation process to be carried out. In this way, the problem is classified as a multi-objective optimisation. Once the model is formulated, an approach that integrates BIM and ABM is adopted. The notations and the objective functions, together with their constraints, are described in the following sections.

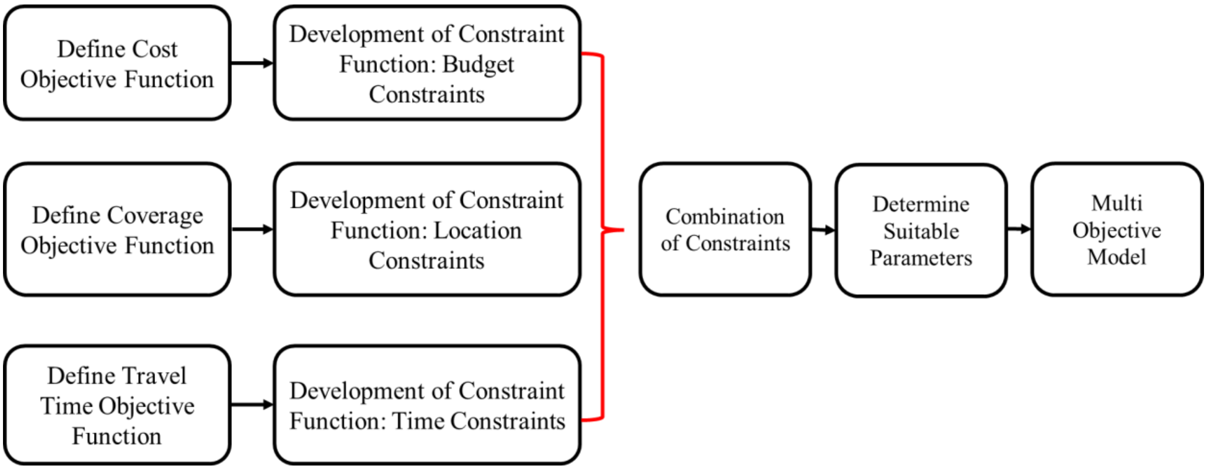


Figure 4.2: Flowchart of mathematical model development stages.

4.2.1.1.Model Overview with Network Representation

The following scenario demonstrates the proposed framework's applicability—a simplistic school layout version, as shown in Figure 4.3 (a). The proposed framework identifies potential egresses located at multiple nodes, denoted as $j \in J$, where evacuees start to leave from the interior room door, denoted as $i \in I$, defined in Table 4.1. The bidirectional real links connect egresses with room doors, while the virtual links connect the dummy nodes with the respective nodes of the network. Hence, the network consists of the following node types: the first type of node represents the room doors in the building; the second type of node represents the potential areas for locating the egresses; the last type of node represents a dummy node. A dummy node labelled E links all flows associated with the egresses to be positioned. Since the location of the egresses is an unknown decision variable in the proposed evacuation problem, the flow of evacuees to the egress through a specific destination node cannot be referenced, as this is obscure at the beginning. Subsequently, the dummy node symbolised as E, is a sink node in the model for all evacuees using any of the egresses that are to be located, seen in Figure 4.3(b). Figure 4.3(b) also displays the network evaluated in this study with the total number of eligible egresses and links in the case considered. A description of the notation of different sets, parameters and variables used in this paper is presented in Table 4.1. The notation description associated with the proposed model is presented in Figure 4.3(b).

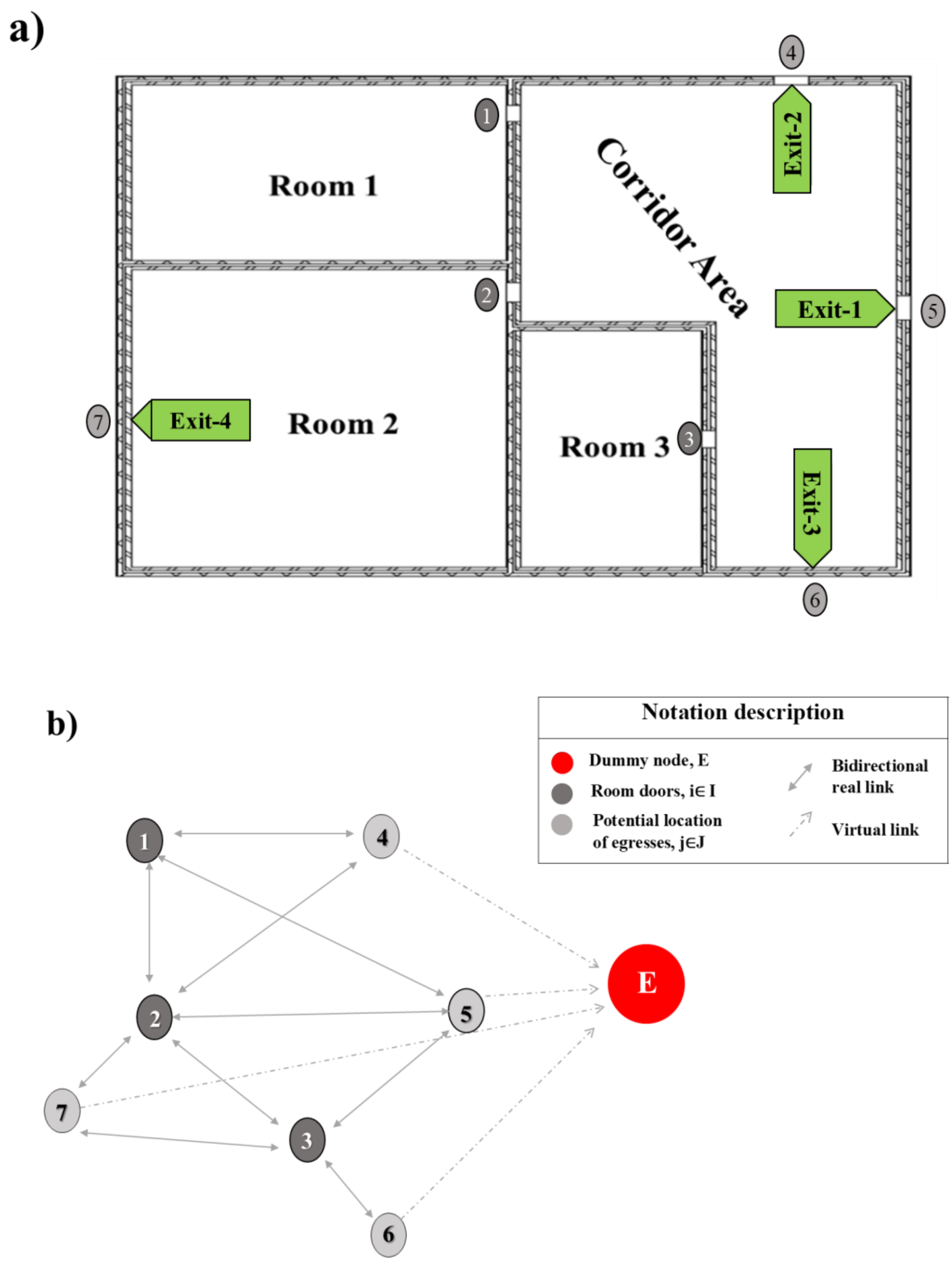


Figure 4.3: (a) The simplified 2D school layout with four eligible egresses and three classrooms. (b) Network representation highlighting nodes.

Table 4.1: Nomenclature-I for mathematical modelling.

Nomenclature-I	
Set & Parameters	*Descriptions*
I	Set of room nodes, $i \epsilon I$.
J	Set of all eligible egress sites, $j \epsilon J$.
B	Set of classroom areas where evacuees are assumed to be, $b \epsilon$ B.
W	Set of non-classroom areas containing evacuees, $w \epsilon$ W.
P	Set of egress to be sited, $p \epsilon$ P.
E	Dummy node.
H	Time threshold for the students to reach the egresses.
M	Large positive constant.
(r, s)	Origin–destination (OD) pairs, where $r \epsilon$ O and $s \epsilon$ D are the origins and destination nodes, respectively.
G, n	Parameters to be estimated.
$q_{i,s}$	Demand between (OD) pair $(r, s) \epsilon \Psi$, which assumed to be non-negative constant.
b_i	Number of evacuees at node i.
c_j	Coefficient of the cost parameter.
cap_{ij}	Capacity corresponding to link $(i, j) \epsilon$ L.
T_{ij}^0	Free flow travel time on the link $(i, j) \epsilon$ L.
Variables	*Descriptions*
x_{ij}	Flow on the link $(i, j) \epsilon$ L, destination dummy node E.
t_{ij}	Time of travel between classroom i and potential egress site i.
$\mathrm{t}_{ij}(\mathrm{x}_{ij})$	Travel cost on the link $(i, j) \epsilon$ L defined as a positive and continuous function of link flow x_{ij}, often representing. average travel time on the link $(i, j) \epsilon$ L.

k_{ij}	Auxiliary binary variable ensures non-equalities to satisfy the complementary condition.
f_m	A binary variable that equals 1 when egress is located at the j^{th} node and 0 otherwise.
y_i	A binary variable which equals 1 if node i is covered by one or more egress stationed within distance 'U, and 0 otherwise.
$\boldsymbol{a_{ij}}$	A binary variable equal **1** if demand node **i** can be covered by an egress located at $\boldsymbol{j}$ and **0** otherwise.

4.2.1.2.Objective Functions

In this study, three objective functions are formulated. The first objective function, Eq. (4.1), minimises the cost of egress spent in constructing the building. It is formulated as follows:

$$\min z\_cost = \sum_{j \epsilon J} c_j \, f_j \qquad (4.1)$$

Within Eq. (4.1), the cost of each egress depends on the space in which the egress is to be installed. All egresses are assumed to be of the same type, so the construction cost parameter c_j is independent of the egress type. The binary variable f_j is used to imply the location of egress j.

The second objective function, Eq. (4.2), maximises the coverage of the egresses in the building by looking at the number of people and accessibility required to escape during an emergency evacuation, and is given as:

$$\max z\_cover = \sum_{i \epsilon I} b_i \, y_i \qquad (4.2)$$

Equation (4.3) minimises the travel time of the whole network (Fontaine & Minner, 2014; Hammad et al., 2017; Farvaresh & Sepehri, 2011). It represents the total travel time spent by evacuees throughout the evacuation procedure by multiplying the total flow variable on the links of the network x_{ij} and a link travel time function $t_{ij}(x_{ij})$. The location of the egresses influences the travel time on the links and the demand on the links. It is formulated as follows:

$$\min z\_time = \sum_{i \epsilon I} x_{ij} \, t_{ij}(x_{ij}) \qquad (4.3)$$

In this problem, the link cost function adopted within Eq. (4.3) is that developed by the Bureau of Public Roads (BPR) (Manual, 2000). Researchers, planners, and engineers have frequently utilised the BPR function to predict travel times on road networks (Lessan & Kim, 2022; Tamakloe et al., 2021; Hammad et al., 2017). This function can also be used for pedestrian assignment and simulation models by calibrating evacuees' travel time function (Lee et al., 2001). It is formulated as follow:

$$t_{ij}\left(x_{ij}\right) = T_{ij}^{0} + G\,(\frac{x_{ij}}{cap_{ij}})^{n} \qquad \forall\ (i,j) \epsilon\ \mathrm{L} \tag{4.4}$$

Given the nature of the modelled objective functions, there is likely conflict between the optimal solutions for each function. For instance, the solution for minimising construction costs is, for example, the one that has the least coverage of the exits for evacuees. Hence, a multi-objective optimisation solution approach is required to handle the three functions formulated.

4.2.1.3.Constraints

There are several constraints formulated in order to define the feasible area of the optimisation problem. Eq. (4.5) ensures that a classroom area i is covered if at least one egress j is in the building. It is formulated as:

$$\sum_{i \epsilon I} a_{ij} y_i - f_j \geq 0 \qquad \forall\ j\ \epsilon\ J \tag{4.5}$$

The constraint in Eq. (4.6) limits the number of egresses in the solution to p. This problem defines the maximum population served and the p egresses that accomplish that maximum coverage. It is formulated as:

$$\sum_{j \epsilon J} f_j = p \qquad \forall\ p \epsilon\ P \tag{4.6}$$

The constraint in Eq. (4.7) ensures that each classroom i must be covered by at least one egress. If this constraint is not satisfied, the solution is considered unfeasible. It is formulated as:

$$\sum_{j \epsilon J} a_{ij} f_j \geq 1 \qquad \forall\ i\ \epsilon\ I \tag{4.7}$$

The constraint in Eq. (4.8) ensures that the flow from the potential egress location to the sink node, $x_{j,E}$,occurs if only egress is placed at that node. Note that in the single-commodity flow problem model, the dummy node E is the destination for all evacuees.

$$x_{i,E} \leq f_i \sum_{r \epsilon O} q_{r,E} \qquad \forall\, i \,\epsilon\, I \tag{4.8}$$

The constraint in Eq. (4.9) is defined to ensure flow conservation in the network and ensures that the demand of evacuation flow will be satisfied and the balance of evacuees is held in each node. The parameter $q_{r,E}$ originates at node i, heading towards the sink node E in this equation.

$$\sum_{(i,j)\epsilon L} x_{ij} - \sum_{(i,j)\epsilon L} x_{ji} = q_{i,E} \tag{4.9}$$

The constraint in Eq. (4.10) ensures students being evacuated on the link connecting the potential egress location to the dummy node E is equal to the sum of all destination flow to evacuate.

$$\sum_{i \epsilon I} x_{i,E} = \sum_{r \epsilon O} q_{r,E} \tag{4.10}$$

The constraint in Eq. (4.11) denotes the time threshold for students to reach the egress j as quickly as possible. It would be much more realistic to define some threshold level to measure students' performance to reach the egresses. In this way, the activity time involves a threshold set-up time.

$$t_{ij} \leq H\, k_{ij} + M\left(1 - k_{ij}\right) \qquad \forall\, i \,\epsilon\, I, \forall\, j \,\epsilon\, J \tag{4.11}$$

The constraints in Eq. (4.12) – (4.14) define that the student in i is covered by at least one egress, i.e., y_j, so that students can escape during an emergency.

$$y_j \leq f_j \qquad \forall\, i \,\epsilon\, I, \forall\, j \,\epsilon\, J \tag{4.12}$$

$$y_j \leq k_{ij} \qquad \forall\, i \,\epsilon\, I, \forall\, j \,\epsilon\, J \tag{4.13}$$

$$y_j \geq f_j + k_{ij} - 1 \qquad \forall\, i \,\epsilon\, I, \forall\, j \,\epsilon\, J \tag{4.14}$$

The final set of constraints, Eq. (4.15) – (4.20), define the variables' domain as follows:

$$\mathrm{x}_j = \{0,1\} \qquad \forall\, j \,\epsilon\, \mathrm{J} \tag{4.15}$$

$$\mathrm{y}_i = \{0,1\} \qquad \forall\, i \,\epsilon\, \mathrm{I} \tag{4.16}$$

$$\mathrm{f}_j = \{0,1\} \qquad \forall\, j \,\epsilon\, \mathrm{J} \tag{4.17}$$

$$\delta_{ij} = \{0,1\} \qquad \forall\, i \,\epsilon\, \mathrm{I}, \forall\, j \,\epsilon\, \mathrm{J} \tag{4.18}$$

$$x_{ij} \geq 0 \qquad \forall\, i \in \mathrm{I}, \forall\, j \in \mathrm{J} \qquad (4.19)$$

$$t_{ij} \geq 0 \qquad \forall\, j \in \mathrm{J} \qquad (4.20)$$

4.2.1.4.Solution Approach

The augmented ε-constraint method is utilised in this study, as described by Mavrotas (2009), to resolve the multi-objective optimisation problem and to determine the Pareto optimal solutions. This method transforms the given set of objective functions into one objective function by considering all the other objective functions as constraints which entails the application of lexicographic optimisation (Zykina, 2004). The pay-off matrix with the best values for each objective function is generated. Since the series of objective functions are optimised as a pay-off matrix, this method can effectively eliminate the dominant optimal solutions in the pay-off matrix. As a result, Pareto optimality is guaranteed with this approach, as seen in Figure 4.4. For further information on the solution method used, the reader is referred to Mavrotas (2009). Pareto optimality refers to solutions in MOO where no other solution can be improved in any objective without degrading at least one of the other objectives. In other words, it represents a set of solutions where there is no single solution that is better than any other solution in the set with respect to all objectives. The set of Pareto optimal solutions is essential in decision-making because it allows decision-makers to consider trade-offs between objectives and make informed decisions based on their preferences (Jafaryeganeh et al., 2020). In the context of evacuation planning, Pareto optimal solutions can help decision-makers balance the objectives of minimising cost, maximising egress coverage, and minimising time, leading to a more effective and efficient evacuation plan.

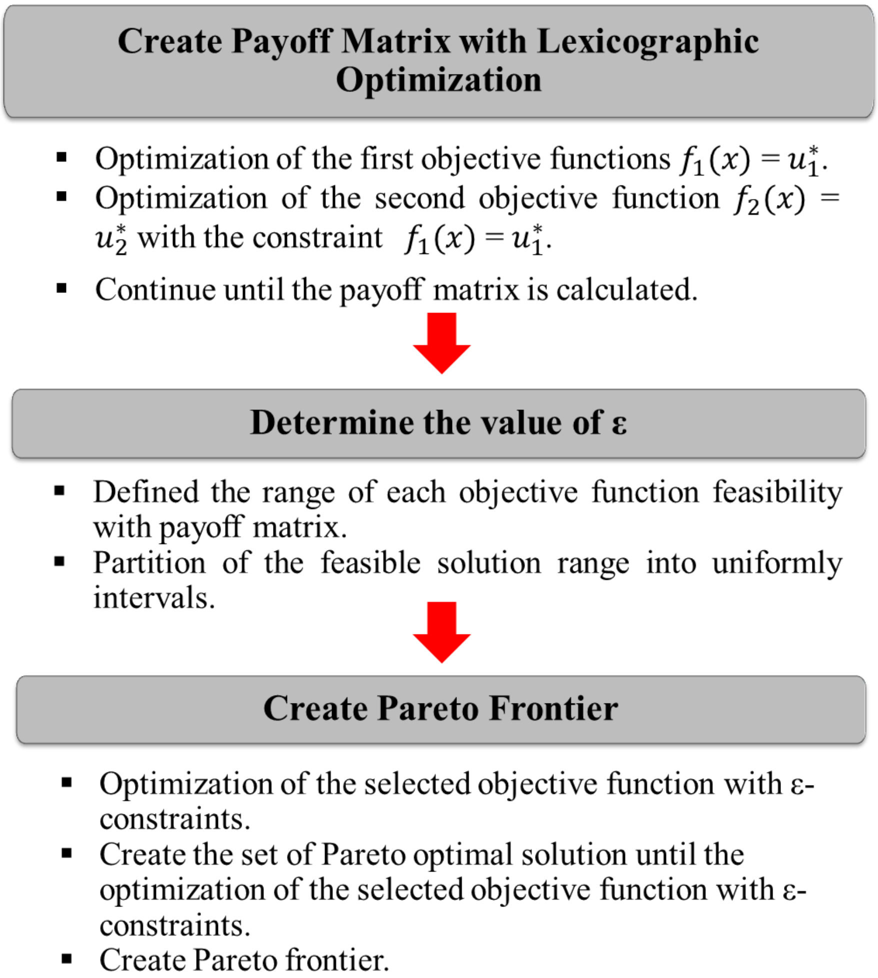


Figure 4.4: Flowchart of the lexicographic optimisation to calculate pay-off table using ε-constraint method.

4.2.2. BIM Model

In order to develop an architectural BIM for the facility of interest, an architectural BIM at Level of Detail (LOD) (Belotti et al., 2016) 300 was initially created using Revit software (Revit, 2022). LOD 300, by definition, represents the geometry of the model elements graphically with geometry; meanwhile, non-graphical information, such as building material properties, is also attached to the model elements. However, it is important to note that non-graphical information (e.g., thermal properties) is not included in an evacuation scenario since such information is not directly relevant; thus, it is out of our scope.

In this work, BIM allowed for visualising the mathematical results for the school layout. At the same time, the graphical information of building geometry was required to represent building components in relation to quantity, size, shape, location, and orientation for evacuation simulation designs. Furthermore, the developed BIM model of a school layout was applied to

Autodesk Revit Structure software which could also provide an Application Programming Interface (API) (Apivatanagul et al., 2012) to facilitate data transfer to other different applications. Consequently, the school layout was exported as a DXF file from Revit and imported into ABM GUIs, AnyLogic (Anylogic, 2021), for evacuation simulation to define the movement of the evacuees' movement within the desired space.

Moreover, the BIM model is employed to extract critical information about the building layout, such as the location of doors and corridors, which are essential for evacuation analysis. While transferring DXF (Drawing Exchange Format) files can provide some of this information, BIM models offer several advantages. Firstly, BIM models can accurately capture the spatial relationships between building components, such as walls, doors, and corridors, which are critical to understanding the flow of occupants during an emergency evacuation. This information can be used to identify potential clashes in the design for better constructability, as well as to create a more comprehensive simulation of building performance. This level of detail can be critical for understanding the flow of occupants during an emergency evacuation, as it can help identify potential clashes in the design and improve constructability. Secondly, BIM models are often used by architects and engineers during the design process, making them readily available and familiar to many professionals in the industry. Lastly, using a BIM model allows for greater interoperability between different software applications, which can enhance the overall modelling workflow (Teo et al., 2017). For instance, a BIM model can be imported into evacuation modelling software, such as AnyLogic, allowing for seamless integration of the building geometry data with the evacuation simulation. Therefore, utilising a BIM model in this research is crucial to achieving the research objectives and developing a comprehensive evacuation simulation framework that can be used as a platform to optimise egress locations for building designers and emergency planners.

4.2.3. ABM Simulation

An agent-based simulation is used to model the movement of evacuees. The proposed simulation model utilised AnyLogic software, which supports graphical modelling language and permits users to construct models using Java codes (Grigoryev, 2015). The APL is a powerful tool for modelling, visualizing, and analysing crowd behaviour in physical environments, considering obstacles, bottlenecks, and environmental conditions that impact pedestrian flow (Karpov et al., 2005).

In this study, the BIM model was initially designed in Revit and then imported into the ABM engine using a customised toolbar built-in Visual C#. The API was necessary to establish the communication between the BIM model and the ABM engine. The BIM model provided the geometry and layout of the building and enabled the simulation to incorporate accurate architectural and structural features such as walls, doors, windows etc. The APL was an advanced tool for crowd analysis and pedestrian simulation in physical environments, providing a modelling, visualisation, and analysis capabilities of crowd behaviour while considering factors that impact pedestrian flow, including obstacles and environmental conditions. Furthermore, the modelling configuration of the evacuees' behaviour simulation engine was defined based on previous studies, as mentioned in Chapter 2. Therefore, the model contained interacting agents with specific properties and decision rules, including the agents' environment.

Finally, the simulation considers the hypothetical environment during an evacuation, which was characterised by the presence of unforeseen obstacles and unexpected behaviour by agents. The model included a set of interacting agents with specific properties and decision rules, such as walking speeds and body sizes, and considers both static (i.e., walls) and dynamic (i.e., walking speed) elements during evacuation. The API facilitated communication between the BIM model and the ABM engine, enabling the creation of a virtual environment that incorporates attributes of the building (Bina & Moghadas, 2021). Figure 4.5 demonstrates a practical process of the evacuees' flow model in the evacuation simulation system, as described in Sun and Turkan, 2020.

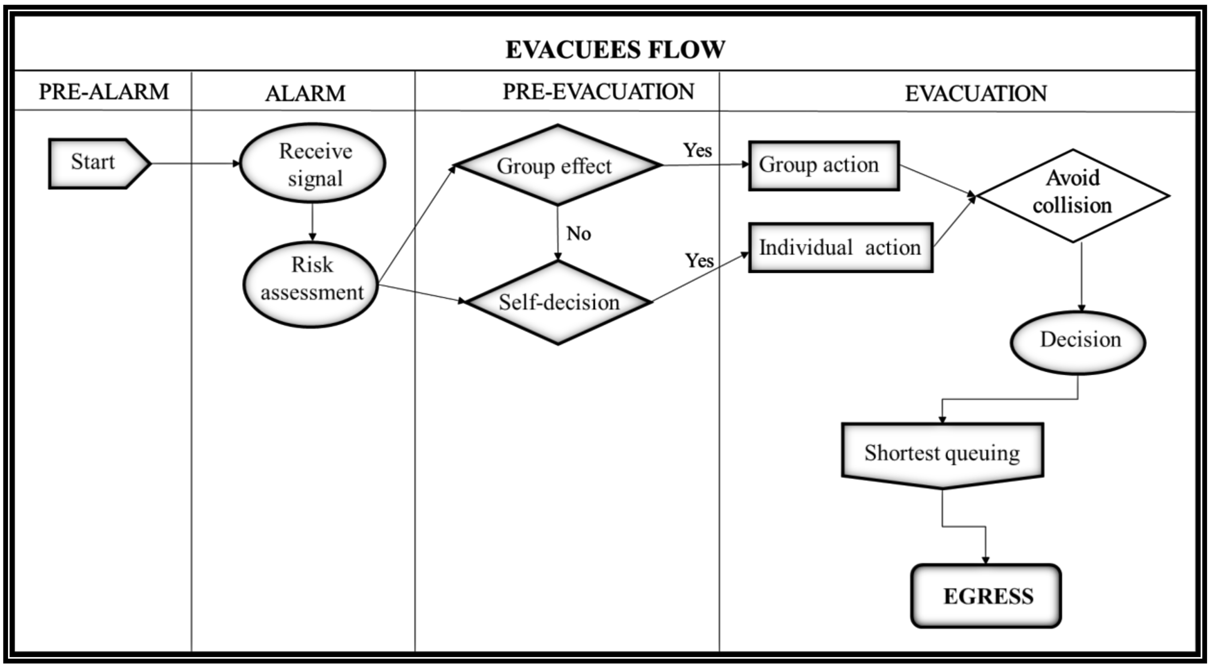


Figure 4.5: Proposed evacuation simulation.

4.3. Numerical Implementation and Analysis

4.3.1. Case Study

A case study is examined to demonstrate the proposed framework's practicality. The proposed framework for emergency evacuation is applied to a typical school building. As mentioned Chapter 3, the case study is representative of the average Australian school (Board, 2015), in terms of the size of the rooms, the number of students, and hallway dimension. A modular multi-room environment with a corridor on a single floor and multiple rooms is used as a case study, as shown in Figure 4.6(a), while the framework proposed is applied to a network, as shown in Figure 4.6(b). Each room/classroom is assumed to have one door to exit. The number of students representing a mid-size school is around 361-540, according to the definitions established in Blass and Bleikh (2018).

To further explore the building evacuation dynamics, 480 people in the school building were to be evacuated during any emergency through multiple potential egress locations. The size of each egress was set to be 1m wide, allowing up to 2 individuals to escape simultaneously (Parisi & Dorso, 2005). It was assumed that the maximum number of evacuees was evenly distributed in the rooms. The desired walking speed for each individual to escape was set to 0.95–1.55 m/sec, and their body diameters range from 0.22–0.29 m (Heliövaara et al., 2012). The range of body diameters and walking speed were selected to reflect typical human behaviour in emergency situations while also accounting for variations in individual speed and size. The limited space available for the crowd to evacuate in a closed environment contributes to these observed characteristics. The delay in evacuee evacuation could range from 0 to 60 sec, depending on the sensitivity of the alarm system and the individual's perception of risk (Kinateder et al., 2015). In summary, these characteristics were chosen based on a review of the literature on pedestrian movement in emergency situations, taking into consideration the limited space for the crowd to escape in a closed environment.

4.3.2. Mathematical Model Results

The school layout is connected to a network representation as seen in Figure 4.6(b). A total of twelve classrooms, two bathrooms, two labs and one food and leisure area are modelled in the network with six potential locations for egresses. The total number of nodes and links considered in the case is 23 and 102, respectively. The demand highlighting the movement of people between nodes is typically predicted as the whole of single trips from origin to destination. Movement between egresses from each egress location is given in Table 4.2. Each egress location is presumed to support the number of evacuees and can be conveniently reached. Table 4.3 displays the free-flow travel time and capacities of each network link. Both free flow capacity and travel time data have been created by considering the building dimensions. The cost variations for doors in Table 4.4 are due to the use of different types of doors in the model. Each door type has a different cost associated with it, based on factors such as material, size, and complexity of installation. These cost variations are based on industry standards and reflect the real-world cost differences encountered when implementing different types of doors in a building. The purpose of including these cost variations is to provide a more accurate representation of the real-world costs associated with implementing different egress strategies in a building.

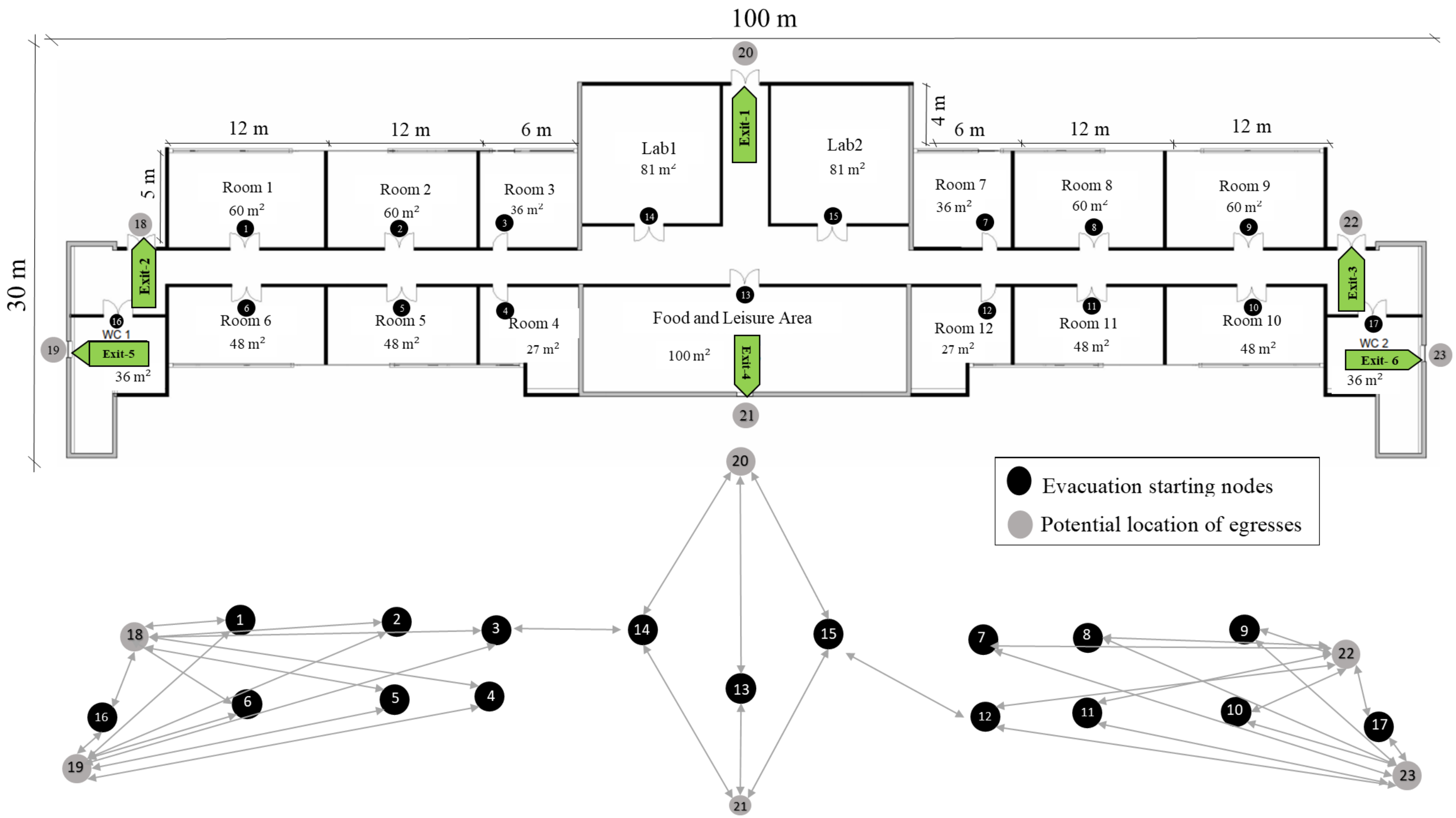


Figure 4.6: (a) Building layout for the typical school with proposed six egress locations, 2D. (b) Network representation highlighting nodes of the school layout (m refers to metre).

Table 4.2: Demand from each room to be evacuated.

Origin node	**Demand level (persons)**
1	30
2	30
3	20
4	20
5	30
6	30
7	20
8	30
9	30
10	30
11	30
12	20
13	50
14	50
15	50
16	5
17	5

[1]*Source: Data, for illustration purposes only.*

Table 4.3: Free flow capacity and travel time between room nodes and eligible egress nodes.

Links	Capacity (person)	Travel Time (sec)	Links	Capacity (person)	Travel Time (sec)	Links	Capacity (person)	Travel Time (sec)	Links	Capacity (person)	Travel Time (sec)	Links	Capacity (person)	Travel Time (sec)	Links	Capacity (person)	Travel Time (sec)
(1, 18)	30	4	(1, 19)	30	4	(1, 20)	30	25	(1, 21)	30	25	(1, 22)	30	45	(1, 23)	30	45
(2, 18)	30	12	(2, 19)	30	12	(2, 20)	30	15	(2, 21)	30	15	(2, 22)	30	40	(2, 23)	30	40
(3, 18)	20	16	(3, 19)	20	16	(3, 20)	20	10	(3, 21)	20	10	(3, 22)	20	35	(3, 23)	20	35
(4, 18)	20	16	(4, 19)	20	16	(4, 20)	20	10	(4, 21)	20	10	(4, 22)	20	35	(4, 23)	20	35
(5, 18)	30	12	(5, 19)	30	12	(5, 20)	30	15	(5, 21)	30	15	(5, 22)	30	40	(5, 23)	30	40
(6, 18)	30	4	(6, 19)	30	4	(6, 20)	30	25	(6, 21)	30	25	(6, 22)	30	45	(6, 23)	30	45
(7, 18)	20	35	(7, 19)	20	35	(7, 20)	20	10	(7, 21)	20	10	(7, 22)	20	15	(7, 23)	20	15
(8, 18)	30	40	(8, 19)	30	40	(8, 20)	30	14	(8, 21)	30	14	(8, 22)	30	12	(8, 23)	30	12
(9, 18)	30	45	(9, 19)	30	45	(9, 20)	30	18	(9, 21)	30	18	(9, 22)	30	4	(9, 23)	30	4
(10, 18)	30	45	(10, 19)	30	45	(10, 20)	30	18	(10, 21)	30	18	(10, 22)	30	4	(10, 23)	30	4
(11, 18)	30	40	(11, 19)	30	40	(11, 20)	30	14	(11, 21)	30	14	(11, 22)	30	12	(11, 23)	30	12
(12, 18)	20	35	(12, 19)	20	35	(12, 20)	20	10	(12, 21)	20	10	(12, 22)	20	15	(12, 23)	20	15
(13, 18)	50	25	(13, 19)	50	25	(13, 20)	50	6	(13, 21)	50	6	(13, 22)	50	25	(13, 23)	50	25
(14, 18)	50	20	(14, 19)	50	20	(14, 20)	50	6	(14, 21)	50	6	(14, 22)	50	22	(14, 23)	50	22
(15, 18)	50	30	(15, 19)	50	30	(15, 20)	50	6	(15, 21)	50	6	(15, 22)	50	30	(15, 23)	50	30
(16, 18)	5	2	(16, 19)	5	1	(16, 20)	5	28	(16, 21)	5	28	(16, 22)	5	50	(16, 23)	5	50
(17, 18)	5	50	(17, 19)	5	50	(17, 20)	5	28	(17, 21)	5	28	(17, 22)	5	2	(17, 23)	5	1

[2]*Source: Data, for illustration purposes only.*

Table 4.4: The cost of egresses.

Potential Egress node	Construction cost ($)
18	1100
19	1450
20	1250
21	1550
22	1150
23	1600

The proposed model was implemented in GAMS (GAMS, 2021) and ran on a personal computer with Windows 10 as the operating system, 8th Generation Intel Core i7 processor and 16GB of RAM. SCIP is adopted as the MINLP solver in this study. Based on information inferred from the solver, solving time for the case study was reported as 22 seconds with 571 variables and 364 constraints.

Planners need to decide on the most effective location of the egresses as all evacuees can easily access a nearby egress and avoid travel delays. Therefore, the analysis incorporates the examination of the evacuees' flow on the network links in Figure 4.6(a) and the number of egresses placed, including the number of persons serviced by each located egress. To achieve this, the problem is solved using the lexicographic approach described in Section 4.2.1.4 within this Chapter and Section 2.5.1.2 in Chapter 2. Here, the trade-offs between the three objective functions are considered.

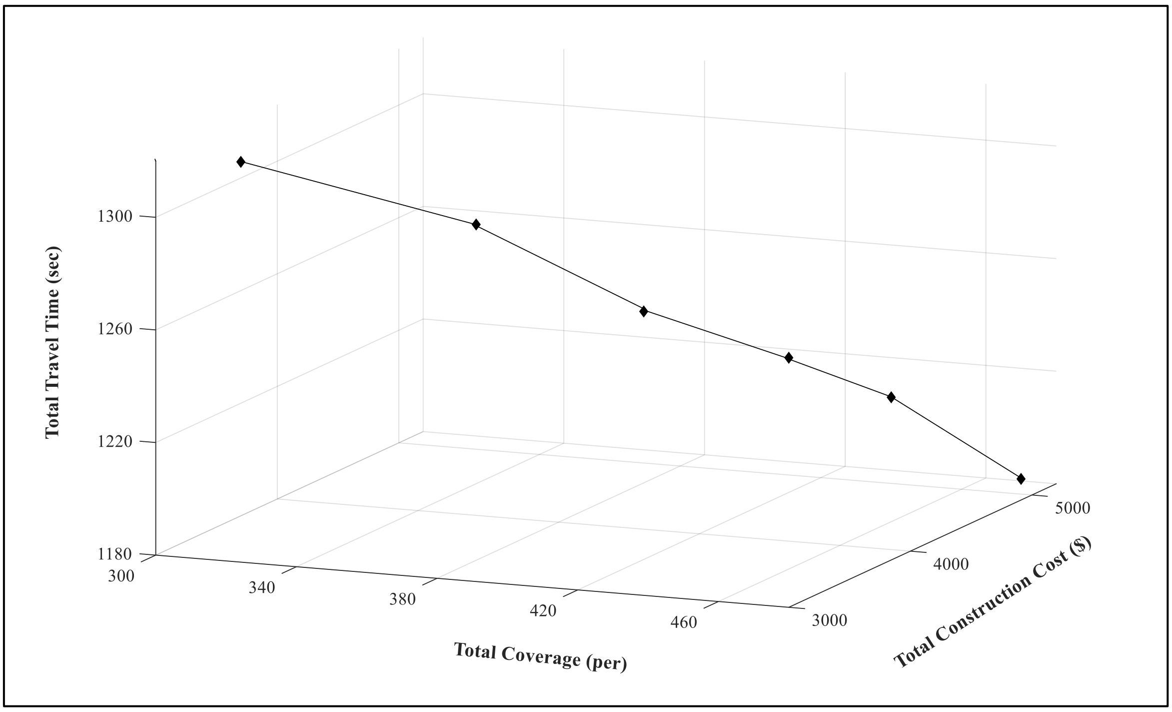


Figure 4.7: Pareto front with the 3 objective functions and cuts generated using coverage and travel time as constraints.

The result of the Pareto frontier with the three objective functions is presented in Figure 4.7. As can be seen, 6 points are plotted, and all of this form an efficient frontier. Hither, there is never a point on the efficient frontier where one of the objective functions can be improved without having a negative impact on the other, so none of the points on the front dominates one another. Looking at the frontier, when the objective of total construction cost is minimised in Eq. (4.1), it takes the value of $3500. For this value, the total coverage in Eq. (4.2) and travel time objective in Eq. (4.3) take 480 person and 1240 seconds values, respectively. Thus, in this case study, achieving maximum coverage is associated with choosing a school layout that minimises costs as much as possible. Given that the value of 1240 seconds is not the minimum value of the travel time objective, as one would expect. However, it provides the highest efficiency in total construction costs and coverage than the other options, thus reducing the overall cost. It is worth mentioning that the recommended evacuation time would depend on a variety of factors, such as the size and layout of the building, the number of exits, and the age and mobility of the occupants; it is generally considered acceptable for a total evacuation time to be around 1240 seconds, as this falls within the acceptable range outlined in NFPA (National Fire Protection Association) (Association & Association, 2018).

Consequently, a desired solution exists in this case, corresponding to locating egresses at 18, 20, and 22 in the network examined. The optimised egress locations, thus, Figure 4.8, can be utilised for the decision-making process in the evacuation plan. Moreover, as the located egresses were selected based on the lowest cost in the model, the construction cost is reduced by 31%, and 480 (100%) people can leave the building within the total travel time of 1240 seconds, using three egresses. Further, increasing the number of egresses to locate in the building is likely to increase the total constructing cost; therefore, cost-effectively considering the number of egresses is necessary to optimise the location of the egresses. The baseline is the point on the Pareto front that represents the best trade-off between cost and evacuation time before implementing the optimise the egress location. The reported 31% reduction in cost and 10% increase in evacuation time are in comparison to other points on the Pareto front.

The major finding that the results underline, however, is the sufficient series of travel time reductions that can be achieved by merely altering the school layout's egress location. The findings of this study demonstrate the importance of taking a multi-objective approach into account for planning school layouts, as considering only one objective function over another can have the opposite effect on the neglected objective function. The Pareto curves of Figure 4.7 also draw attention to the fact that there may be a better layout when considering other objectives than optimising the egress location for minimum travel time. In such situations, the decision maker should take a balanced approach when deciding on an optimal layout configuration for conflicting objective functions. The Pareto front can serve as significant input to the decision-making process for layout planning.

The model could also be extended for use in other layout planning problems, where minimising travel time is an essential requirement. This may include areas such as designing the layout of high-rise buildings and warehouses in highly populated zones, along with other larger-scale urban design problems. However, applications to such more prominent cases may require metaheuristic approaches.

Figure 4.8: The typical school layout with optimised egress locations and 3D building view.

4.3.3. Evacuation Simulation Results

To further explore the evacuation dynamics in the typical school layout, an emergency evacuation simulation was carried out using the AnyLogic simulation platform. The simulation can provide the evacuation time of the school layout, which was adopted from mathematical model results, as seen in Figure 4.8, to visualise the performance of the egresses location chosen. Moreover, concerning the egresses' locations, an evacuation model was set up with the characteristic parameters of the evacuees in order to create a complicated, diversified, and actual evacuation process. The evacuation model generates evacuees with random distribution at the defined locations, and the evacuees' behaviour is identified as a simplified version of the AnyLogic-established model shown in Figure 4.9. It is noteworthy to mention that various scenarios were analysed to consider the impact of different factors on evacuation time comprehensively.

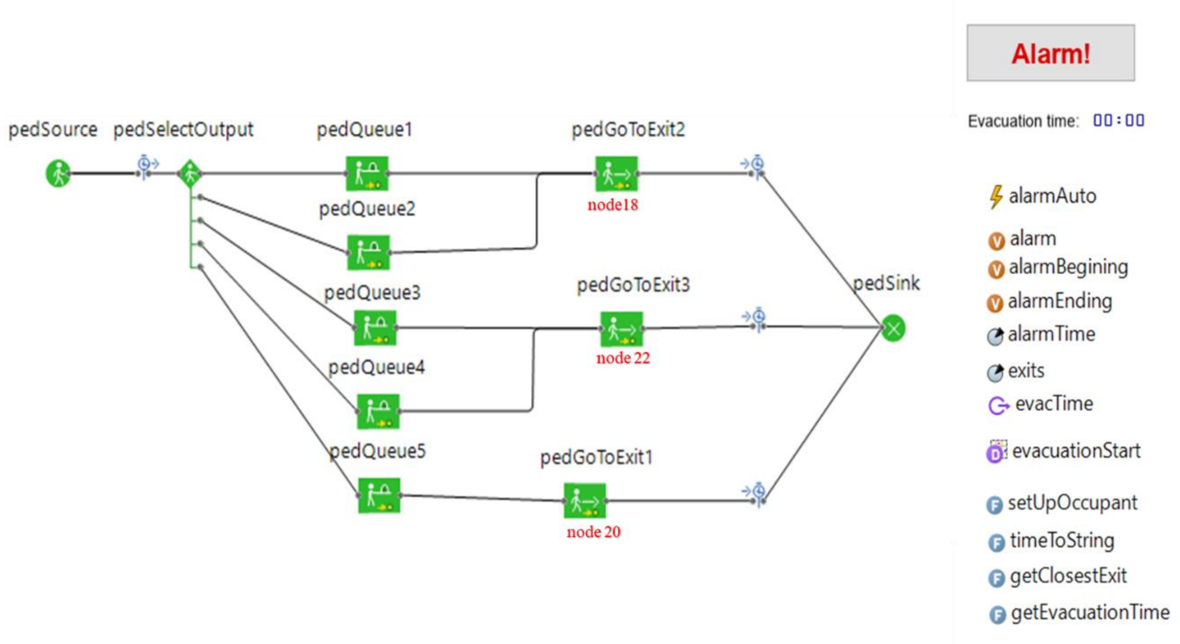


Figure 4.9: A simplified version of evacuees' behaviour in AnyLogic. Relationship of the mathematical model results are also represented by nodes.

Evacuation time is the most widely used measure for assessing the effectiveness of evacuation planning. AnyLogic permits presenting agents' movements as a 2D/3D animation in real time during the simulation process. It is also possible to observe the dynamics of the number of the evacuees in the building, such as their speed and coordinates. Based on the simulation results, our simulation of an emergency evacuation takes 20 minutes on the computer. The estimated mathematical model in Figure 4.10 aligns with the outcome of our ABM simulation, highlighting the accuracy and reliability of our approach.

In the simulation, it is assumed that all evacuees are trying to leave the school building as quickly as possible and are moving to the nearest egress following the created model of their agent-based behaviour. As demonstrated in Figure 4.10, the optimally located egresses effectively reduce the density of evacuees and prevent a potential bottleneck at a single exit point, where the colour depth indicates the level of evacuee density. The purposes of these egresses are to distribute the evacuees more evenly and ensure a safer and more efficient evacuation process. Here, the areas with density values equal to or greater than the critical density thresholds are coloured red. Furthermore, the density distribution represents the population density during the evacuation procedure to detect the areas with critical densities. Hence, the population movement in crowded locations can reflect real-time human traffic. As can be seen from the evacuees' density flow, the evacuation process shows high density in the corridor and lower density in the egress area. This may be because the evacuees must choose the shortest queue in the model simulation, and the egress location might reduce crowding caused by individuals being evacuated to the same exit during the evacuation procedure.

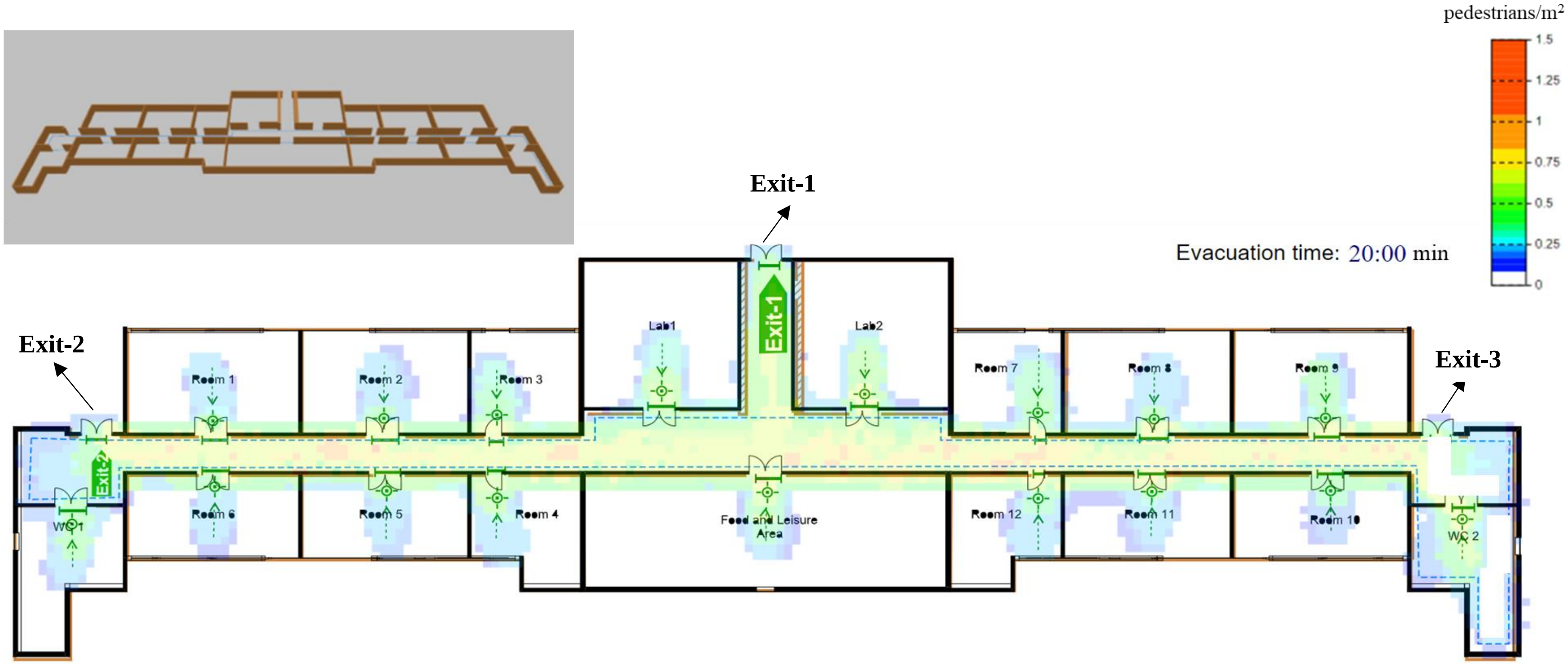
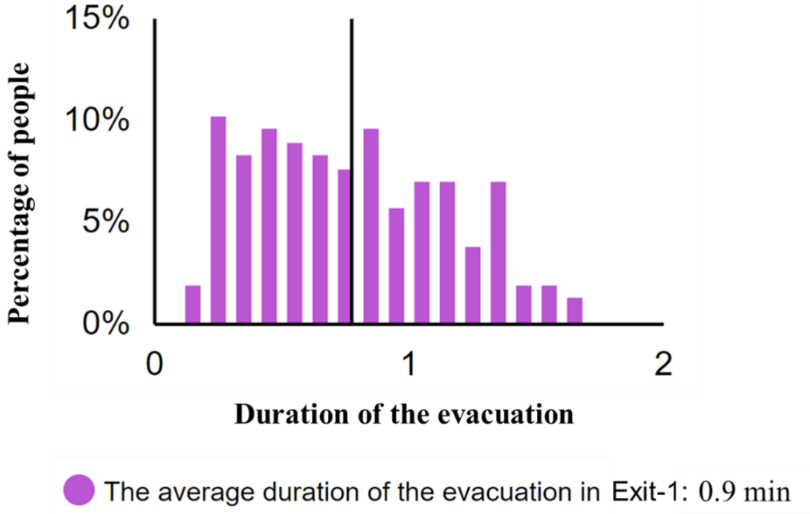


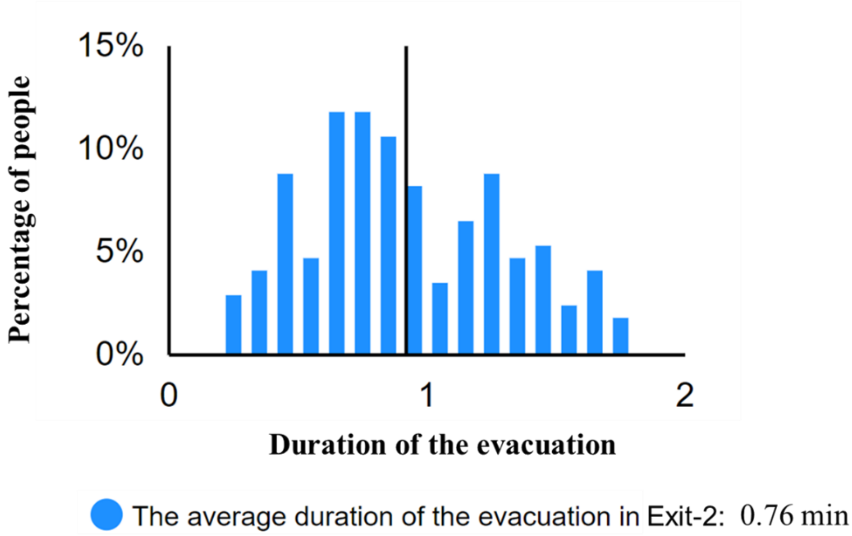
Figure 4.10: Evacuees density map of the school with optimised egresses during the evacuation process. The red colour represents the high density. The blue colour is used for low densities.

The statistical data on all evacuation exits, namely Exit-1 (node 20), Exit-2 (node 18) and Exit-3 (node 22), from the school building, is also collected to specify the average duration of the evacuation as shown in Figure 4.11. Here, the x-axis represents the model time t (min), and the y-axis shows the percentage of evacuees leaving egress. In addition, the black lines indicate the mean value of the evacuation duration. The histograms result in Figure 4.11 are collected after 500 iterations. They show the system's evacuation time distribution, measuring differences between start and end times. According to the statistical data, the average time to escape the school during evacuation via egresses reveals slight differences in the evacuees' average time. As seen in Figure 4.11, the average duration of the evacuation of evacuees travelling in node 20 via Exit 1 in Figure 4.10 is higher than the other two exits. A possible explanation for such a phenomenon is the egress location and number of evacuees at this exit during the evacuation process. Moreover, each egress evacuation in the simulation model is associated with a specific standard deviation value, which reflects the variability in evacuation times that may occur during emergency scenarios. For instance, the evacuation times for Exit 1 in the simulation model have a standard deviation of 0.381 min, Exit 2 has a standard deviation of 0.385 min, and Exit 3 has a standard deviation of 0.251 min. It is worth noting that Exit 3 has the smallest standard deviation with a value of 0.251 min, while Exits 1 and 2 have similar standard deviation values of 0.381 min and 0.385 min, respectively. Consequently, the model shows that agent-based simulation can allow analysing of the performance of the egresses in the school building, as seen in Figure 4.10. It also provides an essential tool for considering a process of perception, decision-making, and action in a school building during an emergency.

a)



b)



c)

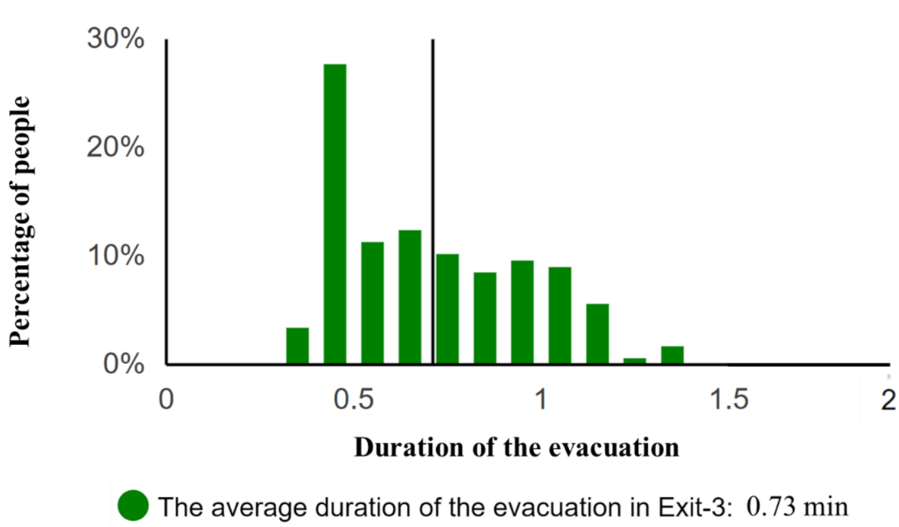


Figure 4.11: Statistical data of evacuees passing through each egress; (a) average duration of the evacuation for Exit-1 (node 20), (b) average duration of the evacuation for Exit-2 (node 18), (c) average duration of the evacuation for Exit-3 (node 22).

Moreover, the limitations of this study need to be acknowledged. First, the proposed model is not designed for every general evacuation scenario (e.g., fire). Second, selecting the appropriate location of the egresses is challenging, and more stochasticity needs to be introduced to the problem, including evacuees' preparedness and response time and event proximity. Third, the exclusion of social attributes due to the limited available data on social behaviour during emergency evacuations, which could affect the accuracy of the evacuation planning process. Lastly, the application of a single-story building supports the proposed framework. Nevertheless, a multi-story building could give additional insights into the evacuation process in buildings.

4.3.4. Mathematical Model for Larger Case Study

Building on insights from the preliminary case study, the framework's adaptability to a larger setting was thoroughly examined. The dataset was doubled, and critical parameters were adjusted to match the complexities of a larger educational facility. This study addresses questions about construction cost, population coverage, travel time, and other critical metrics, providing insights for optimising egress planning on a grander scale.

In the optimization study, the model, featuring 2157 variables and 1567 constraints, produced insightful results summarized in Table 4.5. The table showcases outcomes for minimizing construction cost (Eq. 4.1) and travel time (Eq. 4.3) while maximizing total coverage (Eq. 4.2). The resulting travel time objective is quantified at 1416.8 seconds, allowing the evacuation of 960 individuals using six strategically located egresses. These egresses are selected for cost-effectiveness, representing the most economical choice among proposed options. The baseline on the Pareto front represents the best trade-off between cost and evacuation time.

Table 4.5: Optimal egress locations balancing cost and evacuation time for larger case study.

Total Construction Cost ($)	**Coverage (per)**	**Total Travel Time**
4450.00	960	1416.8

The findings confirm a commendable 10% reduction in evacuation time and a substantial 41% decrease in the total cost of egresses, ensuring the safe evacuation of all individuals. This delicate equilibrium between a total cost of $4450, egress coverage for 960 people, and a travel time of 1416.8 seconds underscores the multifaceted considerations in effective evacuation planning. The decrease in travel time correlates with increased egress coverage, emphasizing the importance of strategically located egresses in facilitating efficient evacuations. However, the potential escalation in total construction costs with increased egresses necessitates a judicious and cost-effective approach to optimize their locations.

In addressing the overarching problem of emergency evacuation planning, this study provides actionable insights by optimising egress locations in a larger educational facility. These findings' practical implications extend to enhancing evacuation procedures' safety and efficiency in real-world scenarios.

4.4. Concluding Remarks

This chapter presents a practical approach to enhance evacuation planning for school buildings. The framework has been developed by combining mathematical modelling, BIM, and ABM to address the challenge of optimising safety and efficiency during evacuations. This integration of a MIP model and simulation techniques serves to identify optimal egress locations and evaluate their practicality in emergencies. The utility of this framework becomes evident in its potential to enhance evacuation outcomes. By accounting for conflicting objectives like total cost, egress coverage, and evacuation time, this approach provides decision-makers with a versatile tool for making informed choices. The use of lexicographic optimisation offers a practical means of managing multiple objectives.

The case study centred on a school evacuation scenario showcases tangible benefits. The reported 31% cost reduction and 10% increase in evacuation time underscore the advantages of this framework. Further, the larger case study offered a more in-depth analysis, addressing whether the potential cost savings justify using such tools. Insights from agent-based simulation further contribute to understanding human movement during evacuations. Combining mathematical modelling, BIM visualisation, and ABM simulation opens avenues for similar evacuation planning across various building types. This approach supports evidence-based decisions and efficient egress configurations, catering to architects, emergency planners, and decision-makers. The convergence of technology and analysis strives to foster safety within the constructed environment.

To refine the proposed model further, future endeavours could centre on expanding its applicability to a broader spectrum of evacuation scenarios, encompassing fires, earthquakes, and diverse disaster scenarios. Incorporating additional stochastic elements for variables such as evacuees' readiness, response times, and event proximity could enhance the model's predictive precision. Furthermore, extending the model's scope to encompass multi-story buildings would yield more profound insights into the intricacies of evacuation processes within structures featuring multiple floors. An in-depth exploration of the impact of various design factors, including exit route dimensions and the number of available exits, would also yield valuable insights. Ultimately, practical testing of the model's viability in real-world emergencies would empirically validate its accuracy and effectiveness in predicting evacuation time and associated costs.

Chapter 5

A Multi-Criteria Decision-Making Framework for Egress Location Selection in Buildings Considering Economic, Technical and Social Factors

5.1. Overview

Continuing from the previous chapters' exploration of egress location in evacuation planning for buildings, this chapter probes further into the crucial realm of evacuation planning, focusing on incorporating MCDM methodologies. Building upon the foundation established in Chapter 4, this chapter extends the discussion by highlighting the significance of incorporating a comprehensive approach to guide decision-makers in designing robust and adaptable evacuation strategies (Kuligowski et al., 2005; Urbina & Wolshon, 2003).

Furthermore, as highlighted in Chapter 4, the essence of evacuation planning lies in its systematic guidelines, aiming to orchestrate safe and efficient evacuations from buildings or areas in times of crisis (Manley et al., 2015). The process encompasses hazard identification, risk assessment, and formulation of a comprehensive evacuation plan (Yazdani & Graeml, 2014). A comprehensive approach considers critical factors such as building design, occupancy rates, available resources, and potential hazards (Shin et al., 2019).

In this chapter, the MCDM is applied to achieve the paramount role of a safe and efficient evacuation plan for minimizing harm risk during emergencies. The MCDM approach is an invaluable tool for designing effective evacuation plans by allowing decision-makers to assess multiple criteria comprehensively (Renne, 2018). This aligns with the overarching theme of the previous chapter that highlighted the need to consider various factors such as timing, spatial coverage, and budget. Besides continuing the discourse on the significance of building design, accessibility, and available resources in evacuation planning, this chapter introduces a comprehensive framework that integrates social, economic, and technical criteria for selecting ideal egress locations during emergencies (Pan, 2008).

Within MCDM, F-AHP stands out as an innovative technique to account for uncertainties and vagueness inherent in real-life emergency scenarios (Munier et al., 2019). This adaptation adds a layer of robustness to the decision-making process involving evacuation planners by enabling consideration of potential variations and unforeseen circumstances. (Leung & Cao, 2000). By leveraging the F-AHP methodology, decision-makers are equipped with the tools to make adaptive and informed choices, ultimately enhancing building occupants' safety and well-being (Reig-Mullor et al., 2020). The chapter underscores the versatility of this approach, citing its applications across various fields, including engineering, management, and environmental sciences (Zalhaf et al., 2021).

The chapter culminates in a practical case study set within a one-storey school building, also used in Chapter 3. This real-world scenario is a tangible example to showcase the proposed MCDM approach's applicability in enhancing evacuation strategies (Kinateder et al., 2021). By assessing different egress options based on clearly defined criteria, the chapter demonstrates how the methodology can guide decision-makers in selecting optimal egress locations tailored to the unique characteristics of different layouts (FEM Agency, 2018). Through this exploration of MCDM and its application within evacuation planning, Chapter 5 reinforces the symbiotic relationship between rigorous research and real-world safety outcomes, building upon the foundation laid in Chapter 4. Note that this chapter comprises material from papers currently prepared for submission. It is presented here as an integral part and contributes to the overall thesis.

5.2. Problem Definition

The framework in this study is divided into three stages: input, process, and output. In the input stage, data analysis is conducted by considering the criteria and alternatives. The criteria represent the technical, economic, and social characteristics that serve as reference points for decision-making. Here, a two-fold approach was adopted to identify these criteria. First, an extensive review of existing literature, relevant studies, and established standards was conducted to identify quantifiable criteria that can be objectively measured and analysed. Second, comprehensive research was conducted to gather in-depth information on each criterion. Academic papers, reports, and reputable online resources were consulted to ensure a comprehensive understanding of the relevance of each criterion to the research topic. Furthermore, the alternatives refer to strategic choices for locations that have implemented egress locations, and six egress locations were considered as alternatives. The summary of sub-criteria, based on the collective findings, is presented in Table 5.1. It is essential to acknowledge that while this list serves as a foundation, adjustments may be necessary to accommodate project location, nature, and stakeholder preferences, ensuring its suitability in various scenarios.

Table 5.1: Summary of evaluation criteria.

Main Criteria	Sub-Criteria/Evaluation Criteria	Sources
Technical	Width and height of the egresses (m)	(Board, 2012, 2015)
	Door arrangement (m)	(Board, 2012, 2015)
	Proper lighting in egress area (lux)	(Board, 2004, 2021)
Economic	Materials cost ($)	(Plus, 2023), (Doorsets, 2023)
	Construction cost ($)	(Plus, 2023), (Doorsets, 2023)
	Maintenance cost ($/ y)	(Plus, 2023), (Doorsets, 2023)
Social	Distance between nearest potential egress location (m)	Figure 5.4
	Width of corridors to access egress area (m)	Figure 5.4
	Presence of intermediate doors before exit access	Figure 5.4

Moving to the process stage, the framework employs a systematic approach to compare and manage the criteria and alternatives using the F-AHP methodology. The F-AHP approach is applied to assign weights to the criteria. This approach involves converting the linguistic criteria into membership functions, calculating fuzzification and defuzzification values, and determining fuzzy vector weights and normalization weights. These steps enable a rigorous and objective evaluation of the criteria.

Finally, in the output stage, the framework generates the results of egress location suitability based on the dominant value derived from the F-AHP calculations. The dominant value helps identify the most suitable egress location among the alternatives. This framework for egress location selection, with its consideration of criteria and alternatives using the F-AHP method, enhances decision-making and enables the development of more accurate and practical evacuation plans. Figure 5.1 presents the framework for egress location selection, offering a comprehensive overview of the evaluation process.

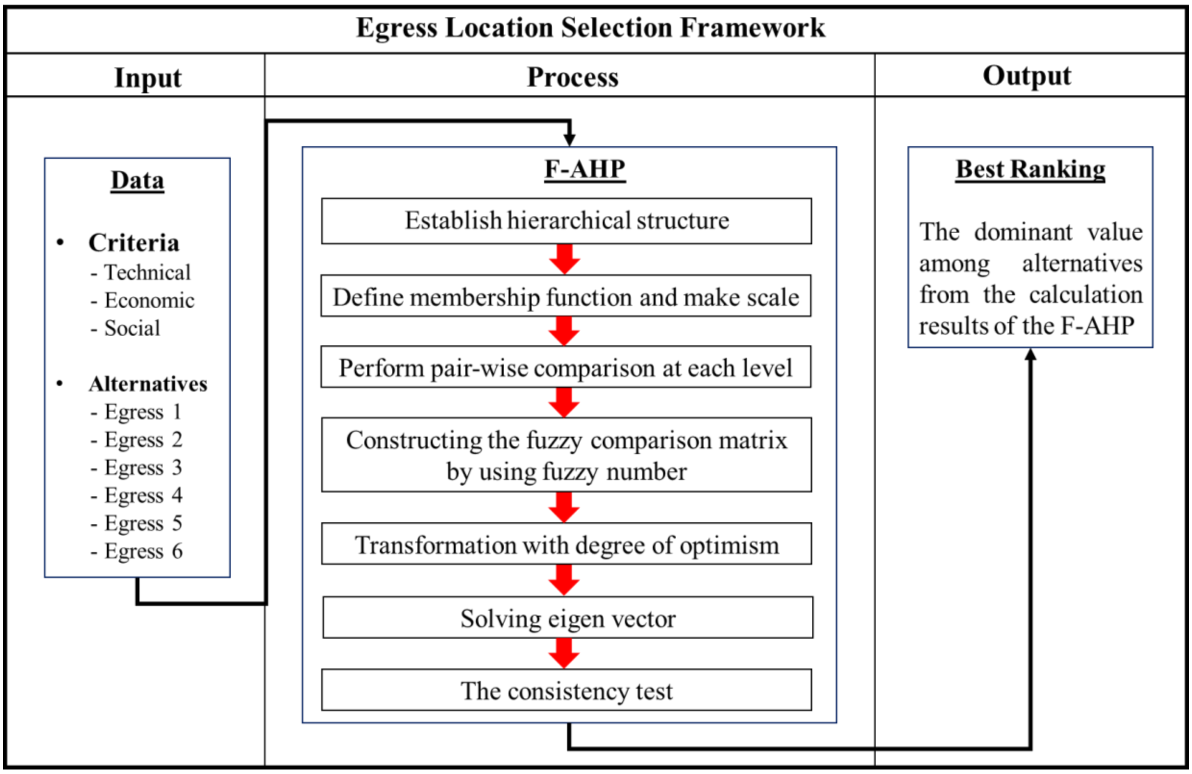


Figure 5.1: Proposed framework indicating model development stages for egress location selection.

A case study was conducted to validate the model, and input was obtained from subject matter experts. This validation process yielded insights and ensured that the model's performance aligned with practical considerations. Incorporating F-AHP in the evaluation process allowed for considering uncertainties and fuzziness inherent in the decision-making process, resulting in a more realistic assessment. This enhanced the accuracy and reliability of the evaluation, ultimately contributing to the selection of the most appropriate egress location for emergency scenarios.

5.2.1. Evaluation Criteria and Hierarchy of the Decision Problem

The assessment of evaluation criteria within the egress location entails the consideration of diverse sub-criteria categorized under three main pillars: technical, economic, and social. The selection of criteria and sub-criteria was based on careful consideration of their relevance and significance in addressing the research objectives and requirements. Besides, the list of sub-criteria for determining the optimal egress location was established by gathering insights from a proposed model developed for this study, along with relevant industry standards (i.e., Board, 2015) and a thorough review of internet sources. These sources provided Australian emergency door price data, substantiating the material, construction, and maintenance cost criteria. This multi-faceted approach ensured that the criteria were grounded in a well-informed understanding of the subject matter, providing a robust foundation for the study. Figure 5.2 illustrates the decision problem hierarchy, containing six alternative egress locations and nine evaluation criteria.

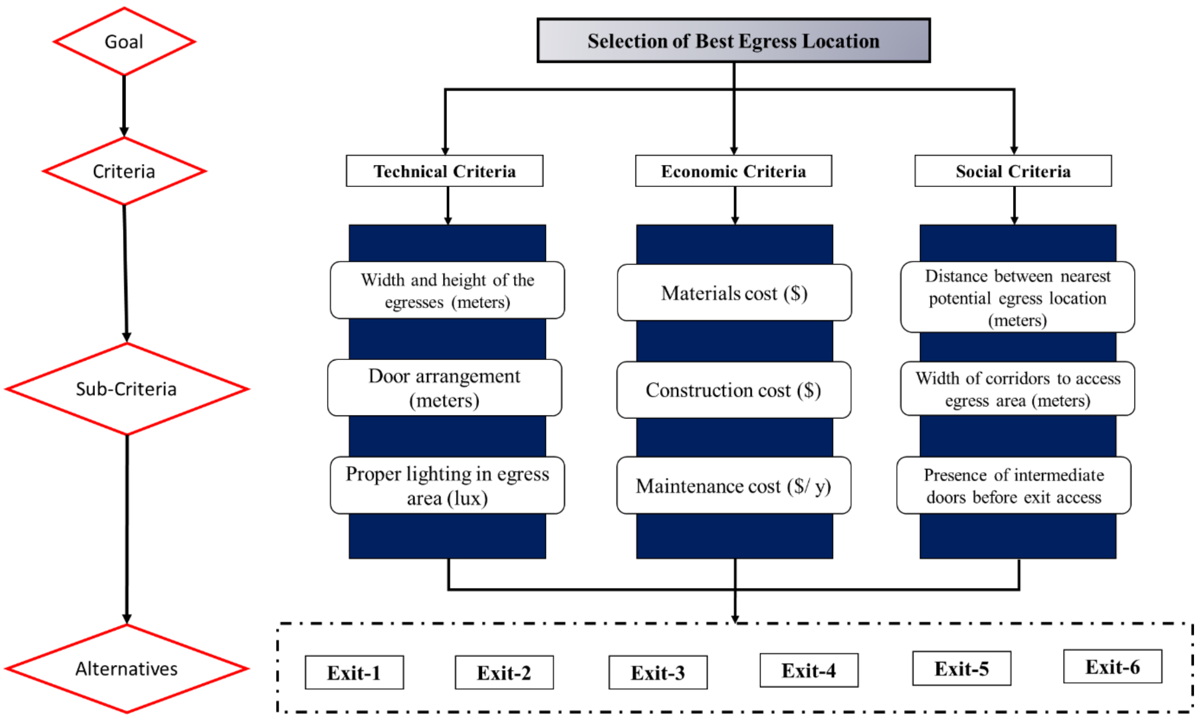


Figure 5.2: Hierarchy of egress location selection decisions.

5.2.2. Triangular Fuzzy Number Design

Triangular fuzzy numbers provide a practical approach to tackling decision-making challenges in uncertain environments. They serve as a means of representing fuzzy comparative judgment, making them well-suited for expert judgment in situations characterized by ambiguity. Unlike crisp numbers, fuzzy triangular numbers (FTNs) represent the minimal, most likely, and maximum values. In the context of the F-AHP, triangular numbers have been used to facilitate pairwise comparisons of criteria and alternatives, as demonstrated in earlier studies by Van Laarhoven and Pedrycz (1983), Buckley et al. (2001) and Chang et al. (2018). Therefore, building upon the significance of FTNs in addressing decision-making challenges, this study adopts the triangular membership function, following the notation established by Yang et al. (2013) and Pan (2008), as seen in Eq. (5.1).

$$P = (l, m, h) \tag{5.1}$$

The membership function of a triangular fuzzy number is illustrated in Figure 5.3(a), with the parameter l denoting the minimal value, m representing the most likely value, and h indicating the maximum value. Figure 5.3(b) illustrates the membership between the FTNs $P1 = (l_1, m_1, h_1)$ and $P2 = (l_2, m_2, h_2)$ and the fuzzy evaluation matrix derived from the results P_i.

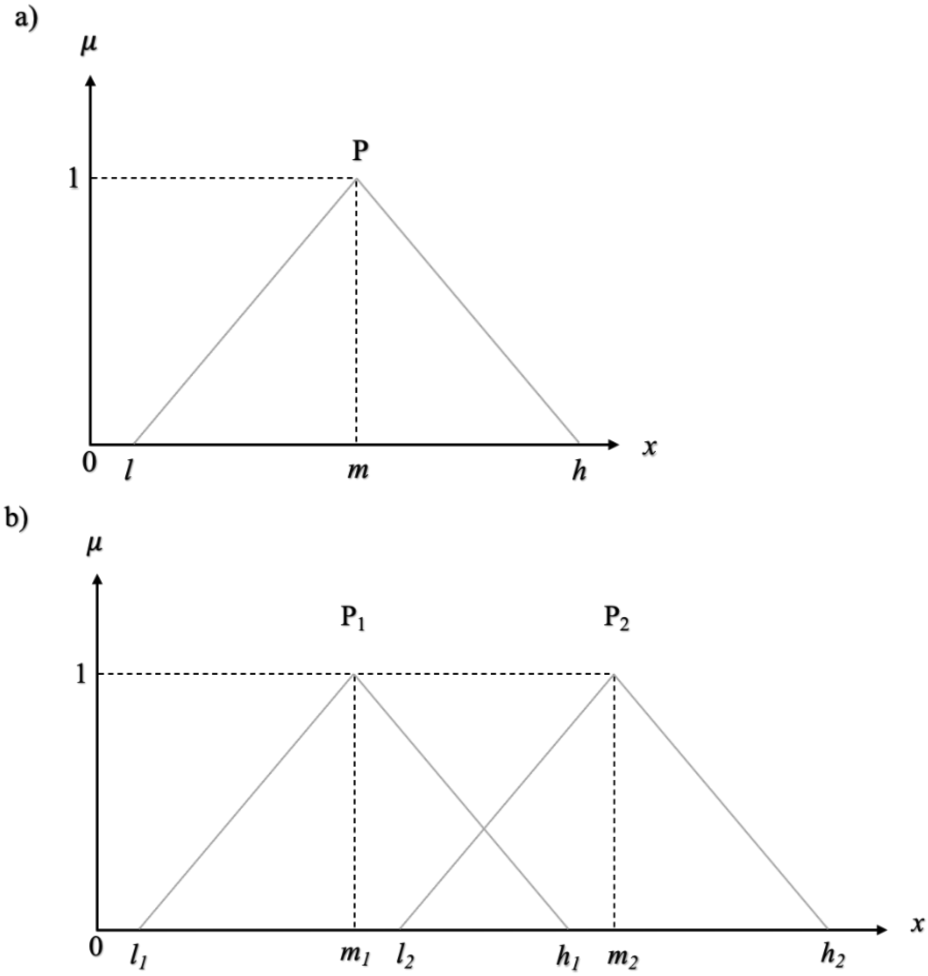


Figure 5.3: (a) Triangular fuzzy number P; (b) Membership function between triangular numbers P1 and P2 in the fuzzy evaluation matrix.

The membership function of $F(\mu)$ is defined by Eq. (5.2).

$$\mu(x|F) = \begin{cases} 0 & x < l, \\ \dfrac{x-l}{m-l} & l \le x \le m, \\ \dfrac{h-x}{h-m} & m \le x \le h, \\ 0 & x > h \end{cases} \tag{5.2}$$

The judgment matrix $R_{d\times d}$, which consists of interval value ratios, is represented by Eq. (5.3). These interval value ratios, namely P_{1n} and P_{n1}, perform an essential part in capturing the relative importance and preferences between factors or criteria in the decision-making process. Specifically, P_{1n} represents the ratio between the interval value of the first factor and the interval value of the n^{th} factor, while P_{n1} represents the reciprocal of P_{1n}. Incorporating these interval value ratios allows decision-makers to quantitatively assess and compare the significance of different factors, aiding in the prioritization and weighting of criteria. The matrix representation of $R_{d\times d}$ in Eq. (5.3) is as follows:

$$R_{d\times d} = \begin{bmatrix} 1 & L & P_{1n} \\ F & O & F \\ P_{n1} & L & 1 \end{bmatrix} \tag{5.3}$$

5.2.3. F-AHP Method

F-AHP is a highly effective and widely employed tool in the field of MCDM for assigning weights to criteria. It employs fuzzy numbers as a scale for pairwise comparisons to determine the relative priorities of different selection criteria and sub-categories. This approach effectively addresses the inherent uncertainty and imprecision in human decision-making processes, providing the decision maker with suitable flexibility and robustness to comprehend and analyse the decision problem (Akadiri et al., 2013). The calculation steps for F-AHP are explained in detail as follows (Dağdeviren et al., 2009; Sirisawat & Kiatcharoenpol, 2018):

Step 1: The process of pairwise comparisons matrix is defined by Eq. (5.4). Here, $\tilde{y}_{ij}^{k}$ represents the k^{th} decision maker's preference of the i^{th}criterion over the j^{th} criterion using FTNs. In this context, the tilde (~) represents triangular numbers. Table 5.2 provides detailed information on the criteria or alternatives using linguistic terms.

$$D = \begin{bmatrix} \tilde{y}_{11}^{k} & \tilde{y}_{12}^{k} & \cdots & \tilde{y}_{1n}^{k} \\ \vdots & & \ddots & \vdots \\ \tilde{y}_{n1}^{k} & \tilde{y}_{n2}^{k} & \cdots & \tilde{y}_{nn}^{k} \end{bmatrix} \qquad i,j = 1,2,3, \dots n \tag{5.4}$$

Table 5.2: Pairwise comparison of criteria (Saaty, 1980).

Saaty Scale	Definition of Importance
1	Equally important
3	Moderately more important
5	Strongly more important
7	Very strongly more important
9	Extremely more important
2 **4** **6** **8**	The intermittent values between two adjacent scales

Step 2: If multiple decision makers are involved, their individual preferences $\tilde{y}_{ij}^{k}$ are averaged to determine the aggregate preference $\tilde{y}_{\,ij}$ using Eq. (5.5).

$$\tilde{y}_{\,ij} = \frac{\sum_{k=1}^{K} \tilde{y}_{ij}^{k}}{K} \tag{5.5}$$

Step 3: To assess the consistency of pairwise comparisons, Saaty introduced the concept of the consistency index (CI) and compared it with a random consistency index value (RI) (Donegan & Dodd, 1991). The RI value is determined based on the matrix size, denoted by the order n. Table 5.3 presents the value of RI from matrices of order 1 to 10, as suggested by Saaty (1980).

Table 5.3: Random inconsistency indices (RI).

N	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0.00	0.00	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

The CI is obtained using the following Eq. (5.6):

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{5.6}$$

If the CR is equal to or less than 0.1, it indicates an acceptable comparison; however, if it exceeds 0.1, it suggests inconsistent judgment. In such cases, the expert should reassess and adjust the original values in the pairwise comparisons (Saaty, 1980). The pairwise contribution matrix is then updated by incorporating the averaged preferences, as illustrated in Eq. (5.7). This process ensures the decision-making framework remains consistent and reliable throughout the evaluation.

$$\widetilde{D} = \begin{bmatrix} \widetilde{y_{11}} & \cdots & \widetilde{y_{1n}} \\ \vdots & \ddots & \vdots \\ \widetilde{y_{n1}} & \cdots & \widetilde{y_{nn}} \end{bmatrix} \tag{5.7}$$

Step 4: Based on (Buckley et al., 2001), the geometric mean of fuzzy comparison values for each criterion is computed using Eq. (5.8). In this equation, $\widetilde{r_i}$ denotes triangular values.

$$\widetilde{r_i} = \left(\prod_{j=1}^{n} \widetilde{y_{iJ}} \right)^{1/n} \qquad i = 1,2,\dots n \tag{5.8}$$

Step 5: Eq. (5.9), which utilizes $\otimes$ (circuit times) and $\oplus$ (circuit plus) operators, is employed to determine the fuzzy weights of each criterion. The process begins by computing the vector summation of each $\widetilde{r_i}$, which represents the transformed values of the original importance rankings for the criteria. Then, the power of (-1) is applied to the summation vector, which adjusts the weights or priorities assigned to the criteria by reflecting their reciprocal scales of importance. Next, the FTNs are replaced to arrange them in increasing order. This step ensures that the fuzzy weights are appropriately arranged and aligned for further analysis and decision-making. Finally, the fuzzy weight of the criterion i ($\widetilde{q_i}$), is obtained by multiplying each $\widetilde{r_i}$ by this reversed vector. These steps collectively contribute to determining the fuzzy weights and ensuring a fluent and systematic approach to the process.

$$\tilde{q}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \dots \oplus \tilde{r}_n)^{-1} = (s_{q_I}, t_{q_i}, u_{q_i}) \tag{5.9}$$

Step 6: In order to defuzzification of the FTNs $\tilde{q}_i$, the centre of area (Coates & Arayici, 2012) method proposed by Chou and Chang (2008) is used. This method involves applying Eq. (5.10) to determine the defuzzification of values.

$$A_i = \frac{s_{q_i} + t_{q_i} + u_{q_i}}{3} \tag{5.10}$$

Step 7: The non-fuzzy number A_i is required to be normalized by applying Eq. (5.12) in order to bring it into a normalized form.

$$N_i = \frac{A_i}{\sum_{i=1}^{n} A_i} \tag{5.11}$$

Overall, the methodology consists of seven sequential steps to determine the normalised weights of criteria and alternatives. These steps involve converting weights into fuzzy values, creating pairwise comparison matrices for each perspective, using a nine-point scale for evaluation, normalising the matrix values, calculating the geometric mean of fuzzy comparison values for each criterion, normalising the criterion weights, and computing the scores for each alternative. The alternative with the highest value is then recommended to the decision-maker. The practical application of this methodology is demonstrated through a case study conducted on a hypothetical one-story school building layout to examine and optimise egress locations in a school building, highlighting its relevance and effectiveness in real-world decision-making scenarios. Furthermore, as the decision-making process involves inherent fuzziness and uncertainties, applying F-AHP can provide a more realistic approach to evaluating and prioritising these criteria, enabling a comprehensive analysis of the egress location problem.

5.3. Numerical Implementation

5.3.1. Case Study

The school building layout comprised 6 possible egress locations, 12 classrooms, 2 WC (water closet) facilities, 2 laboratories, and 1 food and leisure area, following the standard configuration commonly found in Australian schools. The layout is modelled using Revit as the BIM platform. Figure 5.4 shows the architectural view of the building and the structural layout with the 6 possible egress locations. Six potential egress locations were initially identified after carefully analysing the building's layout and structural features. These six locations were considered based on accessibility, proximity to high-occupancy areas, and their ability to facilitate swift evacuation during emergencies. Subsequently, an evaluation was carried out to narrow the options to three final egress locations. This selection was made through an assessment of each location's advantages and limitations. Criteria such as capacity, ease of access, and potential obstructions were considered to determine the 3 ideal egress locations.

Furthermore, these three selected egress locations then served as the foundation for the overall layout design, which is critical to ensuring the safety and efficient evacuation of occupants during emergencies. By strategically positioning these egress points within the building, the evacuation plan maximises the chances of a quick and orderly evacuation, minimising potential bottlenecks and congestion.

The case study conducted a numerical computation of data, systematically ranking and comparing various egress alternatives. The model output was then used to rank the final egress layout design alternatives. In addition, the case study functioned as a rigorous testing ground to evaluate the developed system's consistency and sensitivity. Multiple scenarios were created, and the results were thoroughly analysed to examine the model's robustness and reliability. This process effectively validated the theoretical framework's accuracy and demonstrated its ability to address specific needs and challenges. The case study carefully considered and addressed various limitations and constraints. The model was fine-tuned to account for real-world complexities, ensuring its practical relevance and reliability.

All data calculations for the study were performed using a personal computer with Windows 10, equipped with an 8th Generation Intel Core i7 processor and 16GB of RAM. Excel and a Python-based F-AHP tool were utilised for the analysis and evaluation process.

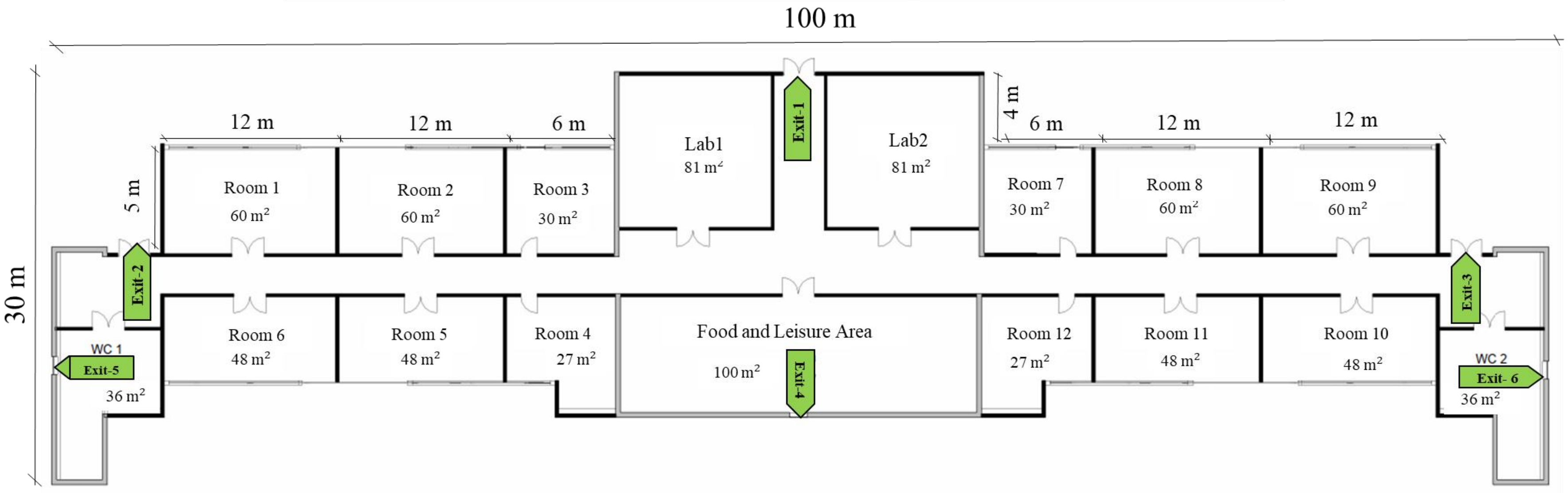


Figure 5.4: The school building and structural layout with 6 possible egress location.

5.3.2. Determining Weights of Criteria

The step-by-step evaluation process involves analysing each egress location alternative against the identified criteria. Each criterion is assigned a weight based on a comprehensive process that involves insights from a school-specific model, analysis of relevant academic papers, consideration of established industry standards, and a thorough review of existing research. These collective insights and data were then used to derive the specific weight assigned to each criterion in the decision-making framework. The evaluation process then objectively compares the alternatives, considering their capacity, ease of access, and potential obstructions. By integrating multiple reliable sources, the evaluation process ensures credibility and provides a basis for decision-making. The measurement process involved both direct measurements and careful approximations, balancing practicality, and ease of implementation to select the optimal egress location for the school building. Table 5.4 provides a list of evaluation criteria along with their corresponding codes.

Table 5.4: Evaluation Criteria and Codes.

Criteria	Sub-Criteria	Code	Influence	Quantified Criteria Sources
Technical	Width and height of the egresses (m)	TEC1	Beneficial criteria	(Board, 2012, 2015)
	Door arrangement (m)	TEC2	Beneficial criteria	(Board, 2012, 2015)
	Proper lighting in egress area (lux)	TEC3	Beneficial criteria	(Board, 2004, 2021)
Economical	Material Cost ($)	ECO1	Cost criteria	(Plus, 2023), (Doorsets, 2023)
	Construction Cost ($)	ECO2	Cost criteria	(Plus, 2023), (Doorsets, 2023)
	Maintenance Cost ($/y)	ECO3	Cost criteria	(Plus, 2023), (Doorsets, 2023)
Social	Width of corridors to access egress area (m)	SOC1	Beneficial criteria	Figure 5.4
	Width of corridors to access egress area (m)	SOC2	Beneficial criteria	Figure 5.4
	Number of doors to access egress route	SOC3	Beneficial criteria	Figure 5.4

5.3.3. Calculation of Weightage for Each Criteria

The weights were transformed into fuzzy values for each criterion to incorporate fuzziness into the weight assignment process, according to Table 5.5. The weightage for each criterion was determined by drawing insights from relevant literature, ensuring a well-informed and reliable weight assignment process. Pairwise comparison matrices were then created for each user to determine the relative priorities of criteria based on their assessments, as depicted in Table 5.6. A nine-point scale was employed to assess the significance of each criterion compared to others. Subsequently, each cell in the matrix was divided by the sum of its corresponding column to obtain the normalized value. All values were rounded to two decimal places for clarity and ease of interpretation.

Table 5.5: Importance index and fuzzy numbers (adapted from Alam and Hammad (2023)).

Definition of Importance	Crisp Number	Fuzzy Number (l, m, h)
Extremely more important	9	8, 9, 10
Very strongly more important	7	6, 7, 8
Strongly more important	5	4, 5, 6
Moderately more important	3	2, 3, 4
Equally important	1	1, 1, 1
Moderately less important	1/3	1/4, 1/3, 1/2
Strongly less important	1/5	1/6, 1/5, 1/4
Very strongly less important	1/7	1/8, 1/7, 1/6
Extremely less important	1/9	1/10, 1/9, 1/8

Ensuring acceptable consistency values while evaluating multiple criteria can be complex, often requiring users to engage in several iterations to achieve consistency. This iterative process involves careful review and adjustment of pairwise comparisons until an acceptable level of consistency is achieved. In this case, with $n = 9$, $\lambda_{max} = 9.70$, $CI = 0.06$, $RI = 1.45$ and $CR = 0.07$, the resulting consistency ratio fell below the threshold of 0.1 (Saaty, 1990), indicating a satisfactory level of consistency.

Table 5.6: Pairwise Comparison matrix for criteria.

Criteria	TEC1	TEC2	TEC3	ECO1	ECO2	ECO3	SOC1	SOC2	SOC3
TEC1	(1,1,1)	(2,3,4)	(4,5,6)	(1/4,1/3,1/2)	(1/6,1/5,1/4)	(2,3,4)	(2,3,4)	(2,3,4)	(2,3,4)
TEC2	(1/4,1/3,1/2)	(1,1,1)	(2,3,4)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(2,3,4)	(2,3,4)	(2,3,4)	(2,3,4)
TEC3	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1,1,1)	(1/6,1/5,1/4)	(1/10,1/9,1/8)	(1/4,1/3,1/2)	(1,1,1)	(1,1,1)	(1,1,1)
ECO1	(2,3,4)	(2,3,4)	(4,5,6)	(1,1,1)	(1/4,1/3,1/2)	(2,3,4)	(2,3,4)	(4,5,6)	(8,9,10)
ECO2	(4,5,6)	(2,3,4)	(8,9,10)	(2,3,4)	(1,1,1)	(2,3,4)	(4,5,6)	(6,7,8)	(8,9,10)
ECO3	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(2,3,4)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1,1,1)	(2,3,4)	(2,3,4)	(4,5,6)
SOC1	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1,1,1)	(1/4,1/3,1/2)	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1,1,1)	(2,3,4)	(1,1,1)
SOC2	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1,1,1)	(1/6,1/5,1/4)	(1/8,1/7,1/6)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1,1,1)	(1,1,1)
SOC3	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1,1,1)	(1/10,1/9,1/8)	(1/10,1/9,1/8)	(1/6,1/5,1/4)	(1,1,1)	(1,1,1)	(1,1,1)

After completing the initial three steps in the methodology, the fourth step entails calculating the geometric mean of fuzzy comparison values for each criterion, as outlined in Eq. (5.9). Table 5.7 displays the geometric means of fuzzy comparison values for all criteria, including their total values and their respective reverse values. The final row of the table presents the rearranged fuzzy triangular numbers, ensuring an ascending order.

Table 5.7: Geometric means of fuzzy comparison values.

Criteria	$\tilde{r}_i$		
TEC1	0.478	0.614	0.83
TEC2	0.583	0.783	1.08
TEC3	2.01	2.33	2.617
ECO1	0.303	0.38	0.5
ECO2	0.201	0.24	0.301
ECO3	0.702	0.945	1.26
SOC1	1.361	1.725	2.092
SOC2	1.937	2.419	2.79
SOC3	2.16	2.487	2.77
Total	9.71	11.87	14.2
Reverse (power of -1)	0.10	0.08	0.07
Increasing Order	0.07	0.08	0.10

In the fifth step of the process, the fuzzy weight of the criterion, represented by $\tilde{q}_i$ is determined using Eq. (5.10). The resulting fuzzy weight values are shown in Table 5.8.

Table 5.8: Fuzzy weights of each criterion.

Criteria		$\widetilde{q_i}$	
TEC1	0.077	0.129	0.213
TEC2	0.059	0.101	0.175
TEC3	0.024	0.034	0.051
ECO1	0.128	0.209	0.329
ECO2	0.212	0.331	0.506
ECO3	0.051	0.084	0.145
SOC1	0.031	0.046	0.075
SOC2	0.022	0.033	0.053
SOC3	0.023	0.032	0.047

In the sixth step of the methodology, the relative non-fuzzy weight A_i of each criterion was computed by averaging the fuzzy numbers associated with each criterion. Subsequently, in the seventh step, the normalized weights of each criterion were computed using the obtained non-fuzzy A_i values. The resulting normalized weight are presented in Table 5.9.

Table 5.9: Fuzzy weights of each criterion.

Criteria	A_i	N_i
TEC1	0.14	0.13
TEC2	0.112	0.104
TEC3	0.036	0.034
ECO1	0.222	0.207
ECO2	0.35	0.326
ECO3	0.093	0.087
SOC1	0.05	0.047
SOC2	0.036	0.033
SOC3	0.034	0.032

5.3.4. Calculation of Alternatives Weightage in Relation to Criteria

Once the normalized non-fuzzy relative weights for criteria have been determined, the same methodology is applied to calculate the corresponding values for alternatives, specifically the egress options. In this analysis, each egress option is included in the pairwise comparison process concerning each criterion, allowing for calculating their relative weights and inclusion in the overall assessment. This process is repeated for all nine criteria to evaluate the alternatives comprehensively. Following the explanations provided in this section, the normalized non-fuzzy weights for each alternative to each criterion are calculated and presented in Table 5.10.

Table 5.10: Normalized non-fuzzy weights of each alternative for each criterion.

Alternative	***Criteria***								
	TEC1	**TEC2**	**TEC3**	**ECO1**	**ECO2**	**ECO3**	**SOC1**	**SOC2**	**SOC3**
EGRESS 1	0.167	0.167	0.257	0.167	0.16	0.155	0.044	0.541	0.291
EGRESS 2	0.167	0.167	0.257	0.167	0.335	0.339	0.23	0.136	0.291
EGRESS 3	0.167	0.167	0.257	0.167	0. 334	0.339	0.23	0.136	0.291
EGRESS 4	0.167	0.167	0.09	0.167	0.04	0.03	0.23	0. 136	0.042
EGRESS 5	0.167	0.167	0.07	0.167	0.045	0.069	0.23	0.026	0.042
EGRESS 6	0.167	0.167	0.07	0.167	0.044	0.069	0.23	0.026	0.042

5.4. Results and Analysis

By employing the F-AHP methodology and gathering input from nine criteria, the comparative significance of each criterion was determined, enabling the prioritization of criteria in the decision-making process. This section provides an overview of the results, highlighting key findings and their implications. The calculated weightage was employed to rank both the criteria and alternatives. The consistency ratio, used to assess the reliability of the results, consistently remained below 10% across all cases. Table 5.11 presents the weightage and ranking of criteria, while Table 5.12 highlights the weightage and ranking of alternatives. As mentioned earlier, the term alternatives in this study refers to potential locations for egresses, which are crucial for ensuring safety in emergencies.

Table 5.11: Ranking results for each criterion according to weight.

Criteria		**Weight**	**Rank**
Technical	TEC1	0.13	3
	TEC2	0.104	4
	TEC3	0.034	7
Economic	ECO1	0.207	2
	ECO2	0.326	1
	ECO3	0.087	5
Social	SOC1	0.047	6
	SOC2	0.032	8
	SOC3	0.033	9
	$\sum$	1	

The weights assigned to each criterion in the evaluation provide insights into their respective contributions to the effectiveness of the evacuation process. Among the technical criteria, TEC1 stands out with a weight of 0.13, signifying its notable consideration in ensuring sufficient space for occupants to exit the building safely. Adequate width and height of the egresses contribute to smoother movement, preventing congestion and facilitating a faster and more orderly evacuation. TEC2 follows closely behind with a weight of 0.104, indicating its substantial impact on door arrangement and its influence on the flow of occupants. TEC3 carries a more modest weight of 0.034, highlighting its relatively lower but still significant influence, particularly in emphasizing the importance of proper lighting in the egress area for enhanced visibility and safe navigation during an evacuation. ECO2 takes the spotlight with the highest weight of 0.326 on the economic front, solidifying its position as the most influential criterion in shaping the evaluation outcomes. Its weight underscores its critical role in cost-effective decision-making while maintaining safety. ECO1 emerges as another prominent player with a weight of 0.207, emphasizing its significance in considering the material cost. ECO3 displays a respectable weight of 0.087, positioning itself as a relevant consideration within the economic criteria by considering maintenance cost, ensuring long-term effectiveness and sustainability. Regarding the social criteria, SOC1 demonstrates a moderate level of importance with a weight of 0.047, contributing meaningfully to the decision-making process by highlighting the importance of corridor width in accessing the egress area, enabling smooth movement and efficient evacuation. SOC2 and SOC3 both have relatively lower weights of 0.032 and 0.033, respectively, but still contribute to the overall evaluation and warrant attention in decision-making. SOC2 considers the width of corridors for efficient access, while SOC3 focuses on the number of doors in the egress route, ensuring adequate access for an effective evacuation. Together, these weights reflect a comprehensive assessment of the technical, economic, and social aspects, contributing to the overall effectiveness of the evacuation process.

The findings highlight the paramount importance of economic criteria in the decision-making process within the context of this study. This indicates that economic considerations play a critical role in determining the effectiveness and feasibility of the evaluated alternatives. Therefore, decision-makers should allocate appropriate attention and resources to address the economic considerations, as they are essential in determining the overall effectiveness and success of the decision. Meanwhile, the technical criteria hold moderate importance, still carry substantial weight, and should be noticed. For this reason, decision-makers should ensure that the technical aspects are adequately addressed to meet the required standards and specifications. Although relatively less influential than the economic and technical criteria, the social criteria still contribute meaningfully to the evaluation process. They all play essential roles in considering the social implications and impacts of the decision to assure that the chosen alternative aligns with social values, community well-being, and stakeholder satisfaction.

Table 5.12: Ranking results for each alternative according to each criterion.

Criteria	***Rank of Alternatives with Respect to Related Criterion***					
	EGRESS 1	**EGRESS 2**	**EGRESS 3**	**EGRESS 4**	**EGRESS 5**	**EGRESS 6**
TEC1	0.167	0.167	0.167	0.167	0.167	0.167
TEC2	0.167	0.167	0.167	0.167	0.167	0.167
TEC3	0.257	0.257	0.257	0.09	0.07	0.07
ECO1	0.167	0.167	0.167	0.167	0.167	0.167
ECO2	0.16	0.335	0. 334	0.04	0.045	0.044
ECO3	0.155	0.339	0.339	0.03	0.069	0.069
SOC1	0.044	0.23	0.23	0.23	0.23	0.035
SOC2	0.541	0.136	0.136	0. 136	0.026	0.026
SOC3	0.291	0.291	0.291	0.042	0.042	0.042
∑	**1.949**	**2.089**	**2.088**	**0.933**	**0.983**	**0.982**
Rank	***1***	***2***	***3***	***6***	***4***	***5***

The significance of these findings becomes apparent when considering the implications of the criteria weightings on the decision-making process. In the technical criteria, TEC1 and TEC2 share equal weightings of 0.167, signifying a balanced approach. However, TEC3 diverges by assigning a higher weight of 0.257 to Egress 1, Egress 2, and Egress 3, indicating the importance of specific technical requirements or performance metrics tied to these egress options. Regarding the economic criteria, while ECO1 treats all alternatives equally with a weight of 0.167, ECO2 and ECO3 show variations, with Egress 2 and Egress 3 receiving higher weights of 0.335 and 0.334, respectively. This variation suggests that unique economic considerations or cost-benefit analyses favour these egress options. In the social criteria, SOC1 places greater weight on Egress 4 as 0.23, reflecting its significance in social and community-related aspects. Conversely, SOC2 assigns the highest weight of 0.541 to Egress 1, highlighting its importance in the overall assessment. SOC3 adopts a balanced approach with a weight of 0.291 for Egress 1, Egress 2, and Egress 3, along with lower weights of 0.042 for Egress 4, Egress 5, and Egress 6, driven by the interplay of various social considerations. These nuanced weightings emphasize the intricacy of the evaluation process, where specific technical, economic, and social factors guide the prioritization of egress alternatives.

Moreover, examining the details reveals distinct patterns and variations in the rankings, providing insights into the significance attributed to each alternative. This analysis helps in understanding the relative importance and performance of the alternatives, aiding in the decision-making process. Egress 1 stands out as a strong contender due to its consistently high rankings across multiple criteria. It receives the highest weight in the social criteria (SOC2) and significant weights in the technical (TEC1, TEC2) and economic (ECO2) criteria. This indicates its importance and effectiveness as an egress location. While Egress 2 emerges as another favourable option. It garners significant weight in the technical (TEC1, TEC2) and economic (ECO2) criteria, highlighting its relevance and suitability in those aspects. Egress 3 demonstrates competitive performance, securing noteworthy weights in the technical (TEC1, TEC2) and economic (ECO2, ECO3) criteria. Its consistent presence in the upper rankings suggests its viability as a vital egress location.

Consequently, considering these factors, Egress 1, Egress 2, and Egress 3 demonstrate robust performance across the evaluated criteria, indicating their suitability and importance as potential options. Their consistent rankings and significant weights across multiple criteria position them as suitable choices that meet requirements for safety, efficiency, and economic considerations. Figure 5.5 presents the three optimal egress locations based on the results obtained from the F-AHP analysis.

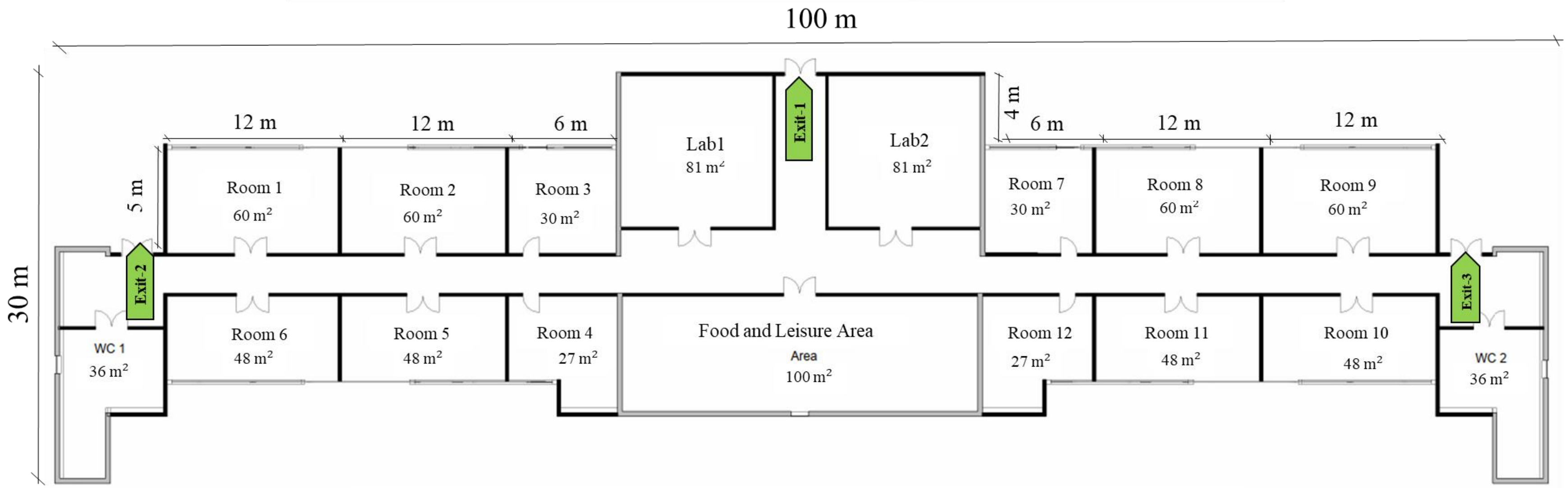


Figure 5.5: The school building and layout with optimal 3 egress location.

5.5. Discussion

The evaluation process results provide valuable insights and practical implications for selecting egress locations in buildings, encompassing not only technical considerations but also economic and social factors. Economic criteria emerged as the most influential, with a weightage of 61.9%, emphasising the significance of cost-effectiveness in decision-making. Technical criteria held a weightage of 26.8%, underscoring the importance of factors such as egress width and door arrangement. Social criteria contributed 11.3% to the evaluation process, emphasising the need to consider smooth movement and accessibility. Accordingly, the optimal egress locations, namely Egress 1, Egress 2, and Egress 3, aligned exceptionally well with economic, technical, and social considerations. These locations offer cost-efficient solutions without compromising safety, as they ensure sufficient space and enable smooth occupant flow during evacuations. Moreover, they prioritise the safety and well-being of building occupants, providing accessible and secure evacuation routes in emergency scenarios. By excelling across all these critical criteria, Egress 1, Egress 2, and Egress 3 stand out as the most suitable choices for effective evacuation strategies. Considering these multiple dimensions, it is possible to identify optimal egress locations that effectively mitigate congestion, enhance efficiency, and address broader socioeconomic considerations.

From a technical standpoint, factors such as the width and height of the egresses (TEC1) and door arrangement (TEC2) play a crucial role in ensuring sufficient space and smooth occupant flow during evacuations (Bukowski, 2009; Kinateder et al., 2021). Adequate lighting in the egress area (TEC3) also enhances visibility and aids safe navigation during emergencies (Cosma, 2014; Pollard & Markos, 2009). Considering these technical criteria allows for the avoidance of congestion and facilitates faster and more efficient evacuations (Center, 2021), (Ran et al., 2014). Likewise, economic considerations are equally important in the decision-making process. Evaluating material cost (ECO1), construction cost (ECO2), and maintenance cost (ECO3) helps achieve cost-effective decisions without compromising safety (Averill et al., 2009; Marzouk & Mohamed, 2019). In the context of social criteria, the distance between potential egress locations (SOC1), the width of corridors (SOC2), and the number of doors in the egress route (SOC3) play crucial roles in establishing accessible and secure evacuation routes. SOC1 significantly influences evacuation times and safety, making minimising this distance imperative for ensuring prompt and efficient evacuation, especially during emergencies (Chu et al., 2014; Larsson et al., 2021). This criterion directly impacts the social aspect of safety and well-being. Meanwhile, SOC2 emerges as a critical factor determining the flow of people during evacuation. A sufficient width fosters smoother movement, reduces congestion, and contributes to individuals' overall safety and comfort (Grimaz et al., 2014; Tian et al., 2012). Lastly, SOC3 directly influences the ease and speed of evacuation. Well-placed doors strategically enhance movement efficiency, improve accessibility, and contribute to overall safety (Pluchino et al., 2013; Camillen et al., 2009). Despite their technical nature, these criteria directly impact social considerations related to evacuation efficiency and effectiveness. While inherently technical, this criterion directly and profoundly influences social considerations, ensuring the efficiency and effectiveness of the evacuation process. These social factors contribute to the overall effectiveness of evacuations by enabling smooth movement and providing sufficient exit points for building occupants (Bernardini et al., 2016; Tubbs & Meacham, 2007). Integrating these economic and social aspects with the technical factors discussed earlier can achieve a complete approach to egress location selection. Therefore, planners should prioritise balancing technical requirements, economic considerations, and social factors when designing evacuation plans. By integrating these critical aspects, a comprehensive approach to egress location selection can be achieved, ensuring the overall effectiveness and practicality of the evacuation strategies. The insights gained from this analysis highlight the importance of balancing these criteria to select egress locations.

The analysis of data and the resulting findings highlight the significant influence of user inputs on the model's decision-making process. The system generates decisions by calculating the weightage of criteria and considering the preferences assigned to different alternatives based on user-provided information. To validate this approach, a comparison was made with previous research utilising F-AHP in evacuation planning (Boonmee et al., 2017; Ping et al., 2018; Trivedi & Singh, 2017). In those studies, F-AHP was employed to assign weightage, prioritise criteria, and rank alternatives. The results demonstrated higher accuracy in capturing stakeholders' preferences and effectively integrating them into decisions, resulting in more distinguished rankings of alternatives. Moreover, this framework exhibited enhanced flexibility in handling uncertainties, enabling better decision-making in emergency evacuation (Ping et al., 2018). Critical criteria overlooked in some previous studies were identified and included (Bukowski & Tubbs, 2016), leading to a more comprehensive assessment of egress location alternatives.

Likewise, the relevance of these findings extends beyond the specific case study conducted on a one-storey school building layout. It can be adapted and applied to various building designs, providing valuable insights for enhancing evacuation strategies in different contexts. This adaptability strengthens the framework's applicability in practical scenarios, contributing to evacuation planning. In addition, this study adopted a comparable approach by integrating the opinions of all project stakeholders to facilitate the selection of the most sustainable decision. By involving diverse perspectives and expertise, the decision-making process becomes more robust and inclusive, ensuring that evacuation plans align with the needs and preferences of all stakeholders (Doyle et al., 2014).

However, despite its advantages, the framework has limitations over human behaviour variability and psychological and cultural factors during emergencies which might need to be fully captured by existing models. Multi-stakeholder collaboration is a critical consideration, prompting the exploration of advanced simulation models that simulate joint response operations among various entities, ensuring coordinated and effective emergency response. Besides, the F-AHP methodology employed in this study has certain limitations when evaluating egress locations. Firstly, the subjectivity inherent in the F-AHP method, particularly in determining the linguistic variables and assigning weights to criteria, can introduce biases and variations in the results. The interpretation of linguistic terms may vary among decision-makers, leading to inconsistent outcomes. Therefore, ensuring clear communication and consensus among stakeholders is essential to mitigate subjectivity. Secondly, the F-AHP methodology relies heavily on data availability and quality. The accuracy and reliability of the evaluation heavily depend on the availability of accurate data for each criterion. Indeed, obtaining comprehensive and reliable data for all the criteria, especially in egress location selection, can be challenging. Lastly, the computation complexity of the F-AHP methodology can be a limitation. Calculating the pairwise comparisons and performing the fuzzy aggregation process can be time-consuming and require substantial computational resources. Large-scale evaluations with numerous criteria and alternatives may need to be revised regarding computational efficiency.

In conclusion, this study contributes both theoretically and practically to emergency decision-making. The multidimensional considerations encompassed in the decision-making process provide practical guidance for designing effective evacuation plans that prioritise the well-being of occupants and minimise potential risks during emergencies. Applying the F-AHP methodology, the comprehensive evaluation of criteria, and identifying optimal egress locations offer valuable insights for stakeholders and decision-makers.

5.6. Concluding Remarks

In conclusion, this chapter highlights the pivotal role of egress location selection in safeguarding individuals' safety during building emergencies. The innovative decision-making framework proposed in this study, integrating social, economic, and technical dimensions through the F-AHP, is a comprehensive solution for identifying optimal egress points. The framework's practical applicability has been demonstrated through a case study centred on a one-storey school building layout.

The research findings highlight the notable significance of economic considerations, which account for 61.9% of the cumulative weight in determining the optimal location of egresses within the evacuation planning process. Technical factors trail at 26.8%, while social aspects contribute 11.3% to the overall decision-making process governing egress placement. By addressing this gap in evaluating and prioritizing parameters that impact egress location choices, this study contributes significantly to evacuation planning. The framework's comprehensive nature facilitates well-informed decision-making and extends valuable insights into the realm of uncertain expert opinions.

Significantly, this research's contributions provide practical guidance for decision-makers who navigate the intricate landscape of egress placement and evacuation strategy, especially in light of the inherent uncertainty in expert opinions. By offering actionable insights, the research aids in crafting evacuation plans that prioritise the well-being of occupants while mitigating potential risks. Various stakeholders, from building proprietors to emergency management authorities, can benefit from incorporating social, economic, and technical considerations into their decision-making processes. This study enhances their decision-making toolkit and advances community resilience by promoting effective evacuation plan development.

Future research endeavours should expand the criteria spectrum to encompass factors such as occupant behaviour, spatial layout, environmental dynamics, and emergency response tactics. By augmenting the scope of considerations, subsequent studies can refine egress location selection to address an even more comprehensive array of influencing variables. In doing so, the evolution of evacuation planning stands to enhance its efficacy and adaptability, fortifying our collective response to emergent challenges.

Chapter 6

A Stochastic Bilevel Programming Problem for Safe Evacuation and Protection of Public Buildings

6.1. Overview

This chapter provides an overview of a proposed stochastic BP model, which complements the discussions in Chapters 4 and 5 by focusing on determining suitable egress locations for enhancing the protection of critical facilities against potential attacks. The chapter introduces the global significance of securing key buildings, particularly in the face of disasters and intentional threats. Indeed, securing key buildings from potential threats has gained global importance for governments in recent years (Bish et al., 2014) and one of the most critical considerations in this regard is the safety of egresses in buildings (Fahy & Proulx, 2001). This chapter explicitly emphasises fortified egresses and the need for effective service systems to plan and implement protection strategies for various public facilities. These buildings are particularly vulnerable to attacks because they are often crowded with people, making it difficult to quickly and safely evacuate in an emergency (Kuligowski et al., 2005). Therefore, the importance of finding reliable service systems for planning and protection strategies for public facilities has been emphasised and is critical (Lochhead & Hedley, 2018). Due to the potential disturbance to both government and public interests in the event of the destruction of these complexes (Kuligowski et al., 2005).

Furthermore, the chapter introduces the concept of stochastic BP modelling as a practical approach to address complex emergency management and security planning challenges. The model presents a complete methodology to shield various buildings from possible attacks by encompassing both egress fortifications and evacuation strategies. It emphasises the inclusion of both DA perspectives in the proposed model. A numerical illustration highlights the model's effectiveness, showcasing its potential for real-world applications in fortifying egress points and refining evacuation planning. This chapter provides a robust shield for public buildings and establishments, ensuring the safety of occupants even in the face of potential threats. Further, the chapter comprises material from papers currently prepared for submission. It is presented here as an integral part and contributes to the overall thesis.

6.2. Problem Definition

This study focuses on analysing the strategic interaction between a defender and an attacker in the context of egress fortification in buildings. Egresses play a vital role in ensuring the safety and well-being of individuals during emergencies. It refers to implementing effective measures and strategies to facilitate the safe and efficient evacuation of people from buildings during natural disasters and security threats. Indeed, the significance of egress protection cannot be overstated, as it directly impacts the ability of occupants to exit a building swiftly and safely, potentially saving lives. Therefore, the fortification of egresses in buildings, such as schools, office buildings, and other public facilities, from potential attacks is a critical concern. The structure of the stochastic BP model is depicted in Figure 6.1.

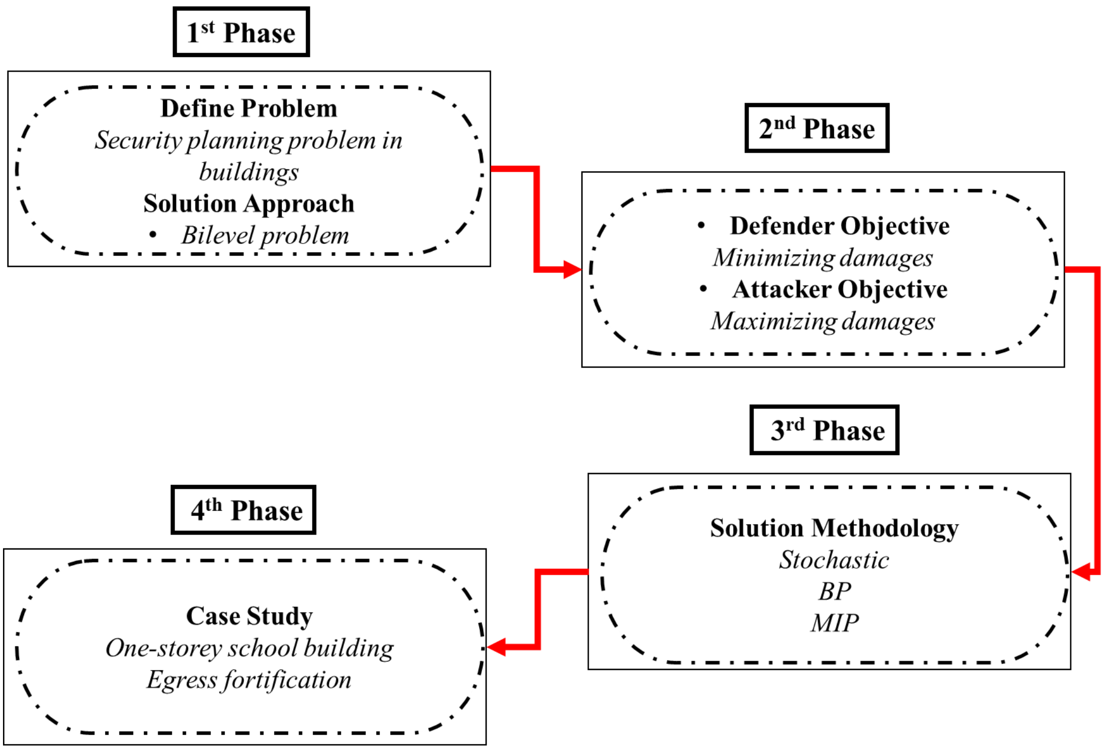


Figure 6.1: The flowchart of the stages involved in this research.

The developed model in this study addresses the problem of egress fortification by considering the dynamics between the defender and the attacker, as seen in Figure 6.2. By employing a sequential DA game model, it investigates the dynamics and decision-making processes involved in this two-player game scenario. The defender's objective is to minimise damages and potential fatalities, while the attacker seeks to maximise the attack's impact. The primary goal of the defender is to ensure the safe evacuation of occupants through egresses. In a scenario where a building is under attack, the planner, acting as the defender, must strategically fortify the egresses within the constraints of a limited budget to effectively safeguard lives. This involves strengthening and reinforcing the structures and systems to prevent easy damage or obstruction during emergency evacuations.

Furthermore, in this dynamic DA problem, the timing of decisions and realizations plays a crucial role. A critical aspect involves understanding the intricate connection between paths $r_w - s_w$ and the egresses that require protection. The selection of paths holds the key to determining which egresses need fortification. The attacker's route across the network influences the egresses chosen for protection. The study assumes that the attacker possesses knowledge of fortified egress locations and strategically selects a path to avoid them. This additional layer of complexity adds to the scenario's realism, enriching the decision-making process of securing specific egress points along potential attacker routes. The sequence of actions starts with the defender fortifying the egresses. Subsequently, the attacker's path choice comes into play as a random origin-destination pair is revealed. The attacker then strategically selects a path to maximise the probability of avoiding the fortified egresses. Notably, the attacker's path selection considers their awareness of the fortified egress locations and ability to navigate the network design. The attacker is also assumed to choose a maximum-reliability path at the lower level.

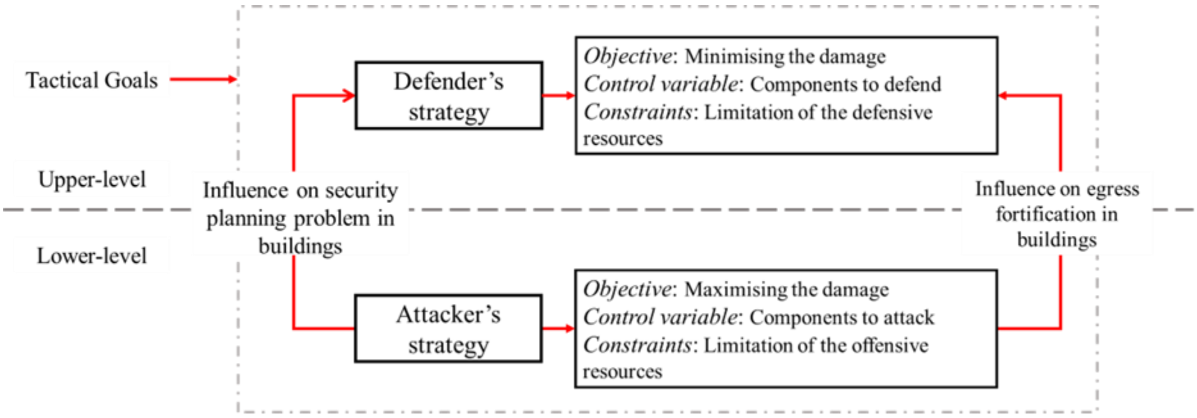


Figure 6.2: Structure of DA model.

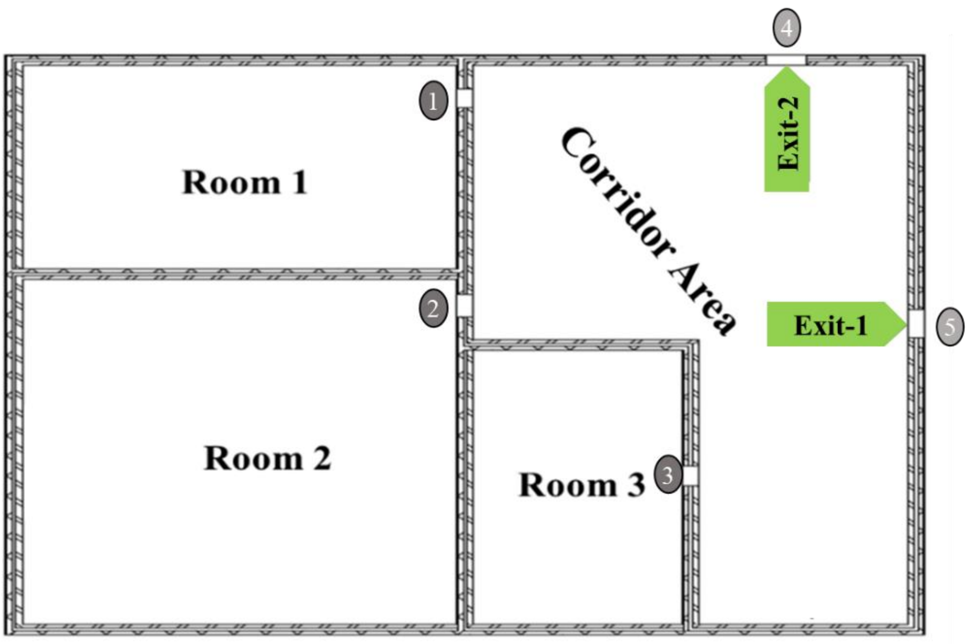
Moreover, the planner often needs more precise information regarding the attacker's capabilities in a realistic scenario. This means that the defensive strategy must be developed based on uncertain information about the attacker, even though the attacker is aware of their resources. The uncertainty surrounding the attacker is captured by modelling it as a random distribution over a set of potential scenarios. This study considers probability values between 0 and 1, following a probability distribution, to capture the uncertainty surrounding the attacker and the likelihood of different attack scenarios occurring. Each attack scenario is assigned a specific probability, representing the relative likelihood of that scenario. By incorporating these probability values, the model accounts for the variability and uncertainty associated with the attacker's behaviour, allowing for a more comprehensive analysis of the defender's decision-making process. The potential attack scenarios and their associated probabilities can fluctuate over time depending on factors such as the attackers' activity patterns, weather conditions, and other variables.

Consequently, constructing a DA model is necessary for each scenario, wherein each scenario corresponds to the attacker's distinct actions. Nevertheless, accurately estimating this uncertainty falls beyond the study's current scope. Anticipations suggest that future evacuation planners and managers may enhance their ability to predict potential attacks. Notably, the numerical illustration of the model is founded on a hypothetical school featuring optimised egress locations. The school's layout and network representation can be observed in Figure 6.3.

The problem is formulated as a stochastic mixed-integer bilevel programming approach using a 'min-max' structure (Pan et al., 2003). The upper-level problem, which represents the defender's decision, is formulated as a minimisation problem where the defender aims to minimise the anticipated value of the attack probability, represented by the weighted sum of all possible origin-destination pairs. This is expose to a budget constraint on the cost of fortified egresses and a constraint that ensures that at least one egress is fortified. Meanwhile, the lower-level problem, representing the attacker's decision, is formulated as a maximization problem where the attacker aims to maximise the damages after at least one of the egresses is destroyed.

The problem is subject to constraints that ensure the attacker can only navigate through one egress, the number of egresses damaged is equal to a given number, and the flow conservation is maintained. By limiting the attacker's ability to navigate through only one egress and specifying the number of egresses to be damaged, the model seeks to explore the implications of strategic decision-making within defined parameters. Besides, maintaining flow conservation ensures that the network's overall integrity is preserved. It is a constraint aimed at ensuring that the total flow of movement or activities within the network of egresses aligns with the principles of mass conservation. This constraint helps ensure that the strategic decisions made by the defender and the attacker do not disrupt the overall flow of individuals or activities within the building's egress system. It is important to note that the scenarios and models presented in this study do not encompass the movement of classes within the building. While our analysis focuses on egress fortification and the strategic interaction between the defender and attacker, the movement of classes, which represents the movement of groups of individuals, is not included in the current scope. This exclusion is a deliberate choice to simplify the model and concentrate on the dynamics of egress protection.

a)



b)

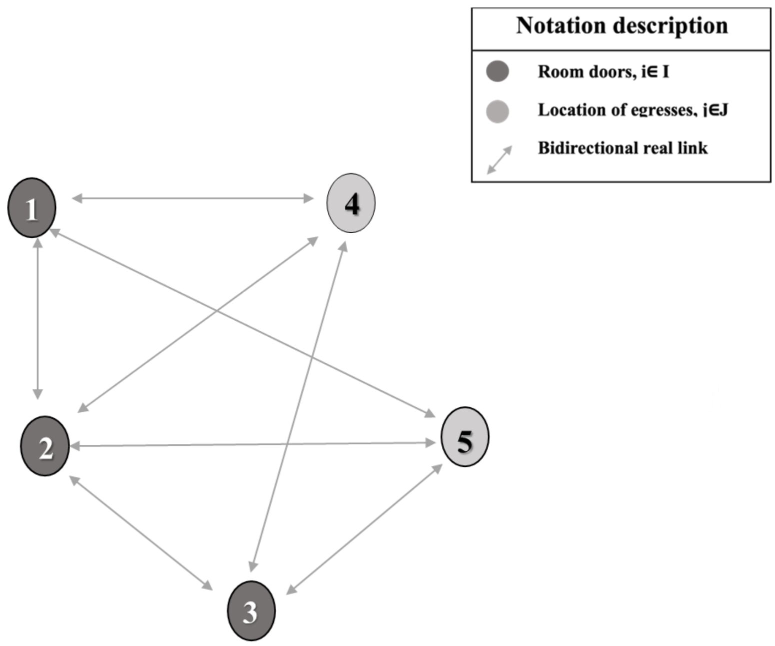


Figure 6.3: (a) Representation of school building layout; (b) the network representation of the building.

6.3. Mathematical Formulation

In the stochastic BP model, the directed network is indicated as G = (N, A), where N is the set of nodes, and A is the set of links. Sets and indices, decision variables, along with constants, are highlighted in Table 6.1, which is followed by a mathematical model.

Table 6.1: Nomenclature-II; the definition of the model notations.

Nomenclature-II

Set & Parameters	*Descriptions*
$G(N, A)$	Directed network with node set N and link set A
I	Set of room nodes, $i \in I$.
J	Set of egress nodes, $j \in J$.
$FS(i)$	Set of links leaving node, i.
$FR(i)$	Set of links entering node, i.
b	Total budget for fortified egresses.

c_{ij}	Cost of fortified egresses j on link $(i,j) \in AD$.
p_{ij}	Probability of an attacker damaging egress *j* when no egress is fortified.
q_{ij}	Probability of an attacker damaging egress *j* when an egress is fortified.
(r_w, s_w)	Realization of a random origin-destination pair.
$w \in \Omega$	Sample point and sample space.
p_w	Probability mass function.
a_{ij}	The number of people in the room i on link (i,j).

Variable	*Descriptions*
x_{ij}	Takes value 1 if an egress j is fortified on link (i,j) and 0 otherwise.
k_{ij}	Takes positive value only if attacker traverses link (i,j) and no egress is fortified on that arc.
u_{ij}	Takes positive value only if attacker traverses link (i,j) and an egress is fortified on that link.
d_{ij}	Takes value 1 if an egress j is damaged/destroyed on link (i,j) and 0 otherwise.
g_{ij}	Takes value 1 if room i assigned to egress *j* and 0 otherwise.

Based on a stochastic BP, the hierarchical structure of the interactions between the upper-level (defender) and the lower-level (attacker) is mathematically formulated as follows:

$$\min Z_{defender} = \sum_{x \epsilon X} p_w f\big(x, (r_w, s_w)\big) \qquad \forall\, w \,\epsilon\, \Omega \tag{6.1}$$

subject to

$$\sum_{(i,j) \epsilon A} c_{ij} x_{ij} \leq b \tag{6.2}$$

$$\sum_{(i,j)\epsilon A} x_{ij} = 1 \tag{6.3}$$

$$x_{ij} \epsilon \{0,1\} \qquad \forall\, i \,\epsilon\, I,\ \ \forall\, j \,\epsilon\, J \tag{6.4}$$

and where,

$$f\big(x,(r_w, s_w)\big) =$$

$$\max Z_{attacker} \sum_{(i,j)\epsilon A} a_{ij} g_{ij} \tag{6.5}$$

such that

$$\sum_{(i,j)\epsilon A} g_{ij} = 1 \tag{6.6}$$

$$\sum_{(i,j)\epsilon A} d_{ij} = 1 \tag{6.7}$$

$$\sum_{r_w, j\epsilon FS(r_w)} \big(k_{r_w j} + u_{r_w j}\big) = 1 \qquad \forall\, w \,\epsilon\, W \tag{6.8}$$

$$\sum_{(i,j)\epsilon FS(i)} \big(k_{ij} + u_{ij}\big) - \sum_{(i,j)\epsilon FR(i)} (\big(p_j k_{ji}\big) + \big(q_j u_{ij}\big)) = 0 \tag{6.9}$$

$$\sum_{(i,j)\epsilon A} a_i g_{ij} - \sum_{(i,j)\epsilon FR(i)} (\big(p_{js_w} k_{js_w}\big) + \big(q_{js_w} u_{js_w}\big)) = 0 \tag{6.10}$$

$$d_{ij} \le 1 - x_{ij} \qquad \forall\, i \,\epsilon\, I,\ \ \forall\, j \,\epsilon\, J \tag{6.11}$$

$$d_{ij} \,\epsilon\, \{0,1\} \qquad \forall\, i \,\epsilon\, I,\ \ \forall\, j \,\epsilon\, J \tag{6.12}$$

$$g_{ij} \,\epsilon\, \{0,1\} \qquad \forall\, i \,\epsilon\, I,\ \ \forall\, j \,\epsilon\, J \tag{6.13}$$

$$k_{ij} \ge 0 \qquad \forall\, i \,\epsilon\, \mathrm{I},\ \ \forall j \,\epsilon\, \mathrm{J} \tag{6.14}$$

$u_{ij} \geq 0 \qquad \forall\, i \in \mathrm{I},\ \forall j \in \mathrm{J} \qquad (6.15)$

In the context of a school building, the defender's objective Eq. (6.1) aims to minimise the expected attack probability for all possible origin-destination pairs (r_w, s_w). This objective calculates the average likelihood of the attacker evading fortified egresses across diverse scenarios. Here, $f\big(x, (r_w, s_w)\big)$ represents the conditional attack probability. The goal is strategically fortifying egresses using $x \in X$ to minimise potential damage from attacks. To ensure the responsible allocation of resources, Eq. (6.2) states that the total cost of fortifying the egresses should be the available budget b at most. This budget constraint prevents the defender from overspending on fortification measures. The left-hand side of the equation represents the total cost of fortification, while the right-hand side represents the available budget. The inequality sign indicates that the total cost should be less than or equal to the budget. Eq. (6.3) specifies that the defender must fortify at least one egress. This ensures a minimum level of egress fortification throughout the school building. Eq. (6.4) is a standard binary constraint applied to the decision variable x_{ij}.

On the other hand, the attacker's objective Eq. (6.5) is to maximise the destruction resulting from attacks on the egresses within the school building. It represents the optimal value indicating the conditional probability that an attacker avoids fortifying a specific egress link, given a particular origin-destination pair (r_w, s_w). This probability quantifies the attacker's likelihood of navigating the network without encountering fortified egresses along the chosen path. Eq. (6.6) guarantees that each room in the network is assigned to precisely one egress, ensuring that all areas are accounted for in the attack strategy. Eq. (6.7) requires that at least one egress is damaged or destroyed by the attacker, indicating their intent to cause harm. Eq. (6.8) and Eq. (6.9) are flow conservation constraints for the attacker. Eq. (6.8) ensures that the sum of the attacker's decision variables k_{ij} and u_{ij}, representing the attacker's flow on link $(i, j) \epsilon A$, is equal to 1 where all links leaving node s_w. This ensures that the attacker enters the network at a designated node (such as an entry point in the school building) and exits through one of the assigned egresses j. Eq. (6.9) ensures that flow conservation is maintained across all intermediate nodes. Eq. (6.10) ensures that the total number of damaged or destroyed egresses equals the probability of an attacker damaging an egress. This constraint ensures that a sufficient number of egresses are fortified to protect against potential damage caused by an attacker. Eq. (6.11) allows the attacker to target unfortified egresses exclusively, and the final set of constraints, Eq. (6.12) – Eq. (6.15), define the variables' domain on the decision variables.

6.4. Numerical Implementation

A case study is conducted on a typical Australian school building to demonstrate the applicability of the proposed approach. The case study was designed to represent an average school, contemplating factors such as room size, number of students, and hallway dimensions (Parisi & Dorso, 2005). A modular multi-room environment with a single-floor corridor and multiple rooms was used, as depicted in Figure 6.4(a). Figure 6.4(b) shows the representation of the network graph of the school. There are 20 nodes, including 12 classrooms, 3 egresses, 2 WC, 2 Labs and 1 leisure area. The student population was selected to represent a mid-size school with a range of 361-540 students (Heliövaara et al., 2012). The problem is modelled in this case as protecting a school from potential attackers, where the model considers the objectives of both the defender (in charge of protecting the school) and the attacker (seeking to cause damage or destruction).

a)

b)

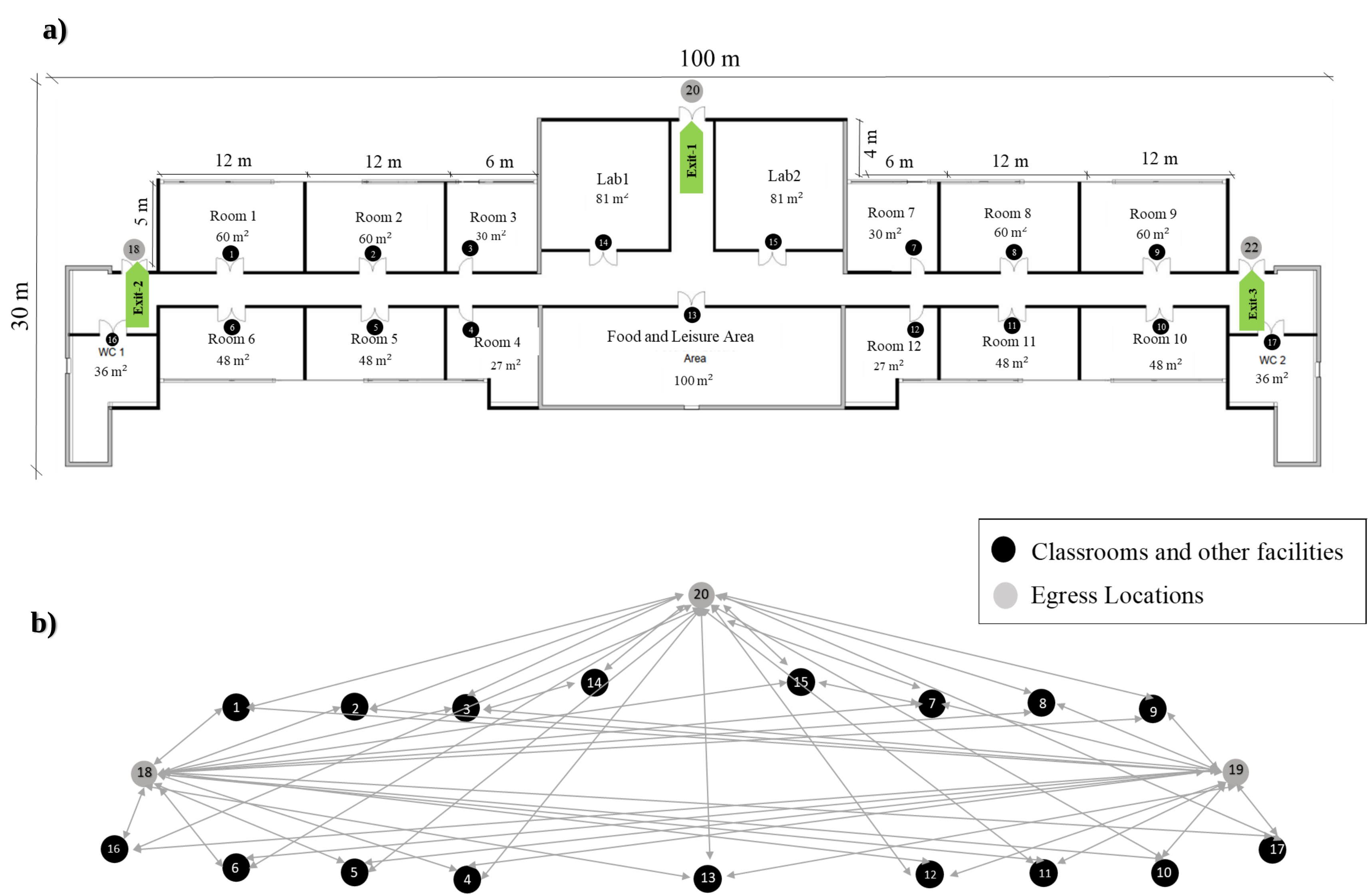


Figure 6.4: (a) The typical school layout; (b) representation of network graph for school layout.

As mentioned in Section 6.2, the attacker selects a path with knowledge of the locations of the fortified egresses. The attacker also knows the probabilities of damage, p_{ij} and q_{ij}, for each $(i, j) \epsilon$ A. The values of p_{ij} and q_{ij} are essential parameters in the model, representing the probability of damage to the network. The attacker also knows the location of all the fortified egresses, x_{ij}, for each $(i, j) \epsilon$ A, as well as the damage probabilities on each link $(i, j) \epsilon$ A.. However, the determination of specific values for p_{ij} and q_{ij}, as well as the precise characterization of the attacker's behaviour, is not the focus of this study.

Furthermore, both the defender and the attacker possess knowledge of the network $G(A, N)$. They are aware of the existence of a path between $r_w - s_w$ for all w ϵ Ω, where Ω represents the set of origin-destination pairs. It is important to note that Ω does not contain any additional information about the specific type of attacker under consideration. The sequence of decision-making and events unfolds as follows: Initially, the defender fortifies egresses on selected network arcs. Subsequently, a random origin-destination pair is revealed, and the evader w strategically selects a $r_w - s_w$ path with the intention of maximising the probability of causing damage. Notably, the attacker selects this path while fully aware of the locations of fortified egresses and the associated probabilities of damages. The model, as described, is designed to reinforce safeguarding particular egress points by leveraging secure links within the network. Besides, the model incorporates a set of potential origin-destination pairs, and its stochastic nature arises from utilising a probability mass function to determine these pairs. To illustrate the model, consider the network graph in Figure 6.5(b), which comprises 20 nodes, including 3 egresses. Table 6.2 provides a summary of the input for each link $(i, j) \epsilon$ A. In this example, the defender is concerned with the possibility of at least one egress being attacked. In addition, the cost value of c_{ij} is uniformly set to 1 for all link pairs (i, j) within the network. The budget (cardinality) constraint is enforced with equality due to the existence of an optimal solution that entails equipping sensors at b designated locations.

Table 6.2: Input data for each links in the network.

Links	q_{ij}	p_{ij}	***Links***	q_{ij}	p_{ij}	***Links***	q_{ij}	p_{ij}
(1, 18)	0.8	0.6	(1, 20)	0.8	0.6	(1, 22)	0.8	0.6
(2, 18)	0.9	0.7	(2, 20)	0.9	0.7	(2, 22)	0.9	0.7
(3, 18)	0.7	0.6	(3, 20)	0.7	0.6	(3, 22)	0.7	0.6
(4, 18)	0.8	0.7	(4, 20)	0.8	0.7	(4, 22)	0.8	0.7
(5, 18)	0.7	0.6	(5, 20)	0.7	0.6	(5, 22)	0.7	0.6
(6, 18)	0.8	0.5	(6, 20)	0.8	0.5	(6, 22)	0.8	0.5
(7, 18)	0.7	0.6	(7, 20)	0.7	0.6	(7, 22)	0.7	0.6
(8, 18)	0.7	0.5	(8, 20)	0.7	0.5	(8, 22)	0.7	0.5
(9, 18)	0.8	0.6	(9, 20)	0.8	0.6	(9, 22)	0.8	0.6
(10, 18)	0.8	0.6	(10, 20)	0.8	0.6	(10, 22)	0.8	0.6
(11, 18)	0.7	0.5	(11, 20)	0.7	0.5	(11, 22)	0.7	0.5
(12, 18)	0.7	0.6	(12, 20)	0.7	0.6	(12, 22)	0.7	0.6
(13, 18)	0.8	0.6	(13, 20)	0.8	0.6	(13, 22)	0.8	0.6
(14, 18)	0.8	0.6	(14, 20)	0.8	0.6	(14, 22)	0.8	0.6
(15, 18)	0.9	0.6	(15, 20)	0.9	0.6	(15, 22)	0.9	0.6
(16, 18)	0.9	0.5	(16, 20)	0.9	0.5	(16, 22)	0.9	0.5
(17, 18)	0.8	0.6	(17, 20)	0.8	0.6	(17, 22)	0.8	0.6

Data Source: Illustration proposes only.

Implementing the proposed stochastic bilevel mathematical model utilizes state-of-the-art Python-based software tools, namely Pyomo and PAO. These open-source optimisation modelling languages serve as the foundation for the approach. Pyomo, built on the Python programming language, offers a flexible and extensible platform for modelling various optimisation problems, including the stochastic BP featured in this study. Its capacity to integrate diverse optimisation techniques and solver libraries makes it an adaptable solution for intricate problems.

As stated in Chapter 2, PAO, a Pyomo library, provides an intuitive interface to address bi-level optimisation problems. Equipped with multiple built-in algorithms, such as the nested optimisation approach, PAO plays a pivotal role in solving the stochastic BP at the heart of this research. This powerful tool collaboratively addresses the complexity of the optimisation challenge, covering decision variables related to both egress fortification and network design for room-to-egress movement. The model's practical applicability is demonstrated by applying it to a middle-sized school scenario. For computational prowess, the formidable CPLEX solver is a high-powered optimisation solver known for delivering swift and dependable solutions to intricate problems. The experiments were meticulously executed on a Windows 10 64-bit system, housing an i7 core processor, ensuring both computational efficiency and result accuracy.

6.5. Results and Analyses

In the case described in the previous sections, the defender initially fortifies the egresses as the attackers aim to cause maximum damage in the school building. A series of varied computational experiments were conducted to understand further the impact of parameter changes on the solved variables. These experiments highlighted the relationship between the defender's budget and the probability of damage in the fortified egress systems across different school sizes and layouts. Different structural characteristics are captured, such as the number and placement of egresses, connectivity of rooms, and potential obstacles.

Despite the variations in network designs, the results consistently demonstrated a clear relationship between the defender's budget and the probability of damage. A smaller budget in this study serves a specific purpose, enabling a focused analysis of the relationship between resource constraints and egress fortification strategies. The intentional selection of a modest budget directs attention towards gaining insights into how the optimisation model performs under controlled conditions. This conscious decision facilitates a thorough exploration of the model's response to limited resources and how it generates recommendations to optimise security outcomes within those constraints. Despite the smaller budget, the consistent patterns observed across different scenarios emphasise the robustness of the model's findings. This consistency underscores the relevance of the results, demonstrating that insights derived from analysing a scenario with a smaller budget can be applied to situations with larger resource allocations. Subsequent studies can involve analyses at varying budget levels to provide a comprehensive understanding of the model's behaviour across different resource scenarios. This approach establishes a foundation for comprehending egress fortification strategies adaptable to real-world scenarios with varying resource availability.

The computational experiments revealed a clear trend, as depicted in Figure 6.5. The relationship between the defender's budget and the probability of damage was examined using a range of budget values from 0 to 26. The upper bound of 26 was chosen for the budget range to encompass a broad spectrum of potential budget allocations, allowing exploration of the full range of budget scenarios that could be realistically encountered in practical situations. The results demonstrated that as the defender's budget increased, the probability of damage decreased. This relationship was observed throughout the entire budget range. For example, when the defender had no budget, the probability of damage was approximately 61.4%. However, as the budget increased to 24, the probability of damage dropped significantly to around 5%. This substantial reduction in the probability of damage highlights the critical role of allocating sufficient budget to fortify egresses, as it directly contributes to lowering the likelihood of damage.

Several numerical comparisons were made to quantify the impact of budget changes further. When comparing the probability of damage between a budget of 0 and 4, the reduction was approximately 16.5%. Increasing the budget from 4 to 12 resulted in an additional reduction of approximately 11.4% in the probability of damage. Furthermore, increasing the budget from 12 to 24 led to a further reduction of approximately 5.8%. These numerical comparisons demonstrate the significant impact that changes in the defender's budget can have on reducing the probability of damage.

The experiments investigated the relationship between the defender's investment level and the attacker's probability of causing damage. The analysis demonstrated that the probability of damage decreased rapidly up to a budget of 4 and then continued to decrease at a slower rate as the budget increased further. This finding suggests that investing in egress systems up to a certain point can significantly reduce the probability of damage. However, beyond a budget of 24, the experiments revealed diminishing returns in reducing the attacker's probability. This indicates that additional investments may not provide substantial benefits in terms of risk reduction. It could be due to factors such as implementing highly effective fortification measures at lower budgets, or the limited incremental improvements achieved by further investments. As a result, decision-makers should consider alternative risk management strategies, including emergency preparedness and response planning, to further mitigate the risk of damages.

Moreover, the data show that the most significant reduction in the probability of damage occurs in the lower range of defender budgets. Investing in fortified egress systems when working with limited budgets is essential. The findings can be further enriched by discussing potential trade-offs between different security measures, the role of attacker behaviour, or the implications of varying threat scenarios. This would add depth to the analysis and demonstrate a more nuanced understanding of the results. Overall, Figure 6.6 highlights the importance of investing in fortified egress systems to reduce the risk of damage during emergencies. By understanding the relationship between the defender budget and the probability of damage, decision-makers can make informed choices about allocating resources to ensure the safety and security of occupants in buildings and structures. For instance, organisations with limited resources may need help allocating sufficient funds to fortify egresses. However, intentionally using a smaller budget was a deliberate choice to conduct a controlled analysis of the relationship between budget constraints and egress fortification strategies. This approach allows a focused examination of the model's behaviour under constrained conditions. The further explanation can be that while the budget size used in the study may appear small, the consistent patterns observed across different scenarios underscore the robustness of the model's findings and applicability to larger resource allocations. On the other hand, organisations with a substantial budget may only benefit from spending some of their resources on fortifying egresses. Instead, they need to identify the optimal budget that maximises the reduction in the probability of damage. Thus, the results provide insight into the trade-off between cost and risk and can help organisations make informed decisions on budget allocation.

One of the model's limitations is that it assumes a fixed budget for fortifying egresses, which may only sometimes be the case in real-world situations. In addition, the model only considers the case of a single school, whereas, in practice, multiple schools or other public facilities may need to be protected simultaneously. Another area for improvement is that the model assumes a uniform attacker strategy, which may not reflect the real-world variability of attack scenarios. Furthermore, the model does not consider the budget allocation strategies for both outsider and insider threats separately and considers the potential interactions between the two types of threats. Future research can address these limitations.

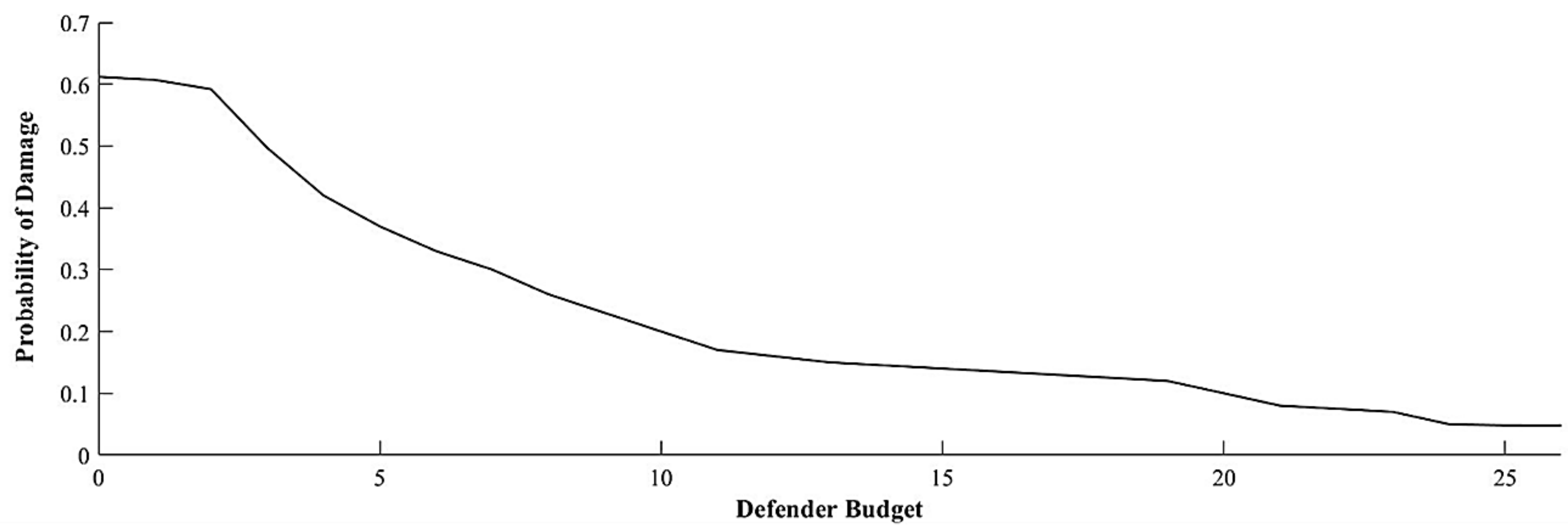


Figure 6.5: The relationship between the probability of attacker damage and the available defender budget.

6.6. Concluding Remarks

This chapter introduced a mathematical approach to safeguarding egresses in buildings for secure evacuations during emergencies and potential attacks. The developed stochastic BP model considers both defender and attacker objectives simultaneously, aiming to minimise building damage from the defender's perspective and maximise potential damage from the attacker's viewpoint. The model introduces uncertainty through probabilistic elements, which impact both the defender’s and attacker’s decision-making processes, making the model more realistic and applicable to situations with uncertain parameters or outcomes. The practical significance lies in its application to emergency management and security planning. By illustrating the model's efficacy using a middle-sized school scenario, it provides actionable strategies for decision-makers.

The results emphasize the direct relationship between budget allocation and damage probability reduction, highlighting the cost-effectiveness of mitigation strategies. Incorporating budget constraints and fortified egress requirements enhances the model's real-world applicability. This research informs optimal budget allocation, guiding fortified egress strategies to minimise damage while maximising protection. It holds practical significance by providing actionable insights for decision-makers in emergency management and security planning. This chapter and the preceding discussions advance understanding of fortified egress strategies, supporting the broader goal of bolstering public safety against evolving threats.

Chapter 7

Conclusions and Future Directions

7.1. Thesis Summary

This thesis is dedicated to improving the effectiveness of evacuation planning and operational efficiency within public buildings, particularly schools. The primary objective is to prioritise and enhance the safety of individuals, safeguard assets, and protect the environment in response to various challenges, including natural disasters and potential threats. Chapter 2 encloses a systematic approach tailored to address the complexities of evacuation planning during emergencies in school buildings. It strongly emphasises the imperative task of thoroughly understanding the distinctive attributes of each specific emergency event, including considerations related to egress locations and fortifications within buildings. It clarifies how these unique event characteristics play a pivotal role in shaping the development of evacuation strategies tailored to specific circumstances, thus increasing their effectiveness and success. Later, Chapter 3 encompasses various quantitative approaches rigorously evaluated for their suitability in addressing evacuation challenges. It provides detailed descriptions of selected methods and their step-by-step implementation. The chapter introduces three distinct frameworks for improved evacuation strategies. Framework-I incorporates multi-objective programming with BIM-ABM simulation, optimising evacuation planning by considering multiple objectives and simulating evacuation processes using BIM and ABM. Framework-II employs an MCDM to select suitable evacuation strategies based on multiple criteria and alternatives, enhancing decision-making efficiency. Framework-III adopts a BP approach to optimise strategic and tactical decisions, resulting in more robust and adaptable evacuation strategies.

In Chapters 4, 5, and 6, the developed solution methods and practical case studies provide more effective solutions to the complex optimisation and decision-making challenges of evacuation planning. In addition, the chapters demonstrate the procedures used to solve the proposed models, integrating computational methods and techniques to analyse and optimise evacuation strategies. Consequently, the chapters establish the foundation for developing context-specific evacuation plans that elevate public safety and emergency preparedness. The thesis finalises with the conclusion Chapter to provide an overall research summary to enhance evacuation strategies in various public buildings, ensuring the well-being of occupants in times of crisis.

In summary, this thesis presents a practical framework for improving evacuation planning in public buildings, explicitly focusing on addressing the complexities of emergencies in school buildings. It accomplishes this by integrating advanced methodologies and computational techniques, emphasising optimising egress locations and fortifications. This research aims to provide a systematic and data-driven approach to enhance public safety during evacuations by optimising strategies based on different scenarios. The framework equips public building stakeholders with tools to improve crisis response, reduce evacuation times, optimise egress locations, fortify buildings, and mitigate risks, contributing to community resilience and security.

7.2. Key Research Findings

The investigation conducted in this thesis has yielded significant insights and contributions to the field of evacuation planning and safety management in public buildings, with a specific focus on school buildings. Through an exhaustive exploration of various methodologies and approaches, the research formulates practical strategies that prioritise human lives, safeguard assets, and protect the environment during emergencies.

One of the key findings of this study is the development of novel methodologies that specifically address the complex challenges of evacuation planning within the context of school buildings. Integrating multi-objective programming with BIM-ABM simulation, as demonstrated in Framework-I, has shown promising results in optimising evacuation strategies by simultaneously considering multiple objectives and simulating evacuation processes. This approach enhances decision-making by providing a comprehensive view of evacuation scenarios and potential outcomes tailored to the unique circumstances of school buildings.

Furthermore, applying an MCDM, as presented in Framework-II, enables the selection of evacuation strategies based on various criteria and alternatives, significantly enhancing decision-making efficiency. This approach strongly emphasises prioritising safety and well-being amidst uncertainties and diverse considerations inherent to emergency evacuation planning within school buildings. Adopting a BP in Framework-III highlights the critical importance of optimising both strategic and tactical decisions in formulating adaptive evacuation strategies. By considering both Defender and Attacker perspectives, this approach ensures the safety of building occupants during evacuations, even in the face of potential threats specific to school environments. The research also underscores the vital role of computational methods and algorithms in effectively addressing the complex optimisation and decision-making challenges associated with evacuation planning in school buildings. The development of solution methods enhances the practical applicability of the proposed methodologies and reinforces their potential impact in real-world emergency scenarios.

In summary, the findings of this research contribute significantly to advancing the understanding of evacuation planning within school buildings, providing valuable tools and insights to enhance safety and preparedness during emergencies. By prioritising the safety of occupants, assets, and the environment, the methodologies presented in this thesis offer practical and context-specific solutions to address the unique challenges of evacuation in school settings. These findings can make a meaningful and tangible impact in the field of emergency planning and safety management within public buildings, particularly school buildings.

7.3. Limitations of the Thesis

Despite the major contributions presented in this thesis regarding evacuation planning and safety management in public buildings, certain limitations warrant consideration. These limitations provide opportunities for future research and highlight the boundaries within which the findings should be interpreted.

Firstly, developing more advanced ABMs provides a nuanced understanding of human behaviour variability during emergencies. By capturing individual actions and reactions under stress, these models offer a more accurate portrayal of evacuation dynamics and guide the formulation of more effective strategies. This approach aligns with the recognition that real-world variability often extends beyond the scope of simplified assumptions. In addition, validation studies using real-world data and historical evacuation incidents is invaluable in enhancing the reliability of the proposed strategies. These studies can enable a rigorous assessment of model predictions against actual outcomes, identifying areas of discrepancy and offering insights into necessary refinements. Besides, the computational complexity associates with specific methodologies, such as MOO and the stochastic BP, poses scalability challenges, urging the exploration of streamlined algorithms and software.

Collaborative integration among various stakeholders, including emergency responders and medical teams, demands attention for obtaining more sophisticated approaches. Developing simulation models that accurately reflect the complex interactions and joint response efforts could yield more effective and coordinated evacuation plans, acknowledging the interdisciplinary nature of the emergency response. Considering the evolving nature of security threats and technological advancements, long-term adaptation strategies should also be explored. Investigating strategies that can flexibly adapt to changing scenarios and innovations would ensure the continued relevance and effectiveness of the proposed methodologies over time. Lastly, ethical considerations and public acceptance of proposed evacuation strategies warrant careful examination. Understanding public perceptions, concerns, and willingness to comply with security measures can guide the implementation of strategies while upholding ethical standards. In sum, while this research significantly advances evacuation strategies, these limitations underscore the importance of future investigations to refine and broaden the applicability and effectiveness of the proposed methodologies.

7.4. Recommendations for Future Work

The recommendations for future work extend a comprehensive roadmap for advancing the domain of evacuation planning and safety management in public buildings. To build upon the current research, several avenues of exploration are suggested that hold the potential to elevate the efficacy of evacuation strategies further and enhance public safety.

Firstly, integrating psychological and cultural factors into the proposed methodologies, as discussed in Chapter 5, presents an exciting opportunity. Incorporating human behaviour nuances, such as panic tendencies and cultural differences in response to emergencies, can significantly enhance the accuracy and realism of evacuation models. By capturing these intricate elements, future research can contribute to more tailored and effective evacuation strategies that cater to diverse occupant demographics. Furthermore, a multi-story building could give additional insights into the evacuation process in buildings, as mentioned in Chapter 4. Likewise, leveraging real-world data from past events can enhance evacuation predictions' accuracy and aid decision-makers in real-time emergency response. Incorporating such data sources can lead to more adaptive and responsive evacuation plans, ensuring occupants' safety in rapidly evolving emergency scenarios.

Considering the ever-growing threats, extending the scope of evacuation planning to include the risk of attacks on building systems is recommended, as highlighted in Chapter 6. Future studies can explore methodologies to integrate security considerations into evacuation strategies. By addressing the vulnerabilities posed by any threats to building systems during emergencies, researchers can contribute to a holistic approach that safeguards occupants from both physical and virtual risks. Collaboration across disciplines is crucial for the advancement of evacuation planning. Therefore, integrating AI algorithms and harnessing big data analytics can further advance evacuation planning research. By leveraging advanced computing techniques, researchers can analyse large datasets, identify patterns, and optimise evacuation strategies more efficiently. This data-driven approach can refine the accuracy of evacuation models and lead to more effective decision-making during emergencies.

Ethical considerations play a pivotal role in emergency planning. Hence, future research should delve into developing ethical frameworks that guide decision-making processes. These frameworks help ensure that evacuation strategies prioritise the well-being of occupants and adhere to moral principles. Integrating ethical dimensions into evacuation planning can lead to more responsible and people-centric emergency management. Adaptability is critical in evacuation planning, as each public building context may present unique challenges. Future research should tailor and adapt methodologies to different building types, occupant profiles, and local conditions. By considering these contextual variations, researchers can develop strategies that are effective and aligned with the specific requirements of different public buildings.

In conclusion, embracing these recommendations will enable future research to propel the field of evacuation planning and safety management to new heights. By integrating psychological insights, real-time data, security considerations, advanced technologies, ethical frameworks, and contextual adaptations, researchers can contribute to more resilient, adaptive, and effective evacuation strategies. Through collaborative efforts and interdisciplinary approaches, the domain can evolve to ensure the safety and well-being of occupants in diverse public buildings during emergencies.

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